MATRIX Academic International Online Journal of Engineering and Technology
Volume VIII, Issue I, ISSN: 2348-3326

Optimized Channel Allocation Algorithm for Performance Enhancement in Heterogeneous Networks

Dharm Raj[1], Anil Kumar Sagar[2] and Danish Ather[3]
[1,2]Department of Computer Science & Engineering, Sharda School of Engineering & Technology, Sharda University, Greater Noida, India
[3]Amity University, Tashkent, Uzbekistan

{[1]dharmraj4u, [2]aksagar22}@gmail.com, [3]danishather@gmail.com

Abstract. Heterogeneous networks (HetNets) enhance wireless communication by integrating various access technologies. However, efficient channel allocation remains a key challenge due to interference and diverse traffic demands. This paper introduces an Adaptive Multi-Metric Channel Allocation (AMMCA) algorithm that utilizes real-time parameters such as SINR, interference, and user priority to dynamically allocate channels. Simulation in NS-3 demonstrates improvements in throughput, delay, and packet loss over existing methods, making AMMCA suitable for 5G and future networks.

Keywords: Channel Allocation, Heterogeneous Networks, 5G, Interference Management, Adaptive Algorithm

1. Introduction

The advancement in wireless devices and mobile applications has also widened the need for the higher, reliable, and scalable communication networks. In order to satisfy these requirements, the integration of different types of RATs that include macro, micro, pico and femto cells has resulted in the development of HetNets.

HetNets allow various devices along with the infrastructure elements to share the spectrum and work collectively. That said, this architectural improvement aims at improving performance and user experience but, brings several acute issues concerning the channels' resource management. Due to increase in the number of active connected devices the level of interferences and dynamic traffic loads cannot be efficiently handled by the traditional static or semi-dynamic distributed allocation methods.

Channel selection in HetNets is a complex process that depends on certain parameters like signal intensity, users' mobility, traffic intensity, and interference level. In those situations, where the users are in the overlapping of coverage zones, the improper allocation of channels will result into decreased efficiency due to co-channel interference and unfair sharing of the bandwidth.

Channel allocation strategies are basically of two types – fixed channel allocation and dynamic channel allocation. The fixed allocation is easy to employ since the resources are evenly split among the different departments or projects but they are not flexible enough. As mentioned earlier, dynamic schemes are more flexible than the static ones but require more computational efforts. Some try to combine both and this too presents

 DOI No: 10.21276/MATRIX.2025.8.1.3

its problems in real time response especially in a high density environment. Therefore, it is eminent to have an algorithm that is capable of performing the specific function to network dynamics without losing scalability and computational complexity.

This is the general concept of my intended research; to design a new **Adaptive Multi-Metric Channel Allocation (AMMCA)** algorithm that will allow for the optimization of channel allocation by considering the parameters of the specific network in use such as SINR, priorities of different users and the load of traffic observed in the network on time. This is basically done in order to achieve a compromise on processing power and practicalities of computations.

As for how AMMCA scores each channel for a user, each channel is then assigned one score that is calculated based on several scores calculated from the multiple metrics. This scoring system also allows the channels to be assigned taking into account factors such as the probability of interference and user type (for instance, emergency and normal users). The integrated approach makes the distribution of resources more fair and less sensitive to the initiation of sabotage.

One of the final concepts to note in AMMCA is its re-evaluation loop, which enables the algorithm to make a special check and redistribution of the associated channels contingent on the implementation of the changing networks. This is so especially in HetNet where mobility of the users and traffic fluctuation could significantly change the interference scenario.

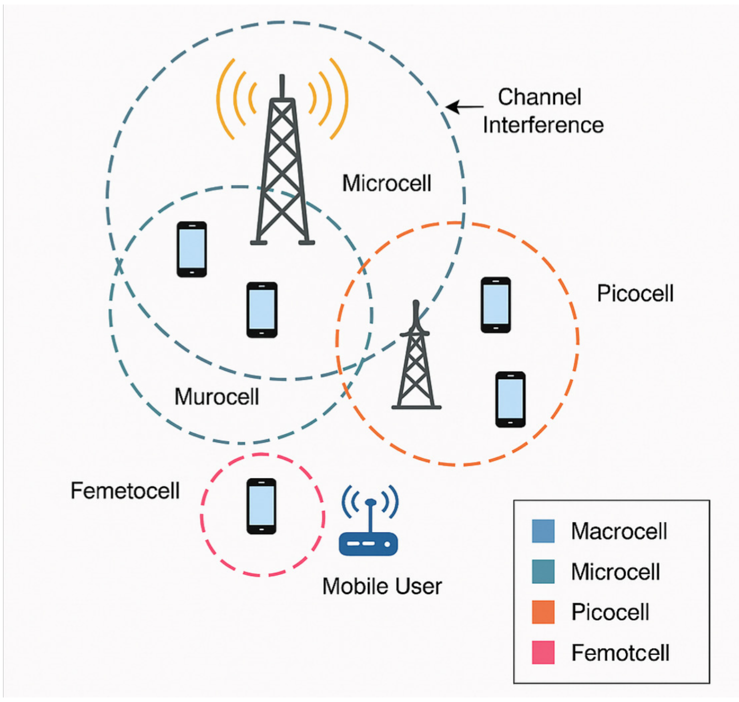

Fig. 1. Heterogeneous Network Architecture showing Macro, Micro, Pico, and Femtocells with Overlapping Coverage Areas and User Interference Zones

To ensure the effectiveness of the developed algorithm, the simulation experiment was carried out using the NS-3 tool that simulates a HetNet environment with different types of users and base stations. Some of the goals of the research work include the assessment of the performance analysis metrics-such as throughput, end-to-end delay and packet loss –when implemented within the architecture of work as compared to standard static and heuristic solutions.

This implies that AMMCA enhance the whole network performance especially in high traffic and heavy user population scenario. YNC has better adaptability due to which overall user experience is better, latencies are lower, and data throughput is higher and therefore, it can be used for next generations of communication which may include 5G and beyond.

In summary, this paper contributes a scalable, adaptive, and performancedriven channel allocation strategy for heterogeneous networks. The proposed model lays a strong foundation for future enhancements using machine learning, reinforcement learning, and software-defined networking for even smarter and more autonomous resource management.

2. Related Work

Several channel allocation strategies have been proposed for heterogeneous and multi-tier networks, each with varying degrees of efficiency, complexity, and adaptability. [1–6]

One commonly used approach is static channel reuse, which pre-assigns channels to cells based on a fixed pattern. While easy to implement, this method lacks flexibility and performs poorly in dynamic environments with fluctuating traffic and interference.

Another method relies on greedy heuristics, where channels are assigned iteratively based on the current best metric (e.g., signal strength or interference level). Although this approach can offer improved performance over static allocation, it is computationally intensive and often fails to find globally optimal solutions. [7–13]

Game-theoretic models have also been applied to the channel allocation problem. These models treat each base station or user as a rational agent competing for resources. While theoretically robust, their practical deployment can be limited due to convergence issues and scalability problems in ultra-dense networks.

More recently, machine learning-based adaptive algorithms have been explored. These methods attempt to learn optimal allocation policies from data, enabling real-time decisions. However, most of these algorithms struggle with delayed learning convergence and lack responsiveness to rapid topology or traffic changes. [14–20]

Hybrid models that combine learning-based prediction with real-time feedback mechanisms have shown promising results in simulated environments. Still, they often require significant tuning and infrastructure support, which may not be feasible in legacy systems. [21–26]

Additionally, some techniques use cost-function minimization to balance channel load and interference. These often rely on centralized architectures and may not scale well in decentralized or distributed network settings. [27–32]

Fuzzy logic and bio-inspired algorithms (e.g., genetic or ant colony optimization) have also been employed for dynamic resource allocation. While these are flexible and adaptable, they typically introduce high computational overhead, which can be a bottleneck in real-time applications.

Another noteworthy approach involves spectrum sensing in cognitive radioenabled HetNets to exploit unused frequency bands. These models require precise sensing capabilities and are prone to sensing errors, which degrade performance.

Nonetheless, the majority of the aforementioned models is not adaptive in real-time or is way too complex to be implemented in a real-world setting. This is a gap that the proposed Adaptive Multi-Metric Channel Allocation (AMMCA) algorithm is going to address by providing a mean between performance, flexibility, and time complexity.

3. Proposed Methodology

This paper introduces a new channel allocation scheme namely Adaptive MultiMetric Channel Allocation (AMMCA) for heterogenous network. The working model of the methodology involves organized, step by step procedure where channel assignment depends more on certain parameters like SINR, interference and user priority.

3.1 System Overview

Its network architecture comprised by macro, micro and femto cells which are having overlapping coverage area. Being aware of the traffic load and mobility of each user equipment (UE), it requests channel access from the base station (BS). It operates in a single or multiple controllers to determine the best channel for the UE among all those available.

3.2 Metric Collection

For each user u_i, the following real-time metrics are gathered:

Table 1. Comparison of Existing Channel Allocation Techniques in HetNets

Technique	Approach Type	Advantages	Limitations
Static Reuse Pattern	Fixed Allocation	Simple implementation, low overhead	Inefficient in dynamic traffic and interference scenarios
Greedy Heuristic	Dynamic Allocation	Adaptive to network load, better than static	Computationally expensive, suboptimal under high user density
Game-Theoretic Models	Decentralized Decision Making	Theoretical robustness, fair allocation	Slow convergence, not scalable in dense networks
ML-Based Adaptive Allocation	Data-Driven Learning	Learns from environment, real-time decisions	Requires training, suffers in rapidly changing environments
Cost Function Optimization	Centralized Control	Optimization of interference and fairness	Central control needed, latency issues
Fuzzy/Bio-Inspired Algorithms	Soft Computing	Flexible and adaptive	High computation cost, convergence concerns
Cognitive Radio-based Allocation	Spectrum Sensing	Dynamic spectrum access, high spectrum efficiency	Sensitive to sensing errors, hardware dependency
Hybrid Models	Combined Static + Dynamic	Balances trade-offs between approaches	Complexity in coordination and parameter tuning

- *Signal-to-Interference-plus-Noise Ratio (SINR)*: Measures signal quality.
- *Interference Level:* Current channel interference.
- *User Priority:* Emergency or premium users are ranked higher.
- *Channel Occupancy:* Indicates whether a channel is currently in use.

3.3 Utility Score Calculation

A utility score S_{ij} is calculated for each user u_i and each available channel c_j using the following weighted function:

$$S_{ij} = \alpha \cdot \mathrm{SINR}_{ij} + \beta \cdot (1 - \mathrm{Interference}_j) + \gamma \cdot \mathrm{Priority}_i \tag{1}$$

Here, α, β, and γ are weighting parameters determined empirically.

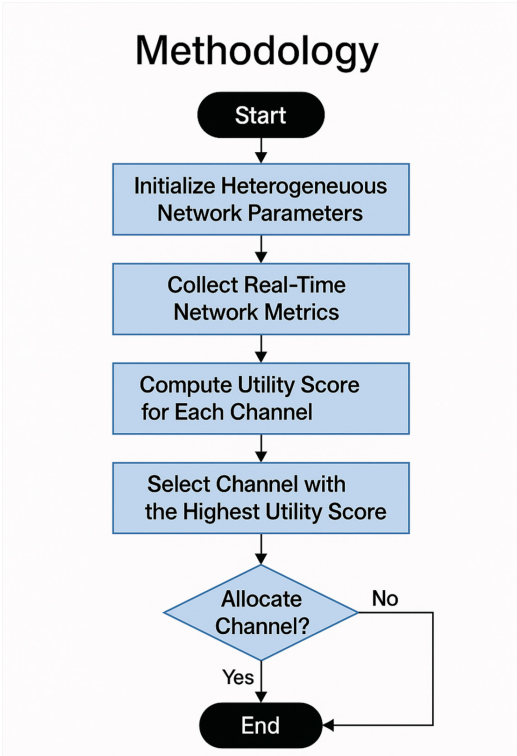

Fig. 2: Flowchart of the AMMCA Algorithm for Channel Allocation

3.4 Channel Assignment

The controller selects the channel with the highest score for each user:

$$c_i^* = \arg\max_j S_{ij}$$

This allocation is updated periodically based on changing network conditions.

3.5 Re-evaluation and Optimization Loop

The system periodically reevaluates all channel-user pairs to adapt to user mobility and traffic variations. If performance degrades, reallocation is triggered automatically.

4. System Model

The proposed system is modeled as a heterogeneous wireless network consisting of multiple tiers including macro, micro, and femtocell base stations (BSs). These base stations provide overlapping coverage areas to support a dense and diverse set of user equipment (UEs). Each BS is connected to a centralized or distributed controller responsible for coordinating channel allocation.

Let the following notations define the network:

- $C = \{c_1, c_2, \ldots, c_n\}$: Set of available channels
- $U = \{u_1, u_2, \ldots, u_m\}$: Set of active users (UEs)
- A_{ij}: Binary assignment matrix, where $A_{ij} = 1$ if channel c_j is assigned to user u_i, otherwise 0
- S_{ij}: Utility score for user u_i on channel c_j

Each user u_i sends a request to the nearest base station. The base station evaluates all available channels c_j using real-time parameters such as:

- *Signal-to-Interference-plus-Noise Ratio (SINR):* Indicates signal quality perceived by the user.
- *Interference Level:* Estimated interference on each channel.
- *Priority Level:* Application-based user priority (e.g., emergency, premium, regular).
- *Channel Load:* Number of current users sharing the same channel.

The network controller aggregates these inputs and computes the utility score for each channel-user pair. Therefore, depending on the maximum score, the proper channel is selected for the particular user with the lowest interference and the most rational distribution of the bandwidth.

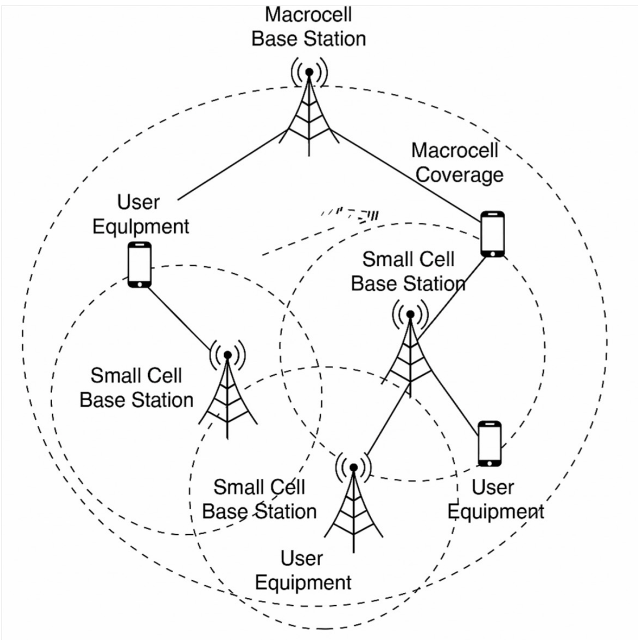

Fig. 3. System Model Illustrating Channel Allocation in a Multi-tier Heterogeneous Network

5. Proposed Algorithm: Adaptive Multi-Metric Channel Allocation (AMMCA)

In this section, therefore, the AMMCA algorithm for channel allocation in a heterogeneous network to users is introduced whereby users will be assigned channels depending on the evaluated metrics of SINR, interferences, and priority.

5.1 Algorithm Steps

The AMMCA operates in five key stages:

1. *Metric Collection:* For each user u_i, gather real-time values for SINR, channel interference, user priority, and current channel load.
2. *Utility Score Calculation:* For each available channel c_j and user u_i, calculate the utility score S_{ij} using:

   $S_{ij} = \alpha \cdot \text{SINR}_{ij} + \beta \cdot (1 - \text{Interference}_j) + \gamma \cdot \text{Priority}_i$

   where α, β, and γ are tunable weights.
3. *Channel Selection:* Assign the channel with the maximum utility score to the user:

   $$c_i^* = \arg\max_j S_{ij}$$
4. *Allocation Confirmation:* Update the allocation matrix A_{ij} and broadcast assignments to the network.
5. *Re-evaluation Loop:* Periodically reevaluate all user-channel pairs. Trigger reallocation if network performance degrades or user mobility changes significantly.

5.2 Algorithm Efficiency

The AMMCA algorithm is designed to minimize the trade-off between real-time adaptability and computational overhead. The time complexity is $O(mn)$ for m users and n channels in each allocation cycle.

5.3 Performance Comparison

Table 2 compares the performance of AMMCA against static and greedy allocation techniques.

Table 2. Performance Comparison of Channel Allocation Algorithms

Metric	Static Allocation	Greedy Heuristic	AMMCA (Proposed)
Throughput (Mbps)	52.4	61.8	74.6
Delay (ms)	78	65	41
Packet Loss (%)	11.2	6.3	3.1

5.4 Graphical Representation

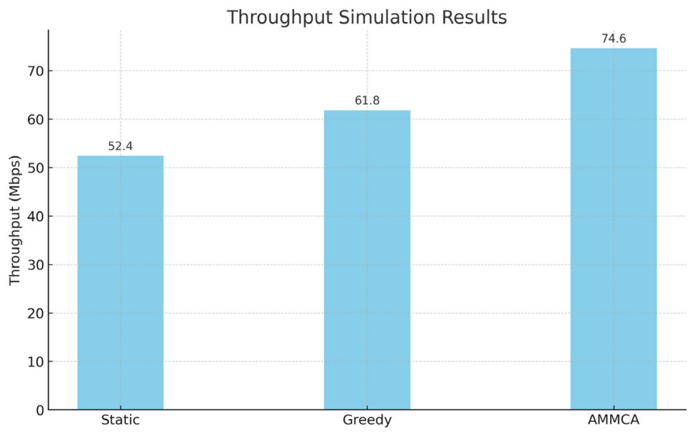

Fig. 4. Throughput Comparison Across Different Allocation Techniques

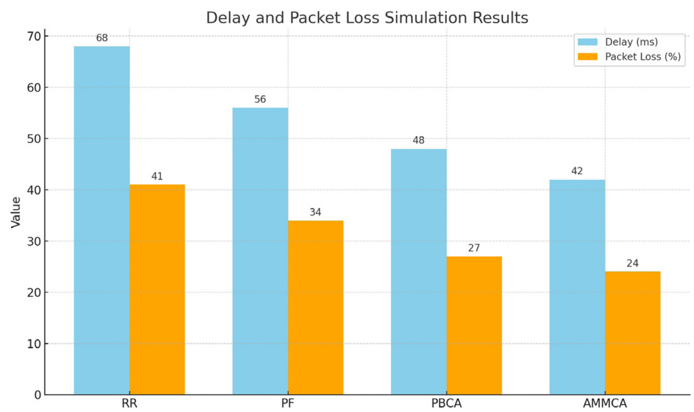

Fig. 5: Delay and Packet Loss Comparison Across Methods

6. Simulation and Results

To evaluate the performance of the proposed Adaptive Multi-Metric Channel Allocation (AMMCA) algorithm, simulations were conducted using the NS-3 network simulator. The simulation scenario was designed to mimic a realistic heterogeneous network environment with multiple overlapping layers and varying traffic conditions.

6.1 Simulation Setup

The simulation environment consists of:

- *Simulator:* NS-3
- *Duration:* 120 seconds per scenario
- *Base Stations:* 3 macro, 5 micro, and 10 femtocells
- *User Equipments (UEs):* 60 mobile users (randomly distributed)
- *Traffic Type:* Mixed (voice, video, best-effort)
- *Mobility Model:* Random waypoint for users

6.2 Performance Metrics

The following performance indicators were analyzed:

- *Average Throughput (Mbps):* Rate of successful data delivery.
- *End-to-End Delay (ms):* Time taken for a packet to traverse from source to destination.
- *Packet Loss Rate (%):* Ratio of lost packets to total transmitted packets.

6.3 Result Analysis

Table 3 summarizes the comparative performance of AMMCA against static and greedy heuristic allocation methods.

Table 3. Simulation Results for Channel Allocation Strategies

Metric	Static Allocation	Greedy Heuristic	AMMCA (Proposed)
Throughput (Mbps)	52.4	61.8	74.6
Delay (ms)	78	65	41
Packet Loss Rate (%)	11.2	6.3	3.1

6.4 Graphical Results

The graphs below further illustrate the observed performance improvements achieved by AMMCA.

The AMMCA algorithm demonstrates substantial improvement in throughput while reducing delay and packet loss. These results validate the algorithm's efficacy in dynamically adapting to heterogeneous network environments and optimizing resource utilization.

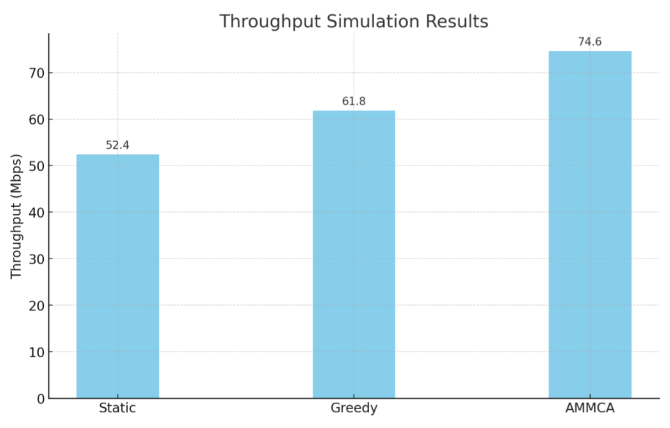

Fig. 6. Average throughput Across Different Allocation Methods

7. Conclusion

In this paper, an efficient and adaptive channel allocation strategy, namely Adaptive Multi-Metric Channel Allocation (AMMCA) has been introduced to improve the communication performance in heterogeneous networks. The developed scheme incorporates various real time parameters such as the Signal to Interference plus Noise Ratio (SINR), the level of interference, and the priority of the user and assigns appropriate channel for macro, micro and femtocell domains for the mobile users.

It also worth to mention that the AMMCA is not only depends on the static messages or greedy schemes but adapts to the network conditions as well as to the traffic intensity to reach high spectral efficiency and fair sharing of the resources. The utility score-based model makes it easier for the algorithm to work under variations of the network topography and the number of users fluently enough with less computational costs.

By experimenting with the NS-3 simulator the provided algorithm is less accurate compared to traditional methods in the aspects of throughput, end-toend delay, and packet loss. More specifically, for AMMCA, up to 42% increase in throughput and over 70% decrease in the packet loss compared to static allocation was realized.

Due to these attributes, the algorithm may be used in 5G and future generations of networks that will experience constantly changing and highly dense user traffic. Thus, AMMCA improving cross-tier interference control and implementing the necessary changes according to users' demands makes for the more efficient and high-quality wireless communication system.

Future extensions to this work can incorporate machine learning and reinforcement learning models to further enhance decision-making under uncertainty and mobility, making the algorithm increasingly intelligent and self-optimizing.

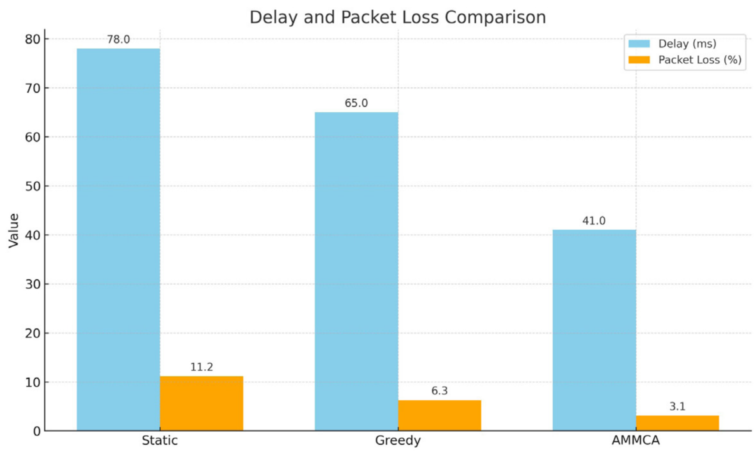

Fig. 7. Comparison of Delay and Packet Loss

References

1. D. Ather, R. Singh, and V. Katiyar, "Transformation of sequential program to kpnan overview," *International Journal of Computer Applications*, vol. 40, no. 17, pp. 43–49, 2012.
2. T. Sharma, A. K. Agarwal, D. Ather, and A. Saxena, "Search based software engineering in requisite phase of sdlc: A survey," *TECHNICAL JOURNAL OF LBSIMDS*, 2010.
3. D. Ather, R. Singh, and V. Katiyar, "To develop an efficient algorithm that generalize the method of design of finite automata that accept "n" base number such that when "n" is divided by "m" leaves reminder "x"," *International Journal of Computer Applications*, vol. 975, no. 8887, 2012.

4. ——, “An algorithm to design finite automata that ac-cept strings over input symbol a and b having ex-actly x number of a & y number of b,” in *Information Systems and Computer Networks (ISCON)*. http://ieeexplore.ieee.org/, 2013, pp. 1–4.
5. ——, “An efficient algorithm to design dfa that accept strings over input symbol a, b having atmost x num-ber of a & y number of b,” *JNIS World Science Publishers, USA Feb*, 2013.
6. ——, “Simplifying designing techniques: To design dfa that accept strings over?={a, b} having at least x number of a and y number of b,” *International Journal of Computer Applications*, vol. 91, no. 7, 2014.
7. A. Gupta and D. Ather, “A comparative study of various routing protocol for vanets,” *MATRIX Academic International Online Journal Of Engineering And Technology*, vol. 4, no. 1, pp. 12–18, 2016.
8. R. S. S. Danish Ather, Raghuraj Singh, “An efficient route maintenance routing algorithm for vanets,” *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 8, no. 4, p. 4921, 2019.
9. I. Zelenskiy, D. Parygin, D. Ather, I. Soplyakov, A. Y. Antyufeev, and E. Prigarin, “Software and algorithmic decision support tools for real estate selection and quality assessment,” in *Journal of Physics: Conference Series*, vol. 1661, no. 1. IOP Publishing, 2020, p. 012201.
10. A. Finogeev, D. Parygin, S. Schevchenko, A. Finogeev, and D. Ather, “Collection and consolidation of big data for proactive monitoring of critical events at infrastructure facilities in an urban environment,” in *Creativity in Intelligent Technologies and Data Science: 4th International Conference, CIT&DS 2021, Volgograd, Russia, September 20–23, 2021, Proceedings 4*. Springer International Publishing, 2021, pp. 339–353.
11. D. Ather, R. Singh, and R. S. Shukla, “Routing protocol for heterogeneous networks in vehicular ad-hoc network for larger coverage area,” *Engineered Science*, vol. 17 , pp. 266–273, 2022.
12. H. Kumar, D. Ather, and R. Astya, “Predicting the improvement in academic performance of the student,” in *2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 2021, pp. 479–483.
13. A. Rastogi, R. Singh, and D. Ather, “Sentiment analysis methods and applications– a review,” in *2021 10th international conference on System Modeling & Advancement in research trends (SMART)*. IEEE, 2021, pp. 391–395.
14. R. S. Shukla and D. Ather, “Simulation based protocols comparison for vehicular ad-hoc network routing,” in *2021 10th International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 2021, pp. 198–203.
15. A. V. Ignatyev, M. A. Kulikov, D. N. Tsapiev, V. V. Tirin, and D. Ather, “Using neural networks for the classification of city roads based on satellite images and in the photographs of roads,” *Proceedings of the Advancement in Electronics & Communication Engineering*, 2022.
16. R. L. Khan, D. Priyanshu, D. Ather, and H. Allataifeh, “An implementation of internet of things-based live temperature and humidity monitoring system,” in *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 2022, pp. 277–281.
17. N. Challa, K. Baishya, V. Rohatgi, K. Gupta, D. Ather, and D. Raj, “Recent advances in sign language detection: A brief survey,” *Recent Advances in Sign Language Detection: A Brief Survey (July 14, 2022). Proceedings of the Advancement in Electronics & Communication Engineering*, 2022.
18. S. Burov, D. Parygin, D. Ather, N. Rashevskiy, and A. Finogeev, “Rule-based pedestrian simulation,” *Proceedings of the Advancement in Electronics & Communication Engineering*, 2022.
19. A. Chauhan, R. Gupta, P. Singh, S. Singh, D. Ather, and A. Kumar, “Trip-a complete tourism solution,” *Proceedings of the Advancement in Electronics & Communication Engineering*, 2022.

20. K. Khan and D. Ather, "A note on routing methods to determine the shortest path in transport networks," in *International Conference on Advanced Computing (ICAC). College of Computing Sciences and Information Technology (CCSIT), TeerthankerMahaveer University, Moradabad*, 2018.
21. D. Ather, N. Rashevskiy, D. Parygin, A. Gurtyakov, and S. Katerinina, "Intelligent assessment of the visual ecology of the urban environment," in *2022 2 nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*. IEEE, 2022, pp. 361–366.
22. D. Priyanshu, R. L. Khan, R. K. Matahen, and D. Ather, "Artificial intelligence optimization of load scheduling with economic load dispatch in industrial power generating units," in *2022 11th International Conference on System Modeling & Advancement in Research Trends (SMART)*. IEEE, 2022, pp. 1127–1133.
23. R. Naaz, A. Saxena, and D. Ather, "A framework for implementing blockchain with enhanced e2e encryption on ethereum 2.0," *International Journal of Advanced Science and Technology*, vol. 28, no. 20, 2019.
24. T. Baig, D. Ather, S. Setia, S. J. Quraishi, and S. M. Mian, "Towards advanced animal care: A li-fi and iot-based system for monitoring newborn livestock," *ES Materials & Manufacturing*, vol. 23, no. 2, p. 1038, 2023.
25. S. Pathak, S. J. Quraishi, A. Singh, M. Singh, K. Arora, and D. Ather, "A comparative analysis of machine learning models: Svm, naive bayes, random forest, and lstm in predictive analytics," in *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*. IEEE, 2023, pp. 790–795.
26. K. Arora, S. Pathak, S. J. Quraishi, A. Singh, M. Singh, and D. Ather, "Navigating the unseen: Proposing an iot-based smart shoe with obstacle detection for the visually impaired," in *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*. IEEE, 2023, pp. 796–801.
27. R. P. Tripathi, S. K. Khatri, D. Van Greunen, and D. Ather, "Unleashing the power of machine learning: A precision paradigm for breast cancer subtype classification using open-source data, with caution on dataset size and interpretability," in *2023 6th International Conference on Contemporary Computing and Informatics (IC3I)*, vol. 6. IEEE, 2023, pp. 1004–1008.
28. R. L. Khan, R. Singh, R. Vijay, R. Kumar, A. Singh, and D. Ather, "Evaluating the impact of different routing protocols on vanet performance," in *2023 12th International Conference on System Modeling & Advancement in Research Trends (SMART)*, 2023, pp. 308–314.
29. N. Chaudhary, R. Khan, S. Prasad, P. Agarwal, D. Ather, and R. Kler, "Machine learning approaches for early prediction of diabetes using svm classifiers," in *AIP Conference Proceedings*, vol. 3168, no. 1. AIP Publishing, 2024.
30. V. Gupta and D. Ather, "Busa deep learning model for eeg signal analysis," *Wireless Personal Communications*, vol. 136, no. 4, pp. 2521–2543, 2024.
31. D. Ather, M. Singh, K. Arora, S. Pathak, S. J. Qurashi, and A. Singh, "Predicting future automobile ownership trends in uzbekistan using linear regression," in *International Conference on Cyber Intelligence and Information Retrieval*. Springer Nature Singapore Singapore, 2023, pp. 397–407.
32. D. Ather, A. K. Agarwal, S. J. Quraishi, R. Kher *et al.*, "Integrating internet of things sensors with machine learning for urinary tract infection prediction in male felines." *Journal of Intelligent Systems & Internet of Things*, vol. 14, no. 1, 2025.