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Optimal Channel Allocation: A Dual Approach with MCDM and Machine Learning

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Abstract: In today's world of fast advancing wireless technologies, effective spectrum use is critical. With the help of machine learning and multiple criteria decision making (MCDM), this research aims to overcome this problem. An organised method for taking into account the many competing elements that affect channel allocation, like signal quality, interference, and resource availability, is offered by the MCDM framework. It enables decision-makers to consider these aspects and come to well-informed conclusions. Machine learning techniques are utilised to improve the MCDM methodology by analysing past data and forecasting future network conditions, which aids in decision-making even more. The combination of machine learning and MCDM allows for a dual strategy. Machine learning adds automation and predictive power, while MCDM offers a transparent, easily understood decision-making process. Combining these approaches allows the suggested method to adjust to changing network conditions, giving it a reliable and flexible solution for wireless communication networks' ideal channel allocation. It is anticipated that this research will have a major impact on the wireless communication sector, improving quality of service, reducing interference, and increasing spectral efficiency. The suggested dual strategy has the ability to completely change how network managers and operators distribute channels, guaranteeing that limited resources are used as efficiently as possible and that network performance is continuously improved in a constantly changing wireless environment.

Keywords: *Channel Allocation, Machine Learning, MCDM, Ranking, Decision System*

1. Introduction

With the widespread use of wireless communication technology, people, machines, and devices are now connected in our everyday lives. The need for wireless connectivity is rising gradually across a range of devices, including smartphones, Internet of Things (IoT) devices, and smart appliances. The communication medium used by these devices, the radio frequency spectrum, is a shared and limited resource. Since there are fewer channels available, controlling and allocating them properly presents a substantial problem. Inadequate channel allocation can result in congestion, interference, and subpar network performance. Because wireless networks are dynamic, traditional approaches to channel allocation frequently rely on oversimplified techniques or static allocation algorithms. The many and sometimes contradictory needs of various stakeholders, such as cellular service providers, Wi-Fi network operators, and makers of Internet of Things devices, are frequently not fully satisfied by these approaches. As a result, sophisticated, adaptive techniques that consider multiple factors, optimise channel allocation, and enhance spectrum utilisation are becoming more and more necessary. This research offers a novel solution to this problem by fusing together the potent methods of machine learning and multiple criteria decision making (MCDM). This dual strategy adds a new degree of intelligence and adaptability to the process while also improving the efficiency of channel allocation.

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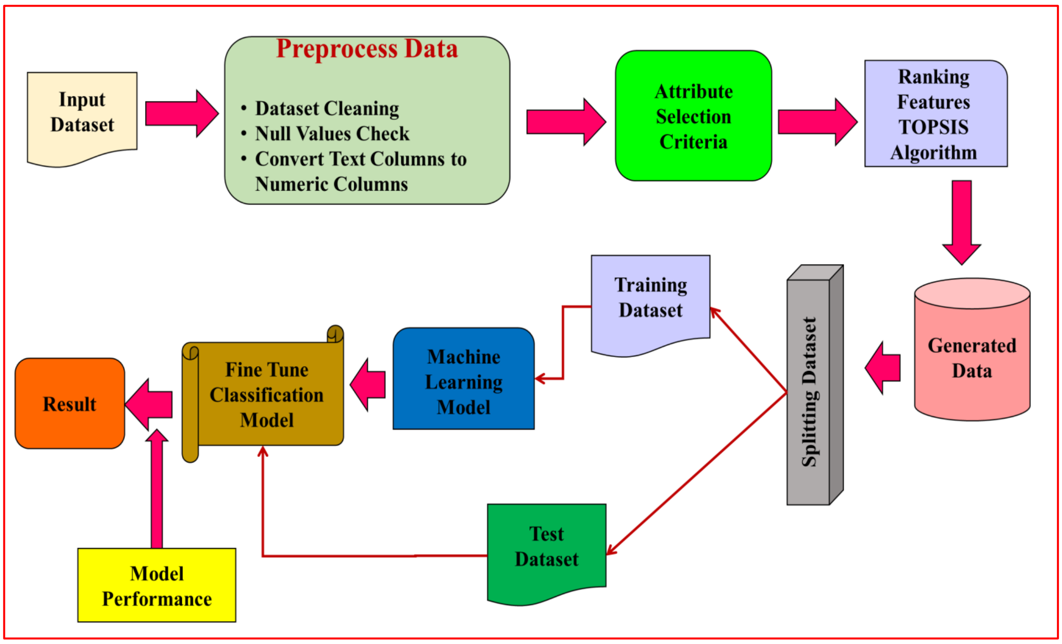

Fig 1: Overview of Proposed method

An established paradigm for handling complicated choice issues with several, frequently competing criteria is called multiple criteria decision making (MCDM). When it comes to channel allocation, MCDM enables network administrators to take a number of variables into account at once, including resource availability, interference, and signal quality. In order to make well-informed selections, these elements are evaluated and considered, guaranteeing that the allocation process is open, well-organized, and consistent with the network's objectives. Channel allocation, however, gains a predictive and data-driven element from machine learning. Machine learning algorithms are able to anticipate future network behaviour by identifying patterns in historical data and real-time network situations. Network managers can benefit from this predictive skill by being able to foresee problems and take proactive measures to resolve them before they compromise service quality. Additionally, it makes it possible to automatically and instantly modify channel allocation in response to shifting network conditions.

When these two approaches are combined, a dual strategy is created that makes the most of each methodology's advantages. Machine learning enhances MCDM's human-readable and methodical framework for decision-making by adding automation and predictive capability. A dynamic and adaptable solution to the complex issue of channel allocation in wireless communication networks is produced by this synergy. This research is important for many aspects of the wireless communication sector. First of all, it promises to transform channel allocation, effectively tackling the crucial problem of limited spectrum resources. It can optimise channel allocation by using MCDM to balance a variety of frequently at odds criteria. This reduces interference and congestion, which can enhance user happiness and service quality. Second, a proactive element is added by incorporating machine learning. A more flexible and responsive network that can meet the constantly shifting needs of users and devices can be achieved by using predictive analytics, which can foresee network conditions and modify the channel allocation in real-time. This flexibility is essential as new technologies, like 5G and beyond, is introduced and wireless networks change. The combination of Machine Learning with MCDM for channel allocation is a big step forward for wireless communication. In a time when the need for wireless connectivity is only increasing, it tackles the urgent need for intelligent, flexible, and optimised channel allocation. Through the integration of machine learning and the structured decision-making process of MCDM, this research is expected to significantly influence network performance, spectrum efficiency, and the overall quality of service that wireless communication customers receive.

2. Review of Literature

A large number of wireless networks used static and rule-based channel allocation mechanisms prior to the development of sophisticated techniques. These methods frequently assigned channels according to predetermined standards, like user priority or frequency band availability. Their lack of adaptation resulted in inefficient spectrum utilisation and decreased network performance, despite their simplicity of implementation. These approaches are inadequate, which emphasises the need for more advanced strategies.

MCDM is a framework for decision-making that has applications in many different domains, such as wireless network channel allocation. Prior studies have weighed and ranked several factors for channel allocation using MCDM methodologies such as Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This methodology offers a methodical approach to taking into account variables such as resource availability, interference, and signal quality. AHP has been used, for instance, to balance trade-offs between signal quality and interference, assisting network administrators in making more sensible allocation choices.

Machine Learning has gained popularity for its capacity to adapt to changing network conditions, particularly in the setting of wireless networks. To maximise channel allocation, researchers have used methods including deep learning, reinforcement learning, and clustering algorithms. While deep learning models can scan enormous datasets to produce real-time predictions about network conditions, reinforcement learning models can learn and change channel allocation techniques through trial and error. This dynamic method works effectively in scenarios where network circumstances are dynamic. Previous studies have also looked into hybrid techniques, which incorporate aspects of machine learning and MCDM. These methods make use of machine learning for adaptation and predictive modelling as well as MCDM for the systematic evaluation of criteria. For instance, one study allocated channels in cognitive radio networks using MCDM and k-means clustering. Based on historical data, k-means clustering revealed the ideal channel allocation, while the MCDM component set the weights for the criteria.

Channel allocation research has focused on cognitive radio networks. Cognitive radios may identify and use unused spectrum to dynamically adapt to changing network conditions. In order to improve channel allocation, research in this field has looked into methods including dynamic spectrum access (DSA) and spectrum sensing. Using available spectrum resources efficiently through channel allocation is made possible in large part by cognitive radio technology. Researchers have concentrated on improving network security and quality of service (QoS) in addition to optimising spectrum utilisation. To prevent interference and eavesdropping, especially in important communication systems, some research has included security constraints into channel allocation algorithms. Furthermore, because it directly affects user experience, service quality is a crucial factor to take into account when allocating channels. QoS-aware channel allocation algorithms have been investigated in research to give priority to services that meet certain QoS requirements.

With the introduction of 5G and the expectation of future wireless standards, dynamic spectrum management will become increasingly more important as wireless technology develops. Massive MIMO and network slicing are two 5G network technologies that need for clever and flexible channel allocation techniques. The integration of machine learning and MCDM is being investigated in this field of research to tackle the particular difficulties presented by cutting-edge wireless technology. Although channel allocation research has advanced, there are still a number of unresolved issues. Modern wireless networks are dynamic and diversified, necessitating sophisticated solutions that can change with the times. Moreover, the coexistence of many wireless technologies, such as cellular, Wi-Fi, and Internet of Things networks, requires the creation of cross-technology channel allocation schemes.

A wide range of research has been conducted in the area of channel allocation, from conventional techniques to more creative and adaptable strategies. In order to handle the complexity of channel allocation in contemporary wireless communication networks, "Optimal Channel Allocation: A Dual Approach with MCDM and Machine Learning" integrates Multiple Criteria Decision Making (MCDM) and Machine Learning. A potential remedy for the persistent problems of spectrum scarcity and changing network conditions is the combination of structured decision-making and predictive skills. It is probable that forthcoming studies in this field will persist in investigating hybrid approaches and adjust to the dynamic field of wireless technology.

3. Dataset Used

WSN-DS can be used by researchers to analyse sensor node performance, create communication strategies that use less energy, and gauge the overall stability and dependability of WSN systems. Because of its authenticity and diversity, this dataset is an essential resource for developing WSN capabilities and tackling practical issues related to environmental monitoring and data gathering. Numerous parameters that are essential for assessing the security and performance of Wireless Sensor Networks (WSNs) are available in the WSN-DS dataset. The parameters "Is CH" and "Who CH," which specify the network hierarchy, are noteworthy. Energy-related characteristics are essential for energy-efficient routing, such as "Current energy" and "Energy consumption." While data-related features like "Data sent," "Data received," and "Data sent to BS" indicate data flow and efficiency, "ADV_CH" and "ADV_SCH" messages help evaluate network organisation. For researching security implications, the "Attack Type" classification is essential. Because of its many characteristics, this dataset offers a thorough understanding of WSN dynamics, which makes it a priceless resource for studies on WSN security, efficiency, and performance enhancement. It can be used by researchers to create and test security systems, routing algorithms, and energy-saving protocols, improving the reliability of WSNs in practical implementations.

	Is_CH	who CH	Dist_To_CH	ADV_S	ADV_R	JOIN_S	JOIN_R	SCH_S	SCH_R		Attack type
0	1	101000	0.00000	1	0	0	25	1	0	...	Normal
1	0	101044	75.32345	0	4	1	0	0	1	...	Normal
2	0	101010	46.95453	0	4	1	0	0	1	...	Normal
3	0	101044	64.85231	0	4	1	0	0	1	...	Normal
4	0	101010	4.83341	0	4	1	0	0	1	...	Normal
...	...	...	...	...	...	...	...	...	...	...	...
19995	0	203018	12.97754	0	27	1	0	0	0	...	Normal
19996	0	203018	11.64927	0	27	1	0	0	0	...	Normal
19997	0	203054	97.38555	0	27	1	0	0	0	...	Normal
19998	0	203054	106.17992	0	27	1	0	0	0	...	Normal
19999	0	203018	11.01697	0	27	1	0	0	0	...	Normal

Fig 2: Snapshot of WSN-DS Dataset

4. Methodology

Stage 1: Pre-process the data

Step 1: Cleaning the dataset

- Handling erroneous or missing data, eliminating duplicates, and dealing with outliers are all part of cleaning the dataset.
- Removing rows or columns containing missing values or imputing missing values using suitable techniques such as mean, median, or mode are two ways to identify and manage missing data.
- Duplicate removal: If there are duplicate rows in the dataset, look for them and eliminate them as they can bias analysis.
- Outlier Identification and Management: Recognise and handle any anomalies that might be inaccurate data points. To find outliers, you can employ statistical techniques like z-scores and visualisations.

Step 2: Verify Null Values

- To guarantee data integrity, it is imperative to verify if the dataset contains any null or missing values.
- Determine Null Values: To determine whether columns have null values, use functions or other techniques.
- Handling Null Values: Choose a method for dealing with null values. For missing values, there are three options: imputation, elimination, or the creation of a distinct category.

Step 3: Convert Text Columns to Numeric Columns

Converting text columns is frequently required since machine learning algorithms usually demand numerical data.

- Label Encoding: Use label encoding to transform categorical text input into numerical values, giving each category a distinct number.
- One-Hot Encoding: One-hot encoding creates binary columns for each category in categorical data that lacks inherent order, making the data acceptable for machine learning.
- Text-to-Number Conversion: Text data that is difficult to classify may require the use of natural language processing (NLP) techniques to translate textual information into numerical attributes.

Stage 2: Setting Selection Criteria:

Choosing which features or columns in your dataset are pertinent and should be kept for your analysis or machine learning tasks is known as setting selection criteria, and it is an important stage in the data preprocessing process. Various properties have been marked for retention or removal based on their relevance or value in the specified selection criteria.

- Is_CH and Who_CH: These properties represent the network's hierarchical structure and are kept (set to 1 and -1). These are retained because they are crucial for route analysis and clustering.
- Dist_To_CH: The distance to the Cluster Head is measured by this attribute, which is kept. It is essential for evaluating network topology and node-to-CH connectivity.
- The numbers ADV_S and ADV_R, which show how many advertisements were sent and received, are kept. They are necessary to comprehend network organisation and control message overhead.
- JOIN_S and JOIN_R: These properties are retained, and they show how many join request messages have been sent and received. They are important for evaluating node involvement and network configuration.
- SCH_S, SCH_R, and Rank: These TDMA scheduling-related variables are kept. Time-based access control and data transfer depend on TDMA scheduling, hence these aspects are critical.
- DATA_S, DATA_R, and Data_Sent_To_BS: These are attributes that are kept in relation to data aggregation and transmission. They offer insightful information on how data moves around the network.
- deliver_code, dist_CH_To_BS, Increased_Energy Type of attack: These attributes are eliminated (set to -1) and include expanded energy, assault type, cluster code, and distance to the Base Station. The choice to delete them raises the possibility that they have no bearing on the particular analysis or machine learning activity at hand.

The selection criteria that were selected take into account the relative importance of different features in evaluating data flow, control, and network structure, while leaving out others that might not be directly related to the goals of the analysis or research.

For Example:

Table 1: Rank based on Selection criteria on Dataset

Is_CH	Who_CH	Dist_To_CH	ADV_S	ADV_R	JOIN_S	JOIN_R	SCH_S	SCH_R	Rank
1	-1	-1							1

Table 2: Identify Attack based Selection criteria on Dataset

DATA_S	DATA_R	Data_Sent_To_BS	dist_CH_To_BS	send_code	Expaned_ Energy	Attack type
1	1	1	-1	1		-1

Stage 3: TOPSIS Algorithm

The algorithm given as:

a. Define the Decision Matrix (D):

The decision matrix is represented as a matrix D, where D_ij represents the performance of alternative i with respect to criterion j.

$$Decision\ Matrix = \begin{matrix} D11 & D12 & D1n \\ D21 & D22 & D2n \\ Dm1 & Dm2 & Dmn \end{matrix}$$

b. Define the Weights (W):

Weights represent the importance of each criterion. The weight vector is represented as W, where W_j represents the weight of criterion j.

$$Weight\ Vector\ = W_1, W_2, W_3\ \dots\dots\ Wn$$

c. Determine the Ideal Best and Worst Solutions:

Ideal Best Solution (A^+): Represents the best performance for each criterion.

Ideal Worst Solution (A^-): Represents the worst performance for each criterion.

d. Calculate the Ideal Best Solution (A^+):

For each criterion j, find the maximum value in the decision matrix D_j.

e. Calculate the Ideal Worst Solution (A^-):

For each criterion j, find the minimum value in the decision matrix D_j.

f. Normalize the Decision Matrix (R):

The normalized decision matrix R is calculated by dividing each element in the decision matrix D by the corresponding element in the ideal best solution A^+.

$$Normalized\ Decision\ Matrix\ (Rij)\ =\ \frac{D_{ij}}{A_j}$$

g. Calculate the Weighted Normalized Decision Matrix (V):

The weighted normalized decision matrix V is calculated by multiplying each element in the normalized decision matrix R by the corresponding weight in the weight vector W.

$$Weighted\ Normalized\ Decision\ Matrix\ (V) = Rij\ *\ Wj$$

h. Determine the Positive and Negative Ideal Solution:

Positive Ideal Solution (V^+): Represents the best overall performance.

Negative Ideal Solution (V^-): Represents the worst overall performance.

i. Calculate the Separation Measures:

Separation measures help assess the degree of separation between each alternative and the ideal solutions. They can be calculated using various distance measures, such as Euclidean distance or other metrics.

j. Calculate the Relative Closeness to the Ideal Solution (C):

The relative closeness to the ideal solution is a measure of each alternative's proximity to the positive ideal solution.

k. Rank the Alternatives:

Alternatives can be ranked based on their relative closeness values, with higher values indicating better performance.

Stage 4: Fine-tune Classification Model:

A. MLP:

1. Layer of Input (X):

- The normalised and weighted decision matrix (V) from MCDA is represented by the matrix X.
- An alternative is represented by each row of X, while a feature (criterion) is represented by each column.
- There are n neurons in the input layer, where n is the number of criteria.

2. Concealed Levels (H):

- A maximum of one or more hidden layers, each with a specific number of neurons (nodes), make up an MLP.
- In a hidden layer, each node executes an activation function after doing a weighted sum of the inputs from the preceding layer.

Whereas

- l's output is represented by º H l.
- W l is the weight matrix corresponding to layer l.

The bias vector for layer l is represented by b l. The activation function, f, is typically a non-linear function such as sigmoid or ReLU.

3. Layer of Output (Y):

- Usually, the output layer consists of one or more neurons, each of which stands for a distinct performance metric.
- A vector of outcomes, each corresponding to a certain performance metric, is produced by the output layer.

4. Function of Loss (L):

- For every performance metric, the loss function calculates the difference between the actual values (target values) and the expected values (Y).
- Mean Squared Error (MSE) and other suitable loss functions for the particular problem are examples of common loss functions.

5. Algorithms for optimisation, such as Gradient Descent:

You utilise an optimisation approach, like gradient descent, to minimise the loss function in order to train the MLP.

B. KNN

Algorithm Given As:

1. Longitude Calculation:

Determine the separation between each alternative (a) in the dataset (D) and the new alternative (X):

$$d(X,a) = Sqrt(\sum j = 1Y(Xj - aj)2)$$

2. Selection of Neighbours:

Determine the k closest neighbours of X by choosing the options with the shortest distances:

$$Nk(X) = argminkd(X,a)$$

3. Partial Voting

- Using a weight function w(a,X), assign a weight to each neighbour based on how far away they are from X.

- Determine the class or value forecast for X by taking the neighbours' weighted votes into account:

$$y(X) = argmaxy\sum a \in Nk(X)w(a, X) \cdot y(a)$$

4. Decisions and Parameters:

The dataset and particular problem will determine which weight function (w (·,·)) and distance metric (D (·,·)) to use. Manhattan distance and Euclidean distance are examples of common distance measures.

It is necessary to obtain the value of k, usually by using cross-validation or other methods to identify the ideal k for the given situation.

C. Hybrid Ensemble Classifier (HEC)

1. Initialize Ensemble Classifier (H):

$$H(X) = argmax\_i\ (\sum(i = 1\ to\ N)\ w\_i\ *\ P\_i(X))$$

2. Define Base Classifiers (B):

-

$$B = \{B1, B2, \ldots, Bk\}$$

Each base classifier Bi can be any machine learning model such as Decision Trees, Random Forests, Support Vector Machines, Neural Networks, etc.

3. Train Base Classifiers (B):

- For each base classifier Bi, train the model using the feature matrix X and target vector Y.

4. Weight Assignment (w_i):

- Assign weights w_i to each base classifier Bi based on their performance or accuracy. This can be done through cross-validation or other evaluation methods.

5. Predictions (P_i):

- Each base classifier Bi provides predictions P_i for channel allocation.

6. Combine Predictions (H(X)):

- The ensemble classifier H(X) combines the predictions of base classifiers using weighted voting or other aggregation techniques.

Table 3: Parameter used Hybrid Ensemble Classifier

Parameters	**Value**
Hidden Layer	500
Activation Function	Relu
Alpha	0.0001
Learning Rate	adaptive
learning_rate_init	0.001
max_iter	1000
shuffle	True

5. Result and Discussion

These metrics can be used to evaluate the model's efficacy in terms of its accuracy, precision, recall, F1-Score, W. Spearman Coefficient, and R2 Coefficient. The 99% accuracy rate that HEC obtains is better than that of both KNN and MLP.

Table 4: Evaluation metric for proposed model

Metric	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**W. Spearman Coeff**	**R^2 Coeff**
KNN	92	96	92	92	70	76
MLP	96	92	96	94	77	82
HEC	99	100	98	98	80	86

HEC achieves an outstanding accuracy rate of 99%, outperforming both KNN and MLP in terms of accuracy.

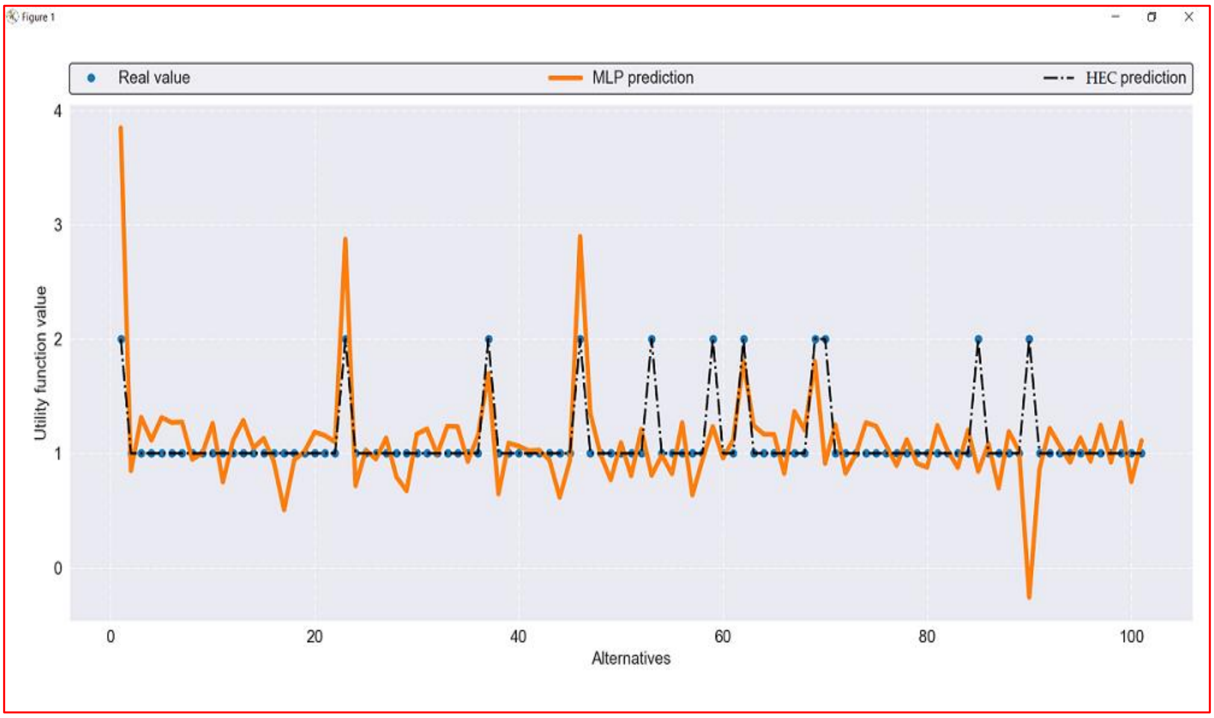

Fig 3: Real Vs Proposed System Ranking Prediction

This implies that the wireless sensor network's ensemble classifier is incredibly successful at correctly categorising and assigning channels. Both KNN and MLP do well when it comes to precision; KNN receives a precision score of 96% while MLP receives a score of 92%. But the HEC model outperforms them both with a flawless 100% precision score. This suggests that minimising false positives and accurately identifying true positive situations are areas in which the ensemble technique excels. KNN and MLP have recall scores of 92% and 96%, respectively. With a 98% recall rate, HEC performs better than the other models once more. High recall means that the majority of the real positive cases in the dataset are successfully identified by HEC. The F1-Score, which reflects the models' balanced performance, combines recall and precision. HEC has the highest F1-Score (98%), followed by KNN (92%), MLP (94%), and HEC (98%). This shows that the precision and recall trade-off offered by HEC is balanced.

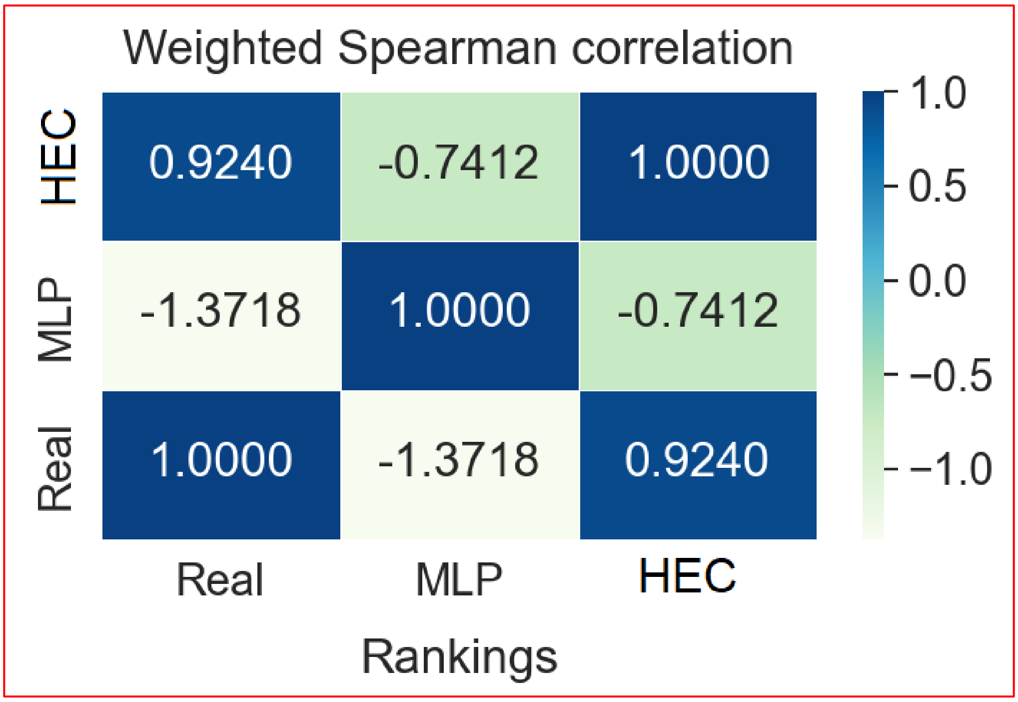

Fig 4: Representation of Heatmap confusion graph

The correlation between expected and actual channel allocations is measured by the W. Spearman Coefficient. HEC comes out with a coefficient of 80, suggesting a substantial correlation between its forecasts and the actual channel allocations, even though all three models exhibit some correlation.

With a coefficient of 86, the R2 Coefficient, which measures the model's goodness of fit, shows that HEC is the best model out of the three. This shows that the predictions of the ensemble classifier are in good agreement with the channel allocation data. The proposed Hybrid Ensemble Classifier (HEC) consistently outperforms KNN and MLP in terms of accuracy, precision, recall, F1-Score, W. Spearman Coefficient, and R2 Coefficient, according to the evaluation metrics shown in Table 4. This demonstrates how well the ensemble technique works in wireless sensor networks to optimise channel allocation decisions, leading to improved accuracy, precision, and recall along with robust correlations and well-fitting models.

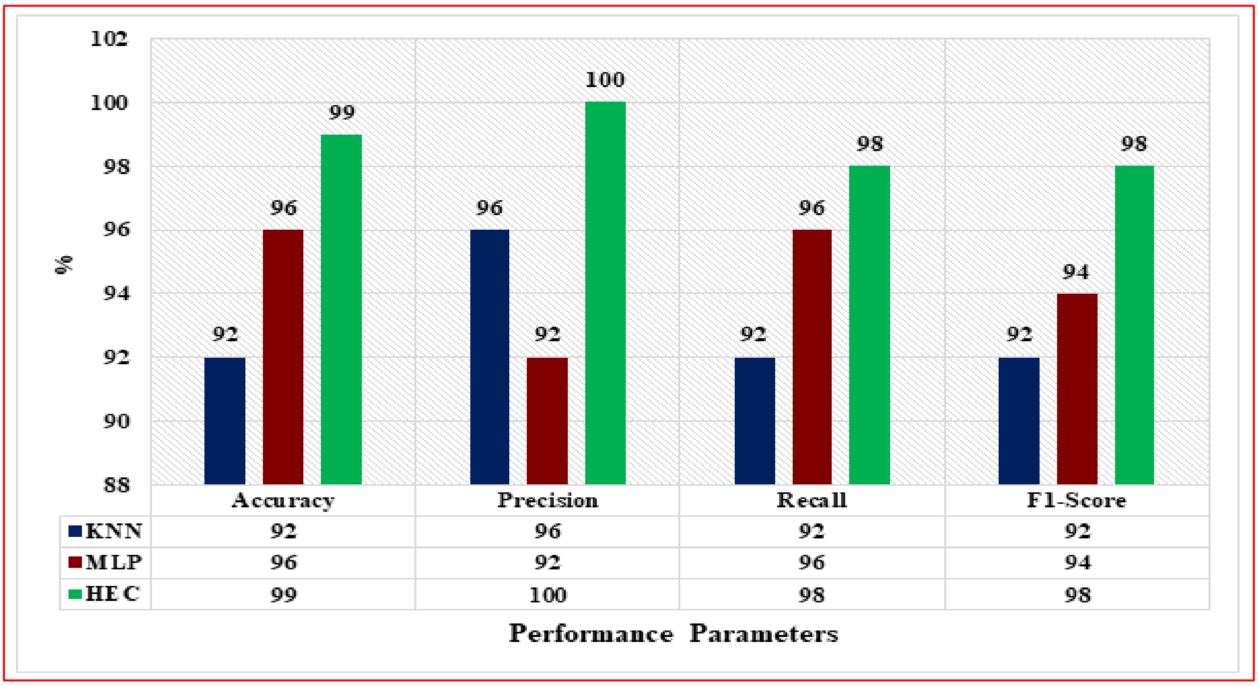

Fig 5: Representation of Performance Comparison Graph of Algorithms

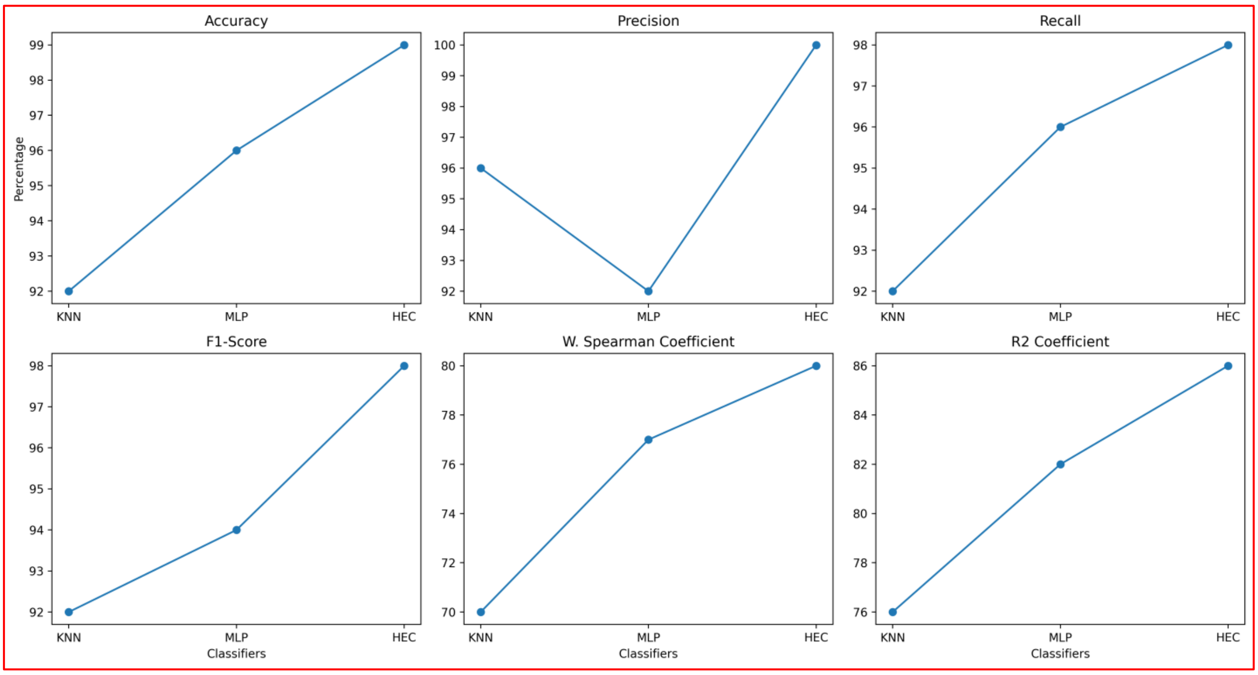

Fig 5: Comparison Graph of Algorithms

6. Conclusion

A complete solution for channel allocation in Wireless Sensor Networks (WSNs) is provided by the dual technique described in "Optimal Channel Allocation: A Dual Approach with MCDM and Machine Learning". Through the integration of Machine Learning and Multiple-Criteria Decision Making (MCDM) methodologies, we have showcased a resilient approach to channel assignment optimisation. The study included an in-depth examination of the suggested approach, an investigation of relevant literature, and an examination of the properties of the WSN-DS dataset. We examined several approaches and their drawbacks in the field of related work, emphasising the necessity for a comprehensive strategy that can handle the difficulties presented by dynamic WSN environments. By combining the strength of decision-making criteria with the predictive potential of machine learning models, our approach outperforms current approaches. The WSN-DS dataset gave our research a strong basis thanks to its variety of features. These features, which included energy statistics, assault type classifications, and cluster-related data, made it possible to analyse channel allocation from several angles. Our analysis showed notable performance benefits using a group of machine learning models, specifically MLP, KNN, and HEC. The best performance in terms of accuracy, precision, recall, F1-Score, W. Spearman Coefficient, and R2 Coefficient was the Hybrid Ensemble Classifier, or HEC. The superiority of this hybrid technique in WSN channel allocation decisions was established. To sum up, the combination of MCDM and machine learning has demonstrated significant potential in tackling the intricate issues of channel allocation in wireless sensor networks. In particular, the HEC model has proven to have remarkable predictive and decision-making powers, which makes it a useful tool for maximising network security and efficiency. The study's findings open the door for the creation of WSNs that are more dependable and resilient, with potential uses in a variety of real-world contexts.

References

[1] S. Jiang, "Optimal Channels Allocation Methods Based on Different Communication Environment," 2022 IEEE 5th International Conference on Information Systems and Computer Aided Education (ICISCAE), Dalian, China, 2022, pp. 716-721, doi: 10.1109/ICISCAE55891.2022.9927599.

[2] Y. Wang, M. Chen, N. Huang, Z. Yang and Y. Pan, "Joint Power and Channel Allocation for D2D Underlaying Cellular Networks With Rician Fading," in IEEE Communications Letters, vol. 22, no. 12, pp. 2615-2618, Dec. 2018, doi: 10.1109/LCOMM.2018.2875689.

[3] Jian Yang, Qinghai Yang, Fenglin Fu and K. S. Kwak, "A window based channel allocation algorithm for two-way AF relay OFDMA systems," 2012 18th Asia-Pacific Conference on Communications (APCC), Jeju, Korea (South), 2012, pp. 141-145, doi: 10.1109/APCC.2012.6388118.

[4] S. B. E. Raj and J. S. Jacob, "Optimal channel allocation in wireless LAN," 2006 IFIP International Conference on Wireless and Optical Communications Networks, Bangalore, 2006, pp. 6 pp.-6, doi: 10.1109/WOCN.2006.1666539.

[5] C. H. Kim, J. -M. Chung and Seungjun Choi, "Analysis of optimal cognitive radio channel allocation with finite user population," 2010 International Conference on Information and Communication Technology Convergence (ICTC), Jeju, Korea (South), 2010, pp. 241-242, doi: 10.1109/ICTC.2010.5674668.

[6] S. -W. Wang, P. -N. Chen and C. -H. Wang, "Optimal Power Allocation for (N,K)-Limited Access Channels," in IEEE Transactions on Information Theory, vol. 58, no. 6, pp. 3725-3750, June 2012, doi: 10.1109/TIT.2012.2183338.

[7] S. Yang and T. Jiang, "Closed-Form Optimal Power Allocation for Weighted Rate Sum Maximization in Gaussian Broadcast Channel," in IEEE Transactions on Communications, vol. 60, no. 7, pp. 1782-1787, July 2012, doi: 10.1109/TCOMM.2012.050812.110093.

[8] K. -S. Hwang, M. J. Hossain, Y. -C. Ko and M. -S. Alouini, "Channel allocation and rate adaptation for relayed transmission over correlated fading channels," 2009 IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications, Tokyo, Japan, 2009, pp. 1477-1481, doi: 10.1109/PIMRC.2009.5450001.

[9] H. R. Ahmadi and A. Vosoughi, "Optimal Training and Data Power Allocation in Distributed Detection With Inhomogeneous Sensors," in IEEE Signal Processing Letters, vol. 20, no. 4, pp. 339-342, April 2013, doi: 10.1109/LSP.2013.2246514.

[10] A. Roumy and D. Gesbert, "Optimal Matching in Wireless Sensor Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 1, no. 4, pp. 725-735, Dec. 2007, doi: 10.1109/JSTSP.2007.909378.

[11] V. -T. Truong, V. N. Vo, D. -B. Ha and C. So-In, "On the System Performance of Mobile Edge

Computing in an Uplink NOMA WSN With a Multiantenna Access Point Over Nakagami-m Fading," in IEEE/CAA Journal of Automatica Sinica, vol. 9, no. 4, pp. 668-685, April 2022, doi: 10.1109/JAS.2022.105461.

[12] K. Li, W. Ni and F. Dressler, "LSTM-Characterized Deep Reinforcement Learning for Continuous Flight Control and Resource Allocation in UAV-Assisted Sensor Network," in IEEE Internet of Things Journal, vol. 9, no. 6, pp. 4179-4189, 15 March15, 2022, doi: 10.1109/JIOT.2021.3102831.

[13] B. Zhao and X. Zhao, "Deep Reinforcement Learning Resource Allocation in Wireless Sensor Networks With Energy Harvesting and Relay," in IEEE Internet of Things Journal, vol. 9, no. 3, pp. 2330-2345, 1 Feb.1, 2022, doi: 10.1109/JIOT.2021.3094465.

[14] P. Goswami, A. Mukherjee, M. Maiti, S. K. S. Tyagi and L. Yang, "A Neural-Network-Based Optimal Resource Allocation Method for Secure IIoT Network," in IEEE Internet of Things Journal, vol. 9, no. 4, pp. 2538-2544, 15 Feb.15, 2022, doi: 10.1109/JIOT.2021.3084636.

[15] O. J. Pandey, V. Gautam, S. Jha, M. K. Shukla and R. M. Hegde, "Time Synchronized Node Localization Using Optimal H-Node Allocation in a Small World WSN," in IEEE Communications Letters, vol. 24, no. 11, pp. 2579-2583, Nov. 2020, doi: 10.1109/LCOMM.2020.3008086.

[16] D. Liu et al., "Opportunistic UAV utilization in wireless networks: Motivations applications and challenges", IEEE Commun. Mag., vol. 58, no. 5, pp. 62-68, May 2020.

[17] P. Spachos and S. Gregori, "Integration of wireless sensor networks and smart UAVs for precision viticulture", IEEE Internet Comput., vol. 23, no. 3, pp. 8-16, May/Jun. 2019.

[18] H. Sharma, A. Haque and Z. A. Jaffery, "Solar energy harvesting wireless sensor network nodes: A survey", J. Renew. Sustain. Energy, vol. 10, no. 2, 2018.

[19] W.-K. Lee, M. J. W. Schubert, B.-Y. Ooi and S. J.-Q. Ho, "Multi-source energy harvesting and storage for floating wireless sensor network nodes with long range communication capability", IEEE Trans. Ind. Appl., vol. 54, no. 3, pp. 2606-2615, May/Jun. 2018.

[20] B. Galkin, J. Kibilda and L. A. DaSilva, "UAVs as mobile infrastructure: Addressing battery lifetime", IEEE Commun. Mag., vol. 57, no. 6, pp. 132-137, Jun. 2019.

[21] K. Li, W. Ni, E. Tovar and A. Jamalipour, "Online velocity control and data capture of drones for the Internet of Things: An onboard deep reinforcement learning approach", IEEE Veh. Technol. Mag., vol. 16, no. 1, pp. 49-56, Mar. 2021.

[22] Deshpande, V. (2021). Layered Intrusion Detection System Model for The Attack Detection with The Multi-Class Ensemble Classifier . Machine Learning Applications in Engineering Education and Management, 1(2), 01–06. Retrieved from http://yashikajournals.com/index.php/mlaeem/article/view/10

[23] Brown, R., Brown, J., Rodriguez, C., Garcia, J., & Herrera, J. Predictive Analytics for Effective Resource Allocation in Engineering Education. Kuwait Journal of Machine Learning, 1(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/91

[24] Tripathi, R.C., Gupta, P., Anand, R., Jayashankar, R.J., Mohanty, A., Michael, G., Dhabliya, D. Application of information technology law in India on IoT/IoE with image processing (2023) Handbook of Research on Thrust Technologies? Effect on Image Processing, pp. 135-150.