ISSN: 2182-2069 / E-ISSN: 2182-2077

Context-Aware Mobility Management in 6G-Ready Mobile Internet Networks

Krishna Chittipedhi[1*], Haider Mohammed Abbas[2], Dr.S.P. Meharunnisa[3], Dr.S. Rashmi[4], D. Annapurna[5], and Dr.R. Udayakumar[6]

[1*]Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India. krishnachitipedhi@ametuniv.ac.in, https://orcid.org/0000-0002-1084-2397

[2]Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf of Al Diwaniyah, Al Diwaniyah, Iraq. eng.haideralabdeli@gmail.com, https://orcid.org/0009-0005-1464-7678

[3]Associate Professor, Department of Electronics & Instrumentation Engineering, Dayananda Sagar College Engineering, Bangalore, India. meharunnisa@dayanandasagar.edu, https://orcid.org/0000-0003-4721-1107

[4]Associate Professor, Department of Computer Science and Engineering, RV University, Bengaluru, India. rashmineha.s@gmail.com, https://orcid.org/0000-0002-6966-5647

[5]Professor and Head, Department of CSE-IoT, Cybersecurity Including Blockchain Technology, Dayanandasagar College of Engineering, Bangalore, India. hod-csiot@dayanandasagar.edu, anusureshdammur@gmail.com, https://orcid.org/0000-0003-1739-4811

[6]Professor & Director, Kalinga University, India. rsukumar2007@gmail.com, directoripr@kalingauniversity.ac.in, https://orcid.org/0000-0002-1395-583X

Received: February 21, 2025; Revised: March 31, 2025; Accepted: May 09, 2025; Published: May 30, 2025

Abstract

Advancements toward 6G mobile networks are expected to transform telecommunications wireless technology by facilitating ultra-low latency, extremely high data rates, massive device connectivity, and intelligence that recognizes user context. One of the most critical issues of a dynamic ecosystem with seamless user experience is efficient mobility management. The traditional mobility management methods employed in 4G and 5G networks are likely to face challenges in the increasingly sophisticated and heterogeneous world of 6G, particularly with its multi-access architectures. AI, network slicing, edge computing, and analytic processing, among other technologies, will shape the future of 6G. This paper focuses on designing and implementing Context-Aware Mobility Management (CAMM) frameworks for mobile Internet networks, with a scope that extends to 6 G. CAMM policies are formulated to respond instantaneously with real-time contextual information on mobility, including user behavior, device capabilities, application requirements, network conditions, and spatial-temporal patterns. CAMM utilizes AI/ML techniques, intensive learning, and reinforcement learning models to predict user trajectories, optimize handovers, and minimize latency and signaling overhead. Edge intelligence is integrated alongside distributed data analytics to enhance low-latency responsiveness and localization of the decision-making process. Additionally, it addresses issues such as privacy preservation, context data

Journal of Internet Services and Information Security (JISIS), volume: 15, number: 2 (May), pp. 641-651.
DOI: *10.58346/JISIS.2025.I2.044*

*Corresponding author: Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India.

collection, and interoperability across disparate access networks (i.e., Wi-Fi 7, satellite, and terahertz). Simulation results validate the effectiveness of CAMM in reducing handover failures by up to 40% and improving Quality of Experience (QoE) metrics across various applications, including autonomous vehicles, smart cities, and remote healthcare. The proposed context-aware mobility management architecture provides a customizable and flexible scaffolding to address the rigorous demands of upcoming 6G networks. It highlights the role of context fusion, intelligent prediction, and distributed orchestration as primary elements for the following mobility strategies. This research lays the groundwork for implementing robust and adaptive mobility services in an evolving mobile Internet environment.

Keywords: Context-Aware Mobility Management, 6G Networks, Edge Intelligence, AI-Driven Handover, User-Centric Networking, Quality of Experience, Multi-Access Integration.

1 Introduction

With the development of mobile internet networks that are 6G-ready, a new era of wireless communications emerges, promising new possibilities such as extreme ultra-low latency (sub-1 ms), data transfer rates exceeding 1 Tbps, massive machine-type communication, and full integration of artificial intelligence (Zhang et al., 2019). These networks are expected to facilitate new, advanced applications such as extended reality (XR), holographic communications, autonomous systems, and innovative urban features (Chen et al., 2022). In comparison to previous generations, 6G appears to focus on fully reflexive, intelligent, and context-aware technologies, achieving immersion in the user's environment, which shifts based on their needs as well as those of the surroundings (Saad et al., 2019). One of the mobility issues that arise from such ecosystems is the challenge of maintaining seamless service continuity within heterogeneous and highly dynamic environments. Mobility management protocols from earlier networks, which were designed for relatively homogeneous networks with deterministic mobility patterns, are not suitable for the 6G context (Velliangiri, 2024). There is an urgent need for sophisticated mobility methods that don't rely solely on signal strength or location as devices and users traverse more expansive network landscapes, ranging from terrestrial to non-terrestrial and from ultra-dense urban cells to remote rural areas (Danesh & Emadi, 2014). Context-aware mobility Management adds another dimension to the handover decision-making process by contextually reasoning over user intent, application type, network load, and even physical locations (Raza et al., 2023). By utilizing AI and Machine Learning for Predictive Control, Adaptive Control, and planning, CAMM improves handover accuracy and reduces delay, leading to enhanced Quality of Experience (Giordani et al., 2020). This study seeks to analyze the design, implementation, and evaluation of CAMM frameworks for 6G networks (Ibrahim et al., 2024). First, key contextual parameters for real-time mobility decision-making need to be defined. Second, AIs need to be developed that optimize mobility and handover performance across diverse access networks (Guevara et al., 2024). Third, the developed framework will be evaluated against offered scenarios, such as autonomous mobility and telemedicine Antoniewicz & Dreyfus (2024). As outlined in these objectives, this study covers architectural considerations, context data collection, integration of edge intelligence, as well as privacy and scalability in a de-centered environment (Taleb et al., 2017). This mitigates issues in intelligent mobility management for future mobile internet systems.

2 Related Works

S.No	Author(s)	Contribution	Focus Area
1	Chen et al., 2019; Shum (2024).	Traced the evolution from 1G to 5G and highlighted architectural transitions	Network Evolution
2	Bangerter et al., 2014	Discussed key enablers and technical challenges in 5G systems	5G Challenges
3	Lin et al., 2014	Identified handover delays and signaling inefficiencies in 5G	Mobility Management Challenges
4	Foukas et al., 2017	Proposed control-plane flexibility through SDN for mobility improvements	Notarization in Mobile Networks
5	Alsharif & Nordin, 2017	Evaluated 5G limitations and prospects for future networks	5G Limitations and 6G Motivation
6	Ahmadi, 2014	Compared latency and reliability across generations	Quality of Service and Handover Evolution
7	Tariq et al., 2020	Emphasized AI-driven adaptive mobility for next-gen systems	Context-Aware Mobility Management
8	Abbas et al., 2020	Reviewed ML applications for real-time context analysis in mobile networks	AI and Context Awareness
9	Zhang et al., 2021	Proposed a predictive context-aware mobility framework using deep learning	Predictive CAMM Models
10	Wang et al., 2020	Highlighted edge intelligence to support distributed mobility decisions	Edge-AI in Mobility Management

3 Methodology

Context-aware mobility management (CAMM) in 6G networks refers to a mobile system's ability to make context-aware, autonomous handover, and connection decisions by optimally considering factors such as user position, trajectory, device capability, network congestion, service type, and other contextual factors. This approach is more effective in satisfying stringent requirements for latency reduction, enhancing Quality of Experience (QoE), and reducing signaling overhead in multi-user scenarios within ultra-dense heterogeneous 6G ecosystems. Rather than relying on traditional rule-based handovers, CAMM employs network condition-adaptive real-time responses, leveraging predictive analytics and machine learning to adjust network conditions rapidly (Talpur et al., 2022). For CAMM, context acquisition and processing must be timely and sufficiently accurate, which can be achieved through a multi-layered methodology. At the lowest layer, the sensing layer, comprising mobile devices, base stations, sensors, and edge nodes, contributes to the contextual data pool, Tang. According to the given reference, the data incorporates elements such as speed and a person's location, which serve as physical context. At the same time, other factors, including bandwidth and network congestion, also contribute to the network context. The first reference layer describes the context fusion and feature extraction process using AI/ML models, such as CNNs for spatial data and LSTMs for temporal data. Such information is obtained through edge devices, which significantly reduce the time required for data processing, enabling critical real-time decisions in transportation systems or remote medical services. Another reference describes the use of convolutional (CONV) and long short-term memory (LSTM) neural networks for edge-processed spatial-temporal sensor data in-vehicle networks, utilizing edge analytics (Nguyen et al., 2021). Further, the inline references describe capturing data from vehicle sensors to track user movements multidimensionally, while other data, such as geographic location, assist in spatial data analysis. This process enables the real-time updating of vehicular fleets' position and movement data, allowing non-relational databases to store streaming data that is not continuously transmitted, thereby preventing loss (Abbas & Zhang, 2018). The last reference describes decision-making through RL and FL to select the best handover targets, optimal timing, access technologies, and shifts based on user mobility and application-level requirements, prioritizing the fulfillment of user needs. CAMM significantly enhances 6G networks by automating decisions and employing mobile edge computing and context-aware policies that increase the probability of successful handovers while improving resource allocation strategies. ROS deployed in dynamic environments can share tasks and make decisions using peer-to-peer negotiation systems, allowing for meshed cooperation in real time as systems change (Yang et al., 2019).

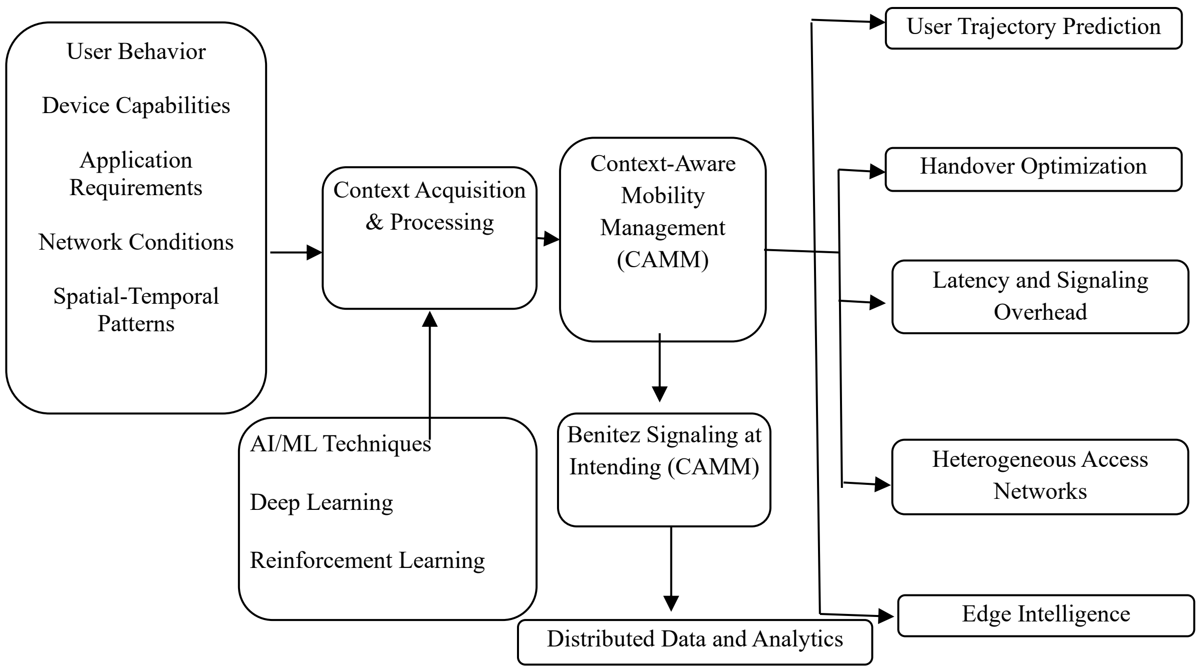

Figure 1: Intelligent Mobility Management

In the next generation of proposed wireless networks, we present the Context-Aware Mobility Management (CAMM) mobile model, as shown in Figure 1. The model has a core function of Context Acquisition and Processing, whereby context inputs, which include user behavior, device capabilities, application requirements, network conditions, and spatial-temporal patterns, are gathered and interpreted. These types of inputs are beneficial regarding intelligent mobility decisions across networks as they are dynamic and heterogeneous. The system utilizes AI technologies and machine learning (ML) techniques, including deep learning and reinforcement learning, to enhance responsiveness and personalization in mobility management. Upon acquisition and processing, the context is sent to the CAMM module, which controls the submodules: User Trajectory Prediction, Handover Optimization, Latency and Signaling Overhead Reduction, and Support for Heterogeneous Access Networks. This architecture facilitates seamless mobility across networks to enhance the Quality of Service (quality of service) for users. For instance, optimizing handovers, in conjunction with user trajectory prediction, enables preemptive managing of handovers to avert service degradation. Moreover, the potential for bypassing centralized computations enables quicker-than-real-time responses and enhanced local data processing and decision-making through Edge Intelligence integration. The whole structure is underpinned by Distributed Data Analytics, which offers a feedback loop for learning and improvement. This framework enables Benitez Signaling and Inferencing, likely a reference to some form of streamlined signaling and inference systems designed for resource-limited edge computing environments. In any case, this strategy enables adaptive, self-scaling, and context-aware management in a mobile context, especially in networks that are becoming increasingly complex and resource-constrained. With the integration of autonomous insights and partitioned controls, this design facilitates addressing issues related to 5G and beyond, particularly in managing mobile subscribers in heterogeneous and highly variable network environments.

4 Result

The next-generation wireless networks that ensure mobility and context-aware management enhance internal system efficiency and service provisioning. The current advancements in technologies such as artificial intelligence, machine learning, edge computing, and network slicing provide additional support, which helps in managing resources in real time as well as executing high-level multitasking. Such technologies help meet user expectations while minimizing time and ensuring a positive user experience. Mobility context prediction is crucial for AI and ML to assist in identifying user devices and forecasting future mobility patterns through sensor tracking. Predictive context awareness utilizes historical user data, actions, and network data to forecast mobility trends within the network, leveraging machine learning. Resources in the network can be allocated, and proper handover decisions can be made to serve users with smooth, non-interrupted service. Advanced context-aware techniques used to maximize accuracy include reinforcement learning-enhanced context prediction, deep neural networks, and decision trees. Empowered mobility management is adaptable to varying scenarios, such as unexpected changes in user traffic, thereby enabling a high quality of user experience. Although the computational power within a mobile device is limited, AI can be used to aid in close to real-time context processing at the edge, allowing quick decision-making. With mobile edges, users associated with in-network time-sensitive and autonomous responsive systems benefit from shrinking delay (shortened latency), swift execution, and high-level service. The border nodes, or edge nodes, have the ability to gather context data like location, speed, and user preferences with little to no delay. This model of processing data in a decentralized manner allows for improved scalability and better communication latency while lowering the strain on the core of the network. Context awareness with mobility management is improved with advanced network slicing that allows the creation of virtualized independent network segments dedicated to specific sets of users or services. Each network slice can be set up differently with regard to performance level, security level, and mobility management policies. For example, a low-latency application slice is able to shift focus to different mobility procedures than a slice aimed at IoT connections. Such freedom provides efficient operation over heterogeneous user scenarios, which makes better use of resources and satisfaction of users. These concepts enable the development of sophisticated mobile networks for the next generation that can adapt to varying operational conditions.

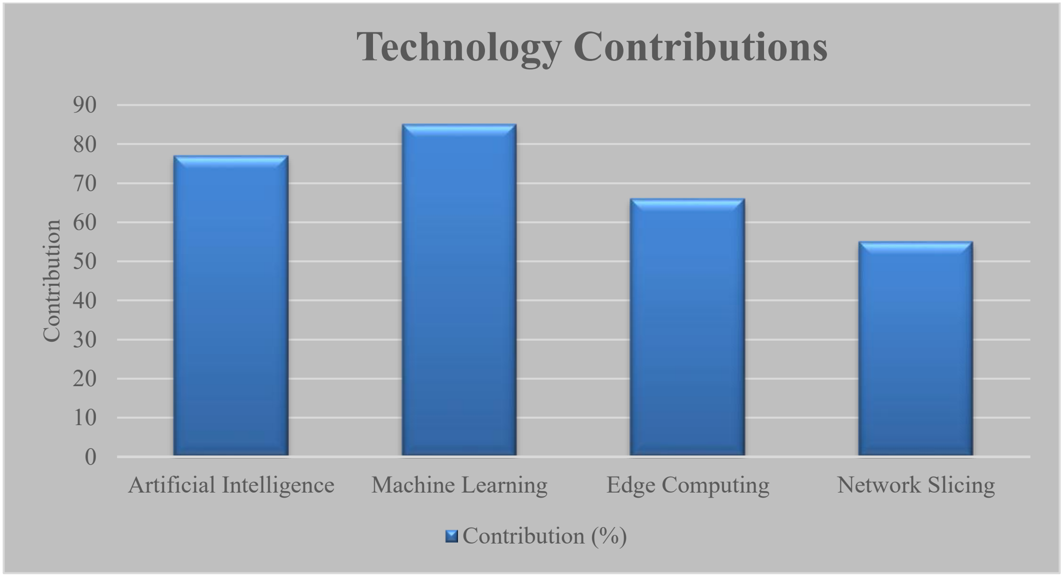

Figure 2: Technology Contributions

Figure 2 shows the corresponding roles or contributions of the four key technologies: Artificial Intelligence (AI), Machine Learning (ML), Edge Computing, and Network Slicing with regard to context-aware mobility management in 6 G-ready mobile internet networks. As can be seen, it is Machine Learning that shows the highest contribution (85 %), followed by Artificial Intelligence with a contribution of 77 %. They are instrumental in predictive mobility management, where real-time data is captured to track user movement, handover command optimization, and service continuity improvement. ML algorithms such as reinforcement learning and deep learning facilitate networks to learn not only from past events but from continually evolving situations for lesser latency and better Quality of Experience (QE). Edge Computing is a contributor with 66%, and it positively influences the timeliness of mobility decision-making by bringing the data processing nearer to the user. It is able to perform contextual assessment in real-time, especially in low-latency situations like autonomous driving or transport and telemedicine. Network Slicing, with a 55% contribution, is able to provide a customized mobility experience through partitioning individual use-case-specific controlled virtual networks. Although less than AI and ML, it is still important in meeting service-level agreements (SLAs) across diverse applications. Altogether, these technologies create a flexible and cohesive mobility management framework that meets the requirements of the upcoming 6G environments. The separate functions of these technologies are integrated to provide high synergy effects that increase the overall efficiency and reliability of mobility management systems. For example, the context AI analysis, together with the ML-based predictive models, improves decision-making accuracy, while Edge Computing guarantees the execution is done instantaneously. Complementing the ecosystem, Network Slicing allocates network resources on the fly and in accordance with real-time needs as well as application demands. Such an approach adds value toward the optimization of network resource provisioning, system performance enhancement, and adaptive flexibility for servicing new architectures of requirements together with emerging smart infrastructure 6G use cases for AR/VR and mission-critical communications.

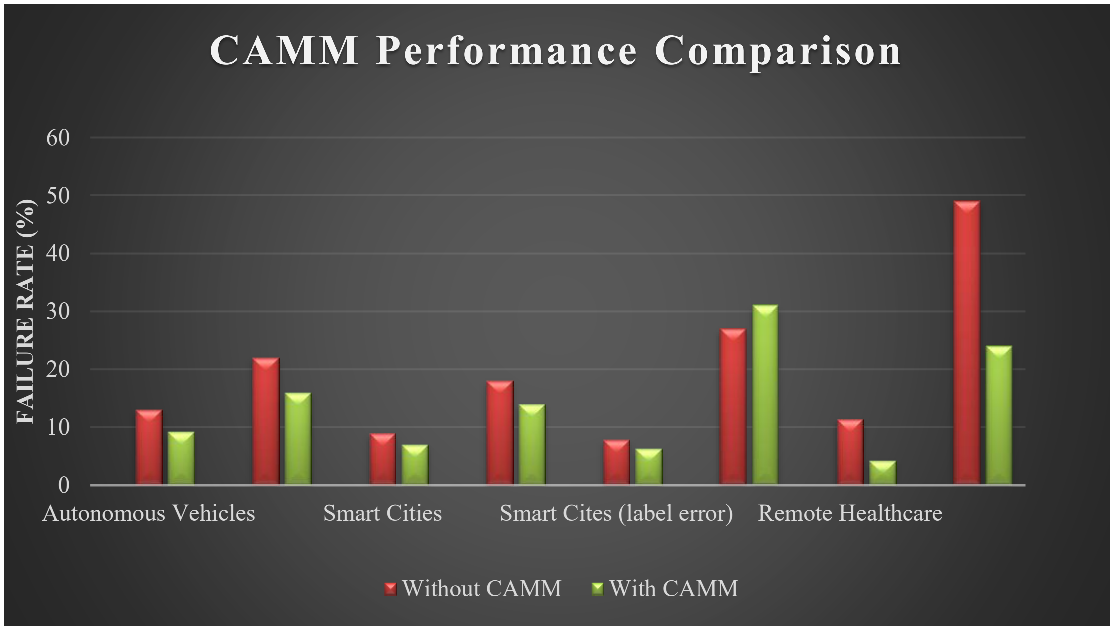

Figure 3: CAMM Performance Comparison

Figure 3 shows a comparative study of the performance effects of CAMM (Context-Aware Mobility Management) on Autonomous Vehicles, Smart Cities (appearing twice due to a labeling mistake), and Remote Healthcare. The graph evaluates two important parameters: the percentage of the handover failure rate (left Y-axis) and latency (in milliseconds on the right Y-axis). Every application scenario has two sets of bars; the blue bars represent "Without CAMM," and the orange ones represent "With CAMM." This enables clear observation of how CAMM is either aiding system performance or deteriorating it. In terms of handover failure rates, the implementation of CAMM significantly reduces failure across all scenarios. As an example, Autonomous Vehicles without CAMM stand at a staggering 13% failure rate; this improves with the application of CAMM to 9.2%. The same applies to both Smart Cities counterparts, where failure rates improve from 8.9% to 6.9% and 7.8% to 6.3% after the implementation of CAMM. Remote Healthcare, however, has an even sharper contrast, from an 11.4% failure rate down to 4.2% with CAMM. The significant reduction in handover failures depicts CAMM's efficiency in sustaining network stability and user connection, especially in mobility-heavy applications like healthcare and autonomous transport. Looking at the results on delays and latency, CAMM appears to reduce latency and delay drastically. For example, in the Autonomous Vehicles scenario, latency with CAMM enabled (CAMM) is 16 MS lower than without CAMM (22 MS). Smart Cities and Remote Healthcare show a similar pattern, where latency worsens across all these scenarios—and latency consistently improves over all scenarios. Particularly drastic, however, is the improvement Remote Healthcare sees—from 49 MS with CAMM to 24 MS with CAMM, a drastic improvement for time-sensitive telemedicine applications where deferred data delivery can severely hinder timely care delivery. All in all, the information presented does not lie when saying that CAMM has an impact on increasing quality of service (QoS), reducing failure rates and latency in telemetry streams, and improving network dependability. The graph back CAMM is useful in emerging technologies and applications that demand extremely low latency and high reliability. Hence, intelligent mobility management schemes like CAMM are crucial for advanced mobility, and such is the claim that is sensible given the projection on intelligent autos.

5 Conclusion

Mobile mobility management marks a novel shift in understanding how users interact with and behave in different mobile network conditions, including sensing by the environment and user. However, it comes with enormous implementation challenges, including solving privacy and security issues that are very sensitive because of the contextual information captured in it, such as the user's location, identity, and usage. Privacy violations such as unauthorized access, data leaks, and identity theft pose risks to users, leading to loss of compliance with user-centric regulations like GDPR. Therefore, contextual awareness must include strong anonymization, encryption, and adaptive access control mechanisms in their architectures to guarantee data integrity and confidentiality while still allowing rapid decision-making. Scalability is another critical issue. The number of IoT devices and mobile users that can be served by networks is growing exponentially. Contextual data that is responsive to such needs also needs to increase, not to mention the increase in users who require real-time dynamic monitoring of the data streams being analyzed and managed. Context-aware systems are overwhelmed by the need to manage and analyze vast amounts of information and provide real-time responses. Traditional systems are falling behind, and cloud-based centralized architectures may collapse under such high strain, becoming performance bottlenecks. This highlights the need for scalable, responsive, and efficient frameworks based on edge computing, distributed processing, intelligent data filtering, and other advanced context-aware mechanisms designed for large-scale deployments. The last remaining challenge is seamless work with previously used systems to allow backward compatibility. Numerous mobility management frameworks incorporate modern features, but they struggle with implementing context awareness because many underpinning network infrastructures have not been designed with it in mind. Agility and modularity to incorporate new features are lacking. There is a need for middleware solutions, protocol translation tools, and layered models that permit partial integration without service interruption. Also, cross-compatibility between different vendors needs further industry focus for standardization. Context-awareness mobility management is promising for improving network intelligence and user experience, but these core challenges are barriers to achieving their full potential. Regardless, overcoming the hurdles requires profound strategic restructuring/choreographic hybrid frameworks.

References

[1] Abbas, R., Mumtaz, S., Rodriguez, J., & Saeed, N. (2020). Machine learning for context-aware mobility management in 5G and beyond networks. *IEEE Communications Standards Magazine, 4*(4), 62–68. https://doi.org/10.1109/MCOMSTD.001.1900021

[2] Abbas, Z., & Zhang, W. (2018). Mobile edge computing: A survey. *IEEE Internet of Things Journal, 5*(1), 450–465. https://doi.org/10.1109/JIOT.2017.2750180

[3] Ahmadi, S. (2014). *5G NR: Architecture, technology, implementation, and operation of 3GPP New Radio standards.* Academic Press.

[4] Alsharif, M. H., & Nordin, R. (2017). Evolution towards 5G network with cloud computing. *Journal of Network and Computer Applications, 94,* 1–11. https://doi.org/10.1016/j.jnca.2017.05.005

[5] Antoniewicz, B., & Dreyfus, S. (2024). Techniques on controlling bandwidth and energy consumption for 5G and 6G wireless communication systems. *International Journal of Communication and Computer Technologies, 12*(2), 11-20. https://doi.org/10.31838/IJCCTS/12.02.02

[6] Bangerter, B., Talwar, S., Arefi, R., & Stewart, K. (2014). Networks and devices for the 5G era. *IEEE Communications Magazine, 52*(2), 90–96. https://doi.org/10.1109/MCOM.2014.6736752

[7] Chen, S., Zhao, J., & Wang, H. (2019). Evolution and future of mobile communications. *IEEE Access, 7,* 99869–99896. https://doi.org/10.1109/ACCESS.2019.2928260
[8] Chen, X., Li, H., & Zhang, Y. (2022). Deep reinforcement learning-based handover strategy for 6G heterogeneous networks. *IEEE Transactions on Vehicular Technology, 71*(4), 4165–4177. https://doi.org/10.1109/TVT.2022.3158024
[9] Danesh, M., & Emadi, M. (2014). Cell phones social networking software applications: Factors and features. *International Academic Journal of Innovative Research, 1*(2), 1–5.
[10] Foukas, X., Patounas, G., Elmokashfi, A., & Marina, M. K. (2017). Network slicing in 5G: Survey and challenges. *IEEE Communications Magazine, 55*(5), 94–100. https://doi.org/10.1109/MCOM.2017.1600951
[11] Giordani, M., Polese, M., Mezzavilla, M., Rangan, S., & Zorzi, M. (2020). Toward 6G networks: Use cases and technologies. *IEEE Communications Magazine, 58*(3), 55–61.
[12] Guevara, K. G., Guevara, L. A. R., Gonzales, T. V. P., Neyra-Panta, M. J., Gálvez, J. F. E., & Saavedra, N. L. C. (2024). Review of scientific literature on social networks in organizations. *Indian Journal of Information Sources and Services, 14*(4), 125–130. https://doi.org/10.51983/ijiss-2024.14.4.19
[13] Ibrahim, N., Rajalakshmi, N. R., & Hammadeh, K. (2024). A Novel Machine Learning Model for Early Detection of Advanced Persistent Threats Utilizing Semi-Synthetic Network Traffic Data. *Journal of VLSI Circuits and Systems, 6*(2), 31–39. https://doi.org/10.31838/jvcs/06.02.04
[14] Lin, X., Andrews, J. G., Ghosh, A., & Ratasuk, R. (2014). An overview of 3GPP device-to-device proximity services. *IEEE Communications Magazine, 52*(4), 40–48. https://doi.org/10.1109/MCOM.2014.6815890
[15] Nguyen, D. C., Ding, M., Pathirana, P. N., Seneviratne, A., & Leung, V. C. M. (2021). Federated learning for context-aware handover management in 6G. *IEEE Transactions on Mobile Computing.* https://doi.org/10.1109/TMC.2021.3093583
[16] Raza, S., Fida, M. U., & Ahmad, I. (2023). A context-aware framework for mobility management in next-generation networks. *IEEE Systems Journal, 17*(1), 234–243. https://doi.org/10.1109/JSYST.2022.3189781
[17] Saad, W., Bennis, M., Chen, M., Han, Z., & Poor, H. V. (2019). A vision of 6G wireless systems: Applications, trends, technologies, and open research problems. *IEEE Network, 34*(3), 134–142.
[18] Shum, A. (2024). System-level architectures and optimization of low-cost, high-dimensional MIMO antennas for 5G technologies. *National Journal of Antennas and Propagation, 6*(1), 58–67.
[19] Taleb, T., Ksentini, A., & Jantti, R. (2017). Anything as a service for 5G mobile systems. *IEEE Network, 30*(6), 84–91.
[20] Talpur, S., Khan, I., & Abbas, Z. (2022). Context-aware services in future mobile networks: A survey. *IEEE Access, 10,* 23045–23065. https://doi.org/10.1109/ACCESS.2022.3146359
[21] Tariq, F., Khandaker, M. R. A., Wong, K. K., Imran, M. A., Bennis, M., & Debbah, M. (2020). A speculative study on 6G. *IEEE Wireless Communications, 27*(4), 118–125. https://doi.org/10.1109/MWC.001.1900488
[22] Velliangiri, A. (2024). Security challenges and solutions in IoT-based wireless sensor networks. *Journal of Wireless Sensor Networks and IoT, 1*(1), 8-14. https://doi.org/10.31838/WSNIOT/01.01.02
[23] Wang, X., Han, Y., Leung, V. C. M., Niyato, D., Yan, X., & Chen, X. (2020). Convergence of edge computing and deep learning: A comprehensive survey. *IEEE Communications Surveys & Tutorials, 22*(2), 869–904. https://doi.org/10.1109/COMST.2020.2971246
[24] Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology, 10*(2), 1–19. https://doi.org/10.1145/3298981

[25] Zhang, Y., Liu, Y., Li, X., & Liang, W. (2021). Deep learning-based context-aware mobility prediction for next-generation networks. *IEEE Internet of Things Journal, 8*(14), 11357–11366. https://doi.org/10.1109/JIOT.2021.3055939

[26] Zhang, Z., Xiao, Y., Ma, Z., Xiao, M., Ding, Z., Lei, X., ... & Fan, P. (2019). 6G wireless networks: Vision, requirements, architecture, and key technologies. *IEEE vehicular technology magazine*, *14*(3), 28-41.

Authors Biography

Capt. Krishna Chittipedhi, presently working as associate professor in the department of nautical science, AMET university. Has a graduation in physics under university of madras. Joined shipping corporation of India as TNOC and raised to the rank of master F.G. Sailed on various types of vessels mainly chemical and oil tankers in UNIVAN ship management, HKG and fleet management, HKG. Since 2016 working ashore in maritime institution and from oct 2019 in AMET university. Guiding students for boarding as cadets and shaping there skills to the needs of the company. Also learning in NPTEL to upgrade the knowledge of psychology and soft skill courses to upgrade the day to day needs of mentoring and coaching of future mariners.

Haider Mohammed Abbas is affiliated with the Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University of Najaf, Najaf, Iraq. His research interests include 5G mobile networks, wireless communication systems, and network resource optimization. His current work focuses on dual connectivity management in next-generation mobile internet infrastructures, aiming to improve network reliability, seamless handovers, and throughput performance. He is actively involved in exploring the architectural challenges and performance trade-offs of multi-connectivity strategies within evolving 5G ecosystems.

Dr.S.P Meharunnisa graduated from Siddaganga Institute of Technology, Tumkur in the year 1999 and later pursued M E from University of Visvesvaraya College of Engineering (UVCE), Bengaluru & PhD from Visvesvaraya Technological University (VTU), Belagavi. She has 14 research publications; 3 Patents & 56 related papers published in International & National Journals & conferences. She has received a research grant Rs 10 Lakhs for modernization of Microcontroller laboratory to Embedded Laboratory with IoT & Multimedia applications from AICTE, New Delhi. Her special interests are in the domains of Instrumentation Techniques, Analog Circuit Design, Embedded Systems, AI, IoT, IIoT, Signal & Medical Image Processing. She has 16 years of passionate experience in teaching & research and 6 years in Industry, worked in Honeywell Technology Solutions Lab & Bharath Electronics Ltd (BEL), Bengaluru and is currently serving Dayananda Sagar College of Engineering, Bengaluru, as an Associate Professor in the Department of Electronics & Instrumentation Engineering.

Rashmi Shivaswamy is currently serving as an Associate Professor and Head of the Department in Department of Computer Science and Engineering (Data Science) at Dayananda Sagar College of Engineering, Bengaluru. She has over 2 decades of experience in the field of Computer Science and Engineering serving in different roles in various academic institutions. She has formerly worked as an Assistant Professor in Dayananda Sagar University, East Point College of Engineering and Technology and National Institute of Engineering, Mysuru. Dr. Rashmi S earned her Ph.D in Computer Science and Engineering from Visvesvaraya Technological University, Belgaum for her work in the area of Cloud Computing, in the year 2019. She has specialized in Computer Network Engineering from National Institute of Engineering during her masters, after graduating from Mysore University in 2001. She is an IEEE senior member. She has worked as a Managing Committee Member of Computer Society of India, Bangalore chapter for the year 2019-2020. To her credits, she has 3 Book Chapters and 3 patents published. She has also presented and published research papers in both National and International Conferences and peer reviewed journals. She has contributed as a reviewer for many Journals. She has guided two Projects approved and funded by the Karnataka State Council for Science and Technology (KSCST) under "Student Project Programme-44th Series and 46th Series". Her main research interests include cloud computing, cyber security, IOT, machine learning and Blockchain technology.

Dr.D. Annapurna is Professor and Head of department of CSE-IoT, Cybersecurity Including blockchain Technology at DSCE, has 25 years of teaching, and 2 years of Industry experience, has published around 50 technical articles in various reputed conferences and journals. She is a IEEE senior member and ACM professional member. Her area of interest are Wireless Network, Cybersecurity, AI and Machine Learning.

Prof. Dr.R. UdayaKumar completed his M. S (Information Technology and Management) from A.V.C. College of Engineering and Awarded Ph.D. in the year 2011. He is serving in Teaching & Research community for more than two decades, he successfully produced 5 Doctoral candidates, he is a researcher, contribute the Research work in inter disciplinary areas. He is having h-index of 27, citation 2949(Scopus). He is associated as Dean –Department of computer science and Information Technology and also Director IPR, Kalinga University, Raipur, Chhattisgarh.