Multisensor Data Fusion Technique For Environmental Awareness In Wireless Sensor Networks

Reyana A*[1], Vijayalakshmi P[2]

[1]*Assistant Professor: Department of Computer Science and Engineering, Hindusthan College of Engineering and Technology, and Scholar, Anna University*
[2]*Professor: Department of Electronics and Communication Engineering, Hindusthan College of Engineering and Technology Coimbatore, Tamilnadu, India*

Email: [1]reyareshmy@gmail.com

Abstract
Sensing in forest area is the most widely used application concerning investigation studies of climate change. Wireless sensor networks with spatially scattered sensors enable the application to record climate change disturbance detecting condition changes in temperature, humidity, sound, wind, etc. The highly automated method herein can pass the observed information bi-directionally to the system sink, empowering sensor activity control. It is common knowledge that a multisensor environment has hundreds or thousands of sensor nodes connected. With recent innovations, the remarkable challenge faced in a multisensor climate is to rapidly acquire specific information from a reliable route exhibiting high data accuracy. This proposed ADKF-DT-MF algorithm for multisensor data fusion combines sensor information in-continuous time, providing a rapid information exchange on climate change for environmental awareness. The findings significantly show a better RMSE of 0.85 than the previous results reported in the literature MHT-EnKF. The quality of estimation was explored, calculating the best costs, ensuring an increase in data fusion accuracy for active awareness. The tests on simulated data applying fuzzy membership optimization function show improvement in the ADKF-DT-MF multisensor fusion system's performance.

Keywords-fuzzy optimization; multisensor fusion; environment; decision tree; temperature;

1. INTRODUCTION

In a multisensor environment, the sensor nodes on continuous-time observation produce a tremendous amount of data. The sensors employed in WSN on exhausting battery power generate erroneous data causing inaccurate measurements. Even though their occurrences are seldom, many sensors misinterpreted false trigger alarms in critical applications. Monitoring natural traits like temperature and humidity are imperative for evaluating climate change. Remote sensing applications face a crucial issue in transmitting the information from sensors in a continuous-time period to the gateway nodes for processing. Correspondingly, sensor nodes are subject to low memory and processing limitations. Currently, the radio-equipped in WSN reports incomplete information to the base station for appropriate action. Eventually, the data transmitted is noisy and inaccurate. Techniques to solve this are computationally demanding in energy and operational lifetime [1] and [14].

Until now, the multisensor data fusion technique is broadly used in image processing, intelligent system design and sensor networks, etc. [1]. Taking advantage of various applications monitoring forest environment has a significant role in supporting detecting agency to make real-time decisions with climate change instead of post-event examination [5]. Ongoing environmental changes have a potential risk in monitoring and anticipating changes to avoid negative consequences [10]. Climate change will inevitably be an issue that influences the forest ecosystem [3]. Current solutions are inadequate to rapidly report threats like wildfire, storms, pest outbreaks, and drought [11], affecting the forest's growth and productivity directly and indirectly. Hence an intensive approach is required to gather observations to assess the forest ecosystems [16].

The primary objective is to implement an Adaptive Decentralized Kalman Filter with Decision Tree (ADKF-DT-MF) Algorithm to combine the sensor information in continuous-time. The detecting parameters temperature and humidity considered are highly relevant to the climate change context. The central objective is calculating the shortest path, receiving accurate data for rapid response, increasing the overall system performance. Also, optimizing and improving performance results in monitoring and fast decision-making in climate change utilizing the multisensor fusion data for applying the fuzzy membership optimization function and improving the overall performance of the multisensor fusion system, fulfilling the objective of the research described.

In this paper, an intricate decision-making system required for reliable condition monitoring is focused. The objective is to develop a decision-making system for situation refinement in a multisensor fusion environment with optimization capabilities. It prevents data estimation delays on the fusion center's side, helping to incorporate knowledge using a decision tree tool. If any of the sensors fails, the information on the current state is incomplete. Hence optimization here ensures low sensing cost calculating the best path. The environment condition is based on the information obtained from the sensors [6]. The rest of the paper's section is organized into Section 2, reviews the various multisensor fusion techniques. Section 3 describes in detail the proposed methodology. Section 4 discusses the simulation results and analysis. Finally, Section 5 presents the conclusion and scope for future improvement.

2. RELATED WORKS

Multisensor based surveillance system has several issues related to difference inaccuracy due to i) data/tracking association and ii) fusion/state estimation. In [18], the authors proposed a modified MHT-EnKF an Enhanced Kalman Filter to deal nonlinearity scenarios in multisensor fusion. The utilized MHT-EnKF realized the low precision observation and calibrated them to high precision. Though the MHT-EnKF was suitable for real-time computations, the data fusion considered only one sensor monitoring each observation step. The authors point on identifying future research on multisensor information fusion problem where several sensors target one source is found as a significant focus in this research. The authors [2] proposed a novel softmax regression model to check the HVCB vibration of different locations to diagnose evidence fusion state for fault diagnosis. The classification proposed uses vibration information to gather various position measures, and the proposed approach showed reasonable accuracy calculation. In [7] proposed a method for classifications of indoor navigation magnetic field conditions using a decision tree. The model measured the analyzed data to obtain the magnetic field's interference for finding the right geomagnetic fields. Then, the Kalman Filter fused the gyroscope and processed the magnetic field. The proposed DT+Kalman reduced the heading angle errors and smaller magnetic anomalies. [12] The evidential decision trees of the iris dataset using classify samples. The wine dataset generates the evidential decision tree for classification. The approach showed an average accuracy of 95%**.** However, the emergence of systems with many (small) sensors justifies a revisit to

MSDF architectures' topic, having in mind their strategic importance related to MSDF classification and optimal selection [9]. The proposed ADKF-DT-MF is the extension of a decentralized Kalman filter. Further, the system utilizes fuzzy-based decision tree optimization to improve the considered complex multisensor fusion environment's performance.

3. METHODOLOGY

To identify the threats, it is necessary to gain knowledge of the observed environment. To solve this issue, the sensed data are to be classified. Considering the wireless sensor environment built with several nodes, sensing of temperature and humidity is required to perform multisensor data fusion in a forest environment. The proposed ADKF-DT-MF (Adaptive Decentralized Kalman Filter-Decision Tree-Multisensor Fusion) algorithm is the hybridized combination of the Decentralized Kalman Filter and Decision Tree algorithm. The ADKF-DT-MF algorithm is tailored to collect temperature and humidity information from different sensors combining in continuous-time and evaluating the cost-efficient shortest path to provide accurate environmental awareness. Due to the environmental complexity, the temperature and humidity are the unique features whose characteristics can be effectively used for several applications. The framework of the proposed system is depicted in Fig. 1.

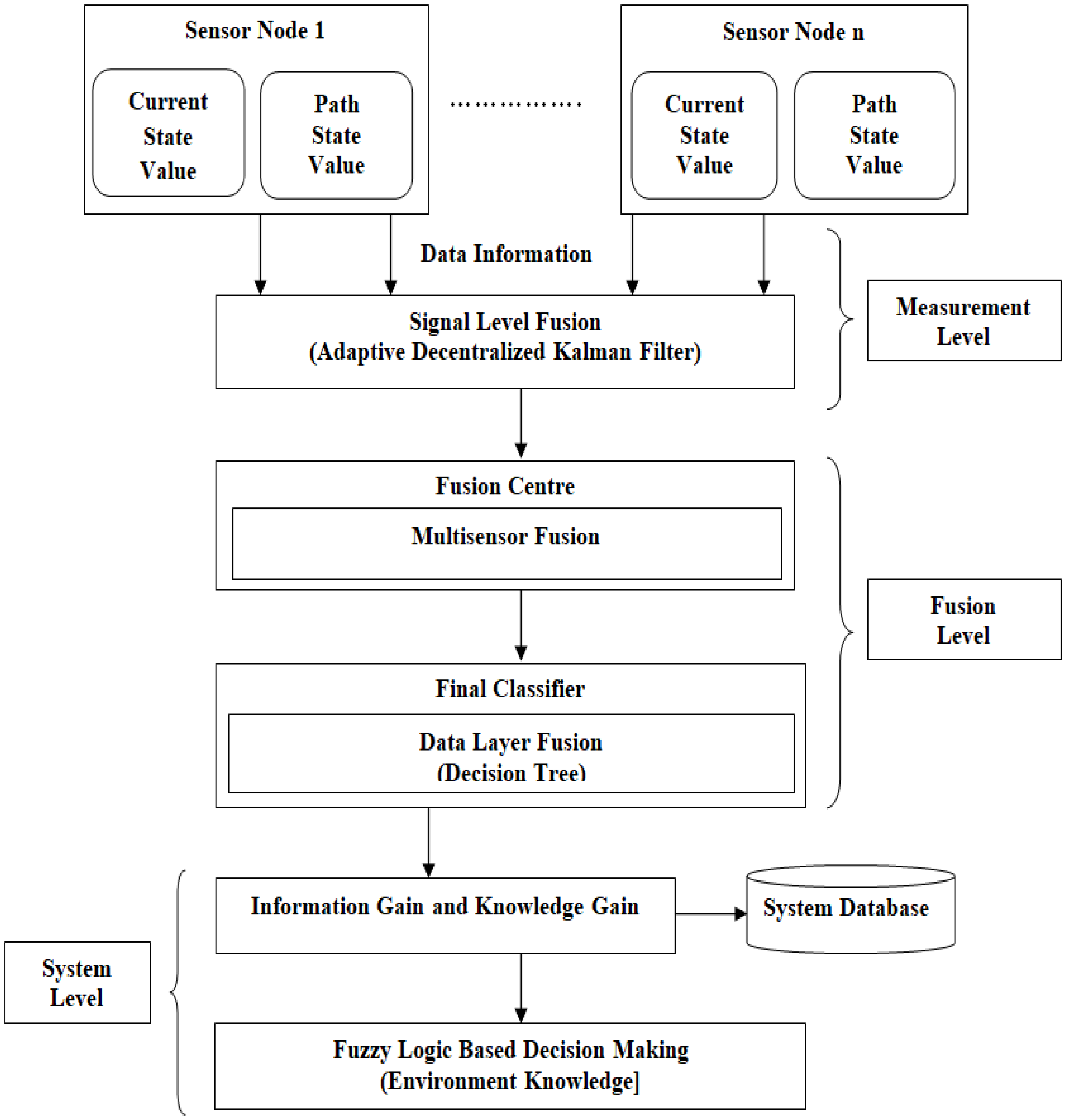

Figure 1. Framework of the proposed ADKF-DT-MF system

European Journal of Molecular & Clinical Medicine
ISSN 2515-8260 Volume 07, Issue 08, 2020

Fig. 1 comprises sensor nodes transmitting the temperature and humidity change variations as local estimations to the sink node. The fusion algorithm combines data streams from different sensor nodes. Energy consumption for data transmission depends on the data packet's size and the distance between the sender and receiver. The Adaptive Decentralized Kalman Filter applied at the sink node calculates the global estimation. The algorithm is fixed with predefined parameters and functions, identifies the adjacent and cost-efficient shortest path to the sink node synthesizing accurate data in information fusion, and interprets a series of continuous-time awareness on climate change. This approach provides accurate data from predefined paths irrespective of sensor failure. The fusion center performs the fusion operation. The signal level fusion stage calculates the optimal estimation, keeping track of the sensor's estimated state and its uncertainty. The parameters inferred could be inaccurate and uncertain observations. The filter performs recursive evaluation with the incoming evidence producing estimates of the state. The filter's input is the system measurement, and the output is the estimated system state [15]. The filter's dynamic model calculates periods between sensor outputs and incorporates multiple sensor measurements sequentially for data fusion. It also deals effectively with uncertainty from the covariance calculated while transmitting noisy sensor data observed within the boundary limits to determine the sensor state [8]. The proposed filter advances previous methods as measurements need not be inverted, making it convenient for real-time processing. To do this, the filter entails calculating timeframes between multiple sensor measurements for information fusion. Likewise, the experiment continues to manage uncertainty from the covariance calculated in Equation (1).

$$Cov(x1, x2) \equiv E(x1 - \overline{x1})(x2 - \overline{x2}) \quad (1)$$

Where x1 and x2 are random variables. At this point, the transmission of data within the boundary limits determines the sensor state. The system makes observation z with Gaussian noise w

$$z(k) \equiv H(k)x(k) + w(k) \quad (2)$$

Where, x (k), the system state vector, and w (k), unknown zero mean.

In the methodology, the subsequent steps are used for information fusion from different sensors in continuous-time. The initial step is the Base Network Configuration configured with 50 nodes connected in a star topology. Subsequently, the distance to the Previous Node improves network performance by verifying the shortest path's accuracy. The resulting is the information fusion using the Adaptive Decentralized Kalman Filter algorithm, as depicted in Fig. 2.

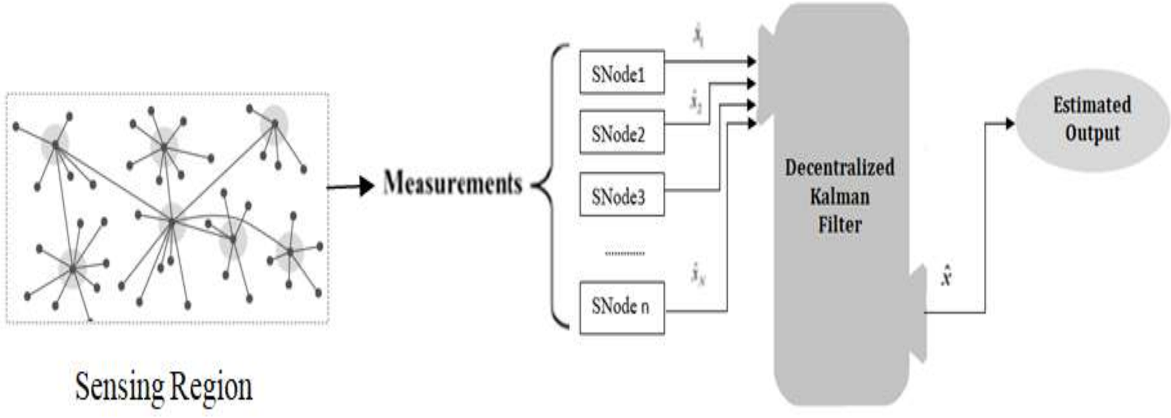

Figure 2. Process of Adaptive Decentralized Kalman Filter

The Decision tree classification in multisensor fusion shown in Figure 1 can successfully solve problems on the sink node side. The data obtained from different sensors on different observations combined using algorithms in a multisensor data fusion system. On identifying the shortest path to the sink, the node reduces the communication traffic. The Decision tree classification determines whether sensor nodes' temperature and humidity rate are in acceptable range on comparing the input measurements with the desired range of sensors. The data classification technique determines predefined classes providing current event-based situational information in a network of sensor nodes. The predefined types are characterized by the attributes of the sensor output signals [17]. The decision tree classifies the forest weather parameters into maximum and minimum temperature, humidity, and speed values. The classification with a set of rules interprets and converts into a standard set of values for environment based situation refinement performing accurate decision making [13]. The decision making procedure is employed at the fusion center. Here the large data set is divided into multiple classes, organized into a hierarchical tree structure for efficient classification and decision making. Decision making shall handle sensor defects, missed out observations/decisions improving the system performance. Complex systems like climate change, forest fire, gas diffusion require reliable condition monitoring. The objective is to develop a decision-making system for situation refinement in a multisensor fusion environment with optimization capabilities. It prevents data estimation delays on the fusion center's side, helping to incorporate knowledge using a decision tree tool. If any of the sensors fails, the information on the current state is incomplete. Hence optimization here ensures low sensing cost calculating the best path [6]. Tests on simulated data carried out by applying the fuzzy membership optimization function show improvement in the multisensor fusion system's performance.

4. SIMULATION RESULTS AND DISCUSSION

In the condition-based environmental monitoring application, the parameters temperature and humidity are considered for the study. The real-time variations in temperature and humidity were sensed for one month and were utilized as a dataset. The simulation setup implemented in Matlab 2018(a) (Reference https://in.mathworks.com/), and the first set of analyses highlighted the base network configuration. This solution enhances previous methods by transmitting signal information from multisensors of similar type finding the best cost-efficient path to the remote-controlled base station. The ADKF-DT-MF (Adaptive Decentralized Kalman Filter-Decision Tree-Multisensor Fusion) algorithm speculates the pre-identified path of higher accuracy to perform rapid filter fusion and estimation.

The assumption here is that the sensor nodes directionally transmit the temperature and humidity change variations to the sink. Due to the environmental complexity, the temperature and humidity are the phenomenal features whose characteristics can be effectively used for several applications. The assumed parameters are depicted in Table 1.

Table 1. Parameter assumptions

Parameters Considered	**Range**
Temperature	−40°C to +120 °C
Humidity	0 to 100% RH
Signal to Noise Ratio	0 to 1
Region Boundary Range	100 x 100m
Number of Sensor Nodes	50
Number of Sink Node	1

First, we configured the Base Network Configuration with 50 nodes fixed statically in a WSN environment. The sensor nodes shown in Fig. 3 directionally transmit temperature and humidity change variations to the sink. The network congestion or traffic is not considered for the study. The range set is i) feasible range and ii) problem range. The feasible range lies within the communication radius i.e. the distance connecting the target pixel and the sensor. The problem range exists on the nodes in the boundary, range of 100 km². The feasible range estimate was 1.5 km for the considered scenario, and the problem range estimation was 4.53 km.

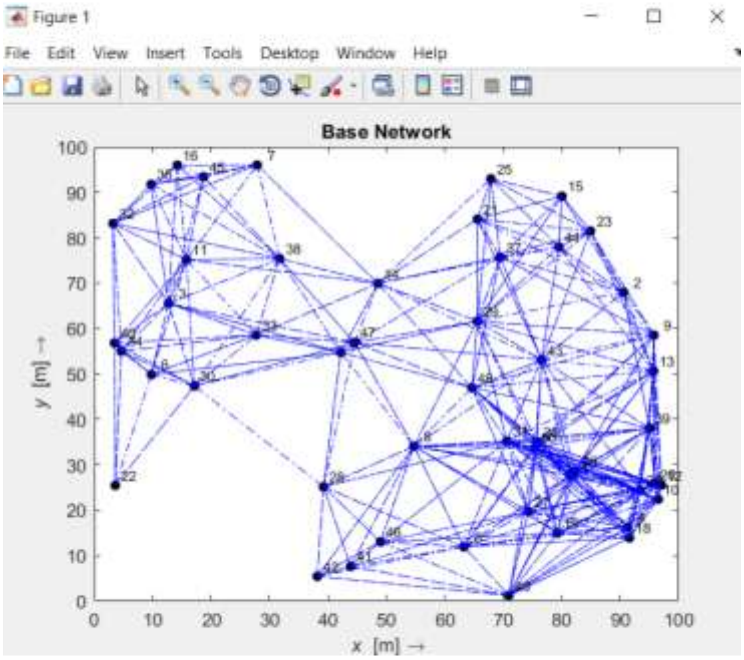

Figure 3. Base Network Configurations

Fig. 3. Show the initial network configuration with 50 sensor nodes. For estimation feasibility, the sensing boundary is fixed to 100m x 100m, with each node a minimum 5m to a maximum 10m distance from the base station.

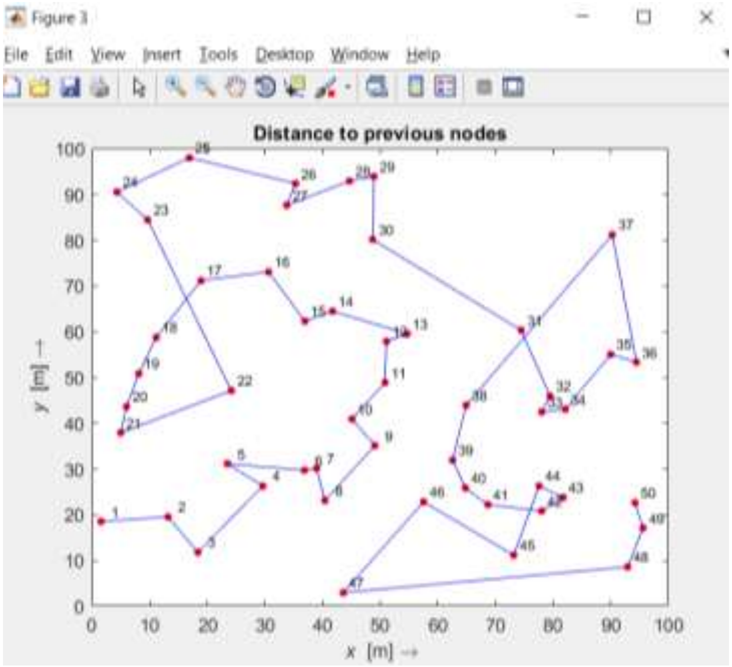

Figure 4. Knowing the Previous Node Distance

Fig. 4. The distance to the previous node improves the sensor network performance, identifies the nearest neighbor on scheming the distance from the last to the first node similarly from the first to the second node.

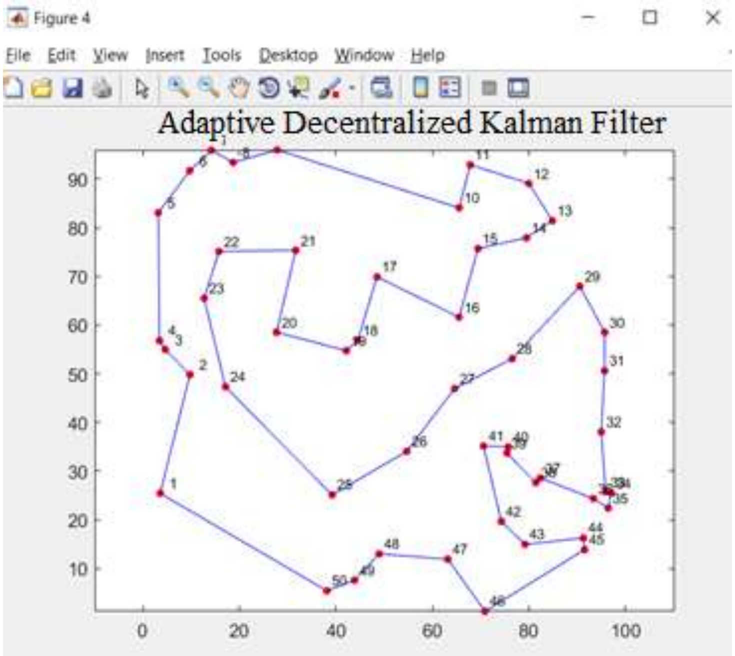

Figure 5. Adaptive Decentralized Kalman Filter Shortest Path Cost

Fig. 5. Show the Adaptive Decentralized Kalman filter based shortest path cost. This guarantees local estimation F_k by implementing a total of (n (n+1))/2 filters on all sensor nodes synthesizing n filter estimation f_k.

The relative certainty of the measurements and the current state estimate is significant to accomplish a fastidious performance. Each sensor node has local estimation transmitted to the nearby node in the predefined path. The sensor node carries its local estimation and the global estimation value transmitted throughout the path. The measurements need not be inverted, appropriate for real-time processing. Table 2 presents the Iteration's Best Cost. Here, node 35, 40, 45, and 50 maintain superior estimate. The best cost of distance is very minimum. The RMSE of 0.85 shows better than the existing MHT-EnKF tracking algorithm having RMSE of 0.56 [18], proving the performance of the algorithm shown in Figure 5 and Table 5.

TABLE 2. BEST COST PATH ESTIMATION

Iterations	**Best Cost1**	**Best Cost2**
1	2448.7512	2169.8609
5	1857.6746	1649.2223
10	1411.1342	1226.6465
15	1117.9864	1002.4892
20	893.9166	848.4576
25	729.6586	735.268
30	653.3597	653.0902
35	629	613.1793
40	629	602.501
45	629	602.501
50	629	602.501

Table 2. presents the best cost path estimation for node iterations.

The objective is to develop a decision-making system for situation refinement in a multisensor fusion environment. Hence, there is a need to provide the optimization capabilities to prevent data estimation delays on the fusion center's side, helping to incorporate knowledge using decision tree tools. If any of the sensors fails, the information on the current state is incomplete. Hence optimization here ensures low sensing cost calculating the best path. The environment condition is based on the information obtained from the sensors [9]. The tests on simulated data applying fuzzy membership optimization function show improvement in the performance's multisensor fusion system. The fuzzy-based decision tree model is used to adjust the signaling devices, respectively, to optimize the decision-making system. The fuzzy decision model considers the membership functions of the inputs and output shown in Figures 6, 7, and 8. According to this, they are three membership functions such as low, medium, high. The membership function is the degree for which the input belongs. The value varies between 0 and 1. The range of membership degrees of the proposed fuzzy model is shown in Table 3.

Table 3. Membership priority consideration rule table

No.	**Temperature**	**Humidity**	**Confident factor**	
1	High	High	Very High	First
2	High	Low	Low	Second
3	Medium	Medium	Medium	Second
4	Medium	High	Medium	Second
5	Low	Low	Very Low	Third
6	Medium	Low	Low	Third

Table 4. Range table

Function	Parameters	Range	low	Medium	high
Input 1	Distance	[0,n]	[n/5,0]	[n/5,n/2]	[n/5,n]
Input 2	Max Degree	[0,mD]	[0,mD/6,mD/3]	[mD/3, mD/2 ,mD*2/3]	[mD*2/3, mD*2.5/3, mD]
Output	Priority	[0,n]	[n/20,n/10]	[n/5, n/2]	[n/20, n-n/10]

Table 3. presents the inference rules related to membership priority calculations, and Table 4 shows the various range of tables such as low, medium, and high.

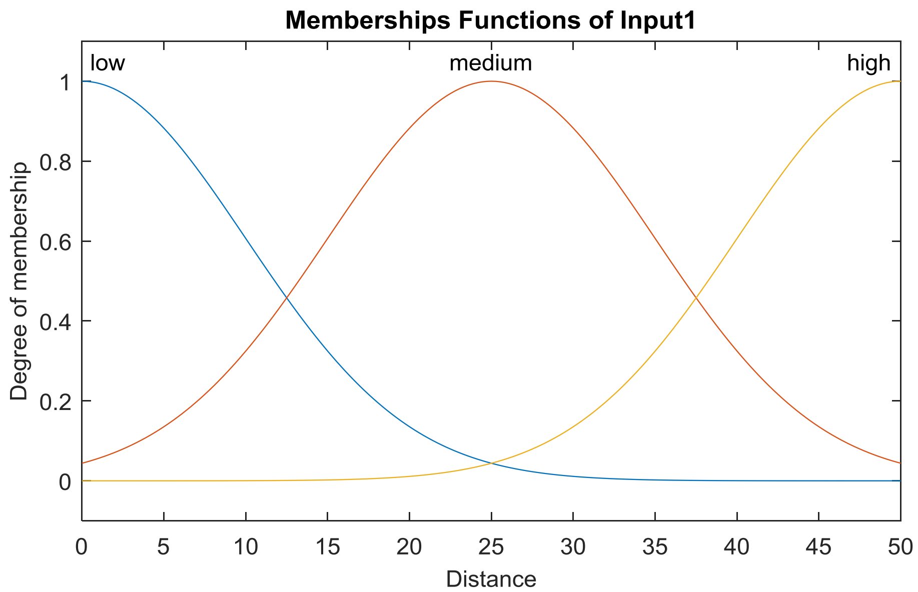

Figure 6. Membership Function of Input1 -Distance

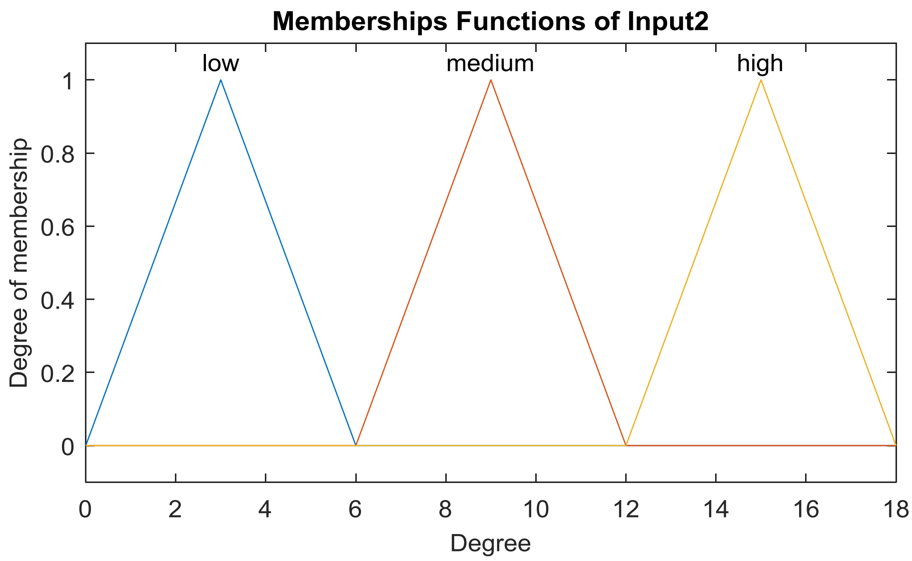

Figure 7. Membership Function of Input2-Degree

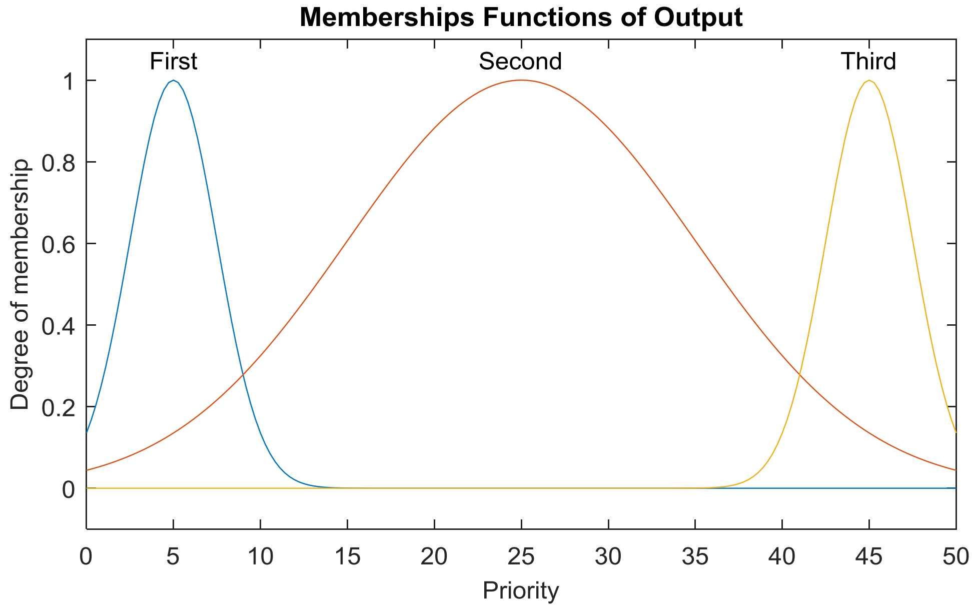

Figure 8. Membership Function of Output-Priority

The system is herewith processed, and the inputs and output membership functions are depicted in Fig. 6, Fig. 7, and Fig. 8. The membership functions exhibit priority transmissions based on the low, medium, and high degree and distance values. The decision tree algorithm is simple to understand and gives a suitable decision tree information discovery. Fig. 9 shows the decision tree's optimized view to form a rule in the phase time calculation of the proposed fuzzy model.

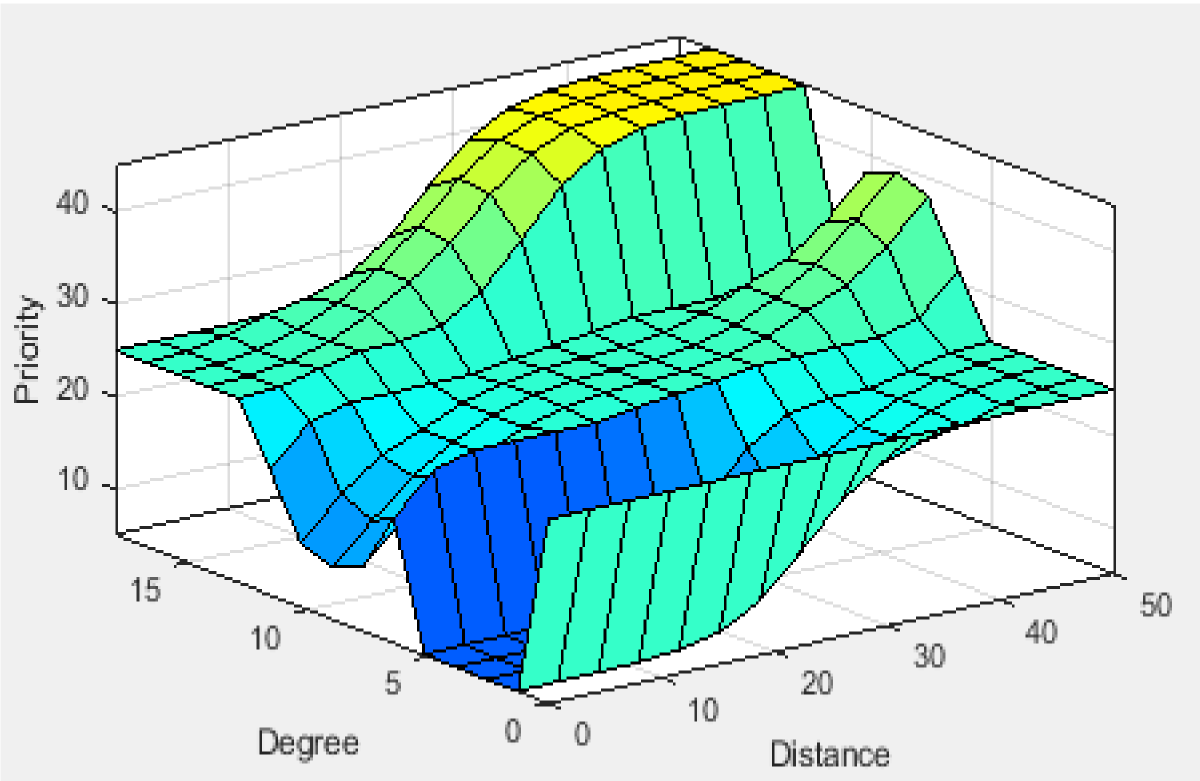

Figure 9. Optimized view of the ADKF-DT-MF Model

Table 5. Rmse performance evaluation

	Existing MHT-EnKF	**Proposed ADKF-DT-MF**
RMSE	0.56	0.85

Thus the ADKF-DT-MF algorithm is tailored to collect temperature and humidity information from different sensors combined in continuous-time and evaluate the cost-efficient shortest path to provide accurate environmental awareness. This solution enhances the previous method MHT-EnKF [18] by transmitting signal information from multisensors of similar type finding the best cost-efficient path to the remote-controlled base station. The performance results obtained in the Table 5 show that ADKF-DT-MF algorithm showing better multisensor data fusion compared to the MHT-EnKF [18] by carrying out real-time computing problems for the multisensor data fusion where several sensors can detect one target. Thus, the study implemented a complex multisensor environment to monitor and perform decision-making in climate change. The results are summarized by estimating the sensor's state, calculating the distance covered, obtaining the best cost for the iterations. The performance report of the few nodes depicted in table 2. The study enables us to detect the environmental changes using estimations for anticipating a change to avoid negative consequences.

5. CONCLUSION

Sensing in forest area is the complex and most widely used application concerning investigation studies of climate change. Wireless sensor networks with spatially scattered sensors enable the application to record climate change disturbance detecting condition changes in temperature and humidity. The highly automated method herein can pass the observed information directionally to the system sink, empowering sensor activity control. The proposed ADKF-DT-MF algorithm multisensor data fusion combines sensor information in-continuous time, providing a rapid information exchange on climate change for environmental awareness. The findings significantly show better RMSE of 0.85 than the previous results reported in the literature MHT-EnKF [18]. The performance improvement shown in the reported simulation result. The quality of estimation explored, calculating the best costs, ensuring an increase in data fusion accuracy for active awareness. Despite the promising results obtained for a reliable route with high accuracy, the optimization in processing efficiency and reduction in power consumption are the areas to focus on future research.

REFERENCES

[1] Abdulhafiz WA. Prof. Alaa M. KHAMIS. International Journal of Robotics and Automation. 2013; 28(2):112-22.

[2] Balta M, Özçelik İ. A 3-stage fuzzy-decision tree model for traffic signal optimization in urban city via a SDN based VANET architecture. Future Generation Computer Systems. 2020 Mar 1; 104: 142-58.

[3] Crowley MA, Cardille JA, White JC, Wulder MA. Multisensor, multi-scale, Bayesian data synthesis for mapping within-year wildfire progression. Remote Sensing Letters. 2019 Mar 4; 10(3):302-11.

[4] de Farias CM, Pirmez L, Delicato FC, Pires PF, Guerrieri A, Fortino G, Cauteruccio F, Terracina G. A multisensor data fusion algorithm using the hidden correlations in Multiapplication Wireless Sensor data streams. In2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC) 2017 May 16 (pp. 96-102). IEEE.

[5] Díaz-Ramírez A, Tafoya LA, Atempa JA, Mejía-Alvarez P. Wireless sensor networks and fusion information methods for forest fire detection. Procedia Technology. 2012 Jan 1;3: 69-79.

[6] Gerdes M, Galar D, Scholz D. Decision trees and the effects of feature extraction parameters for robust sensor network design. Eksploatacja i Niezawodność. 2017; 19(1).

[7] Hu G, Zhang W, Wan H, Li X. Improving the heading accuracy in indoor pedestrian navigation based on a decision tree and Kalman filter. Sensors. 2020 Jan; 20(6):1578.

[8] Jahja M, Farrow D, Rosenfeld R, Tibshirani RJ. Kalman Filter, Sensor Fusion, and Constrained Regression: Equivalences and Insights. In Advances in Neural Information Processing Systems 2019 (pp. 13187-13196).

[9] Jevtić M, Zogović N, Graovac S. Multi-sensor Data Fusion Architectures Revisited.

[10] Keenan RJ. Climate change impacts and adaptation in forest management: a review. Annals of Forest Science. 2015 Mar 1; 72(2):145-67.

[11] Kleeman L. Understanding and applying Kalman filtering. In Proceedings of the Second Workshop on Perceptive Systems, Curtin University of Technology, Perth Western Australia (25-26 January 1996) 1996 Jan.

[12] Li M, Xu H, Deng Y. Evidential decision tree based on belief entropy. Entropy. 2019 Sep; 21(9):897.

[13] Nowak R, Biedrzycki R, Misiurewicz J. Machine learning methods in data fusion systems. In2012 13th International Radar Symposium 2012 May 23 (pp. 400-405). IEEE.

[14] Stateczny A, Bodus-Olkowska I. Hierarchical hydrographic data fusion for precise port electronic navigational chart production. In International Conference on Transport Systems Telematics 2014 Oct 22 (pp. 359-368). Springer, Berlin, Heidelberg.

[15] Sun SL, Deng ZL. Multi-sensor optimal information fusion Kalman filters. Automatica. 2004 Jun 1; 40(6):1017-23.

[16] Tewari VP. Forest inventory, assessment, and monitoring, and long-term forest observational studies, with special reference to India. Forest science and technology. 2016 Jan 2; 12(1):24-32.

[17] Yang H, Fong S, Sun G, Wong R. A very fast decision tree algorithm for real-time data mining of imperfect data streams in a distributed wireless sensor network. International Journal of Distributed Sensor Networks. 2012 Dec 5; 8(12):863545.

[18] Zhang Z, Fu K, Sun X, Ren W. Multiple target tracking based on multiple hypotheses tracking and modified ensemble Kalman filter in multisensor fusion. Sensors. 2019 Jan; 19(14):3118.