International Journal of Civil Engineering and Technology (IJCIET)
Volume 15, Issue 3, May-June 2024, pp. 11-20, Article ID: IJCIET_15_03_002
Available online at https://iaeme.com/Home/issue/IJCIET?Volume=15&Issue=3
ISSN Print: 0976-6308 and ISSN Online: 0976-6316
Impact Factor (2024): 21.69 (Based on Google Scholar citation)

TOWARDS GREEN WIFI NETWORKS: AN ML AND AI-BASED FRAMEWORK FOR ENERGY EFFICIENCY OPTIMIZATION

Sree Harsha
Aruba HPE, USA

ABSTRACT

The increasing demand for wireless connectivity has led to a significant rise in energy consumption by WiFi devices, necessitating the development of efficient energy management strategies. This paper presents a novel framework that leverages machine learning (ML) and artificial intelligence (AI) techniques to optimize the energy efficiency of WiFi devices without compromising network performance. The proposed approach utilizes predictive models to analyze historical data on device usage and network activity, allowing for the identification of energy-saving opportunities. In addition, AI-driven algorithms are used to adapt to changing environmental conditions and user behaviors, enabling real-time optimization of energy consumption. The framework additionally integrates predictive maintenance techniques to proactively identify and address energy inefficiencies and hardware issues. Experimental results show significant improvements in energy efficiency, with energy consumption reduced by up to 30% compared to traditional approaches. The findings emphasize the potential of ML and AI in improving the sustainability and cost-effectiveness of WiFi networks, opening up opportunities for future research and development in this field.

Keywords: Energy efficiency optimization, Machine learning in WiFi networks, Artificial intelligence for energy management, Predictive maintenance for WiFi devices, Sustainability in wireless networks.

Cite this Article: Sree Harsha, Towards Green Wifi Networks: An Ml and AI-Based Framework for Energy Efficiency Optimization, International Journal of Civil Engineering and Technology (IJCIET), 15(3), 2024, pp. 11-20.
https://iaeme.com/Home/issue/IJCIET?Volume=15&Issue=3

INTRODUCTION

The rapid growth of wireless networks and the increasing number of connected devices have resulted in a significant increase in energy consumption, which presents challenges for network providers and end-users [1]. WiFi devices, specifically, contribute significantly to this energy consumption, given their widespread use and constant need for connectivity [2]. As a result, enhancing the energy efficiency of WiFi devices has emerged as a crucial issue, given its direct influence on the sustainability, cost-effectiveness, and user experience of wireless networks [3]. Advancements in machine learning (ML) and artificial intelligence (AI) have created new opportunities for tackling this challenge, allowing for the creation of intelligent and adaptive energy management strategies [4]. Through the utilization of ML and AI techniques, WiFi devices have the ability to enhance their energy consumption patterns by taking into account usage, environmental factors, and network conditions. This results in notable energy savings and improved network performance [5].

RELATED WORK

Existing approaches to energy efficiency in WiFi devices

Technique	Energy Savings	Complexity	Adaptability
Power Saving Mode (PSM)	Low	Low	Low
Transmission Power Control	Medium	Medium	Medium
Adaptive Sleep Scheduling	High	High	High
ML-based Prediction	High	High	High

Table 1: Comparison of energy-saving techniques for WiFi devices [30]

Several studies have examined different methods to enhance the energy efficiency of WiFi devices. A common technique involves the utilization of power saving modes (PSM), enabling devices to enter a low-power state when not in use [6]. The PSM defined by the IEEE 802.11 standard allows devices to wake up periodically to check for incoming data and go back to sleep if no data is found [7].

Proposed enhancements to the PSM include the adaptive PSM and the automatic power save delivery (APSD), which aim to optimize energy consumption [8]. Additional approaches involve the utilization of dynamic transmission power control (TPC), which adapts the transmit power according to the necessary data rate and channel conditions [9], as well as energy-efficient scheduling algorithms that prioritize data transmission based on urgency and importance [10].

Applications of ML and AI in wireless networks

Machine learning and artificial intelligence have been utilized in various ways in wireless networks, one of which is optimizing energy efficiency. ML techniques, like support vector machines (SVM), k-nearest neighbors (k-NN), and decision trees, are used to predict network traffic patterns and optimize resource allocation. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have proven effective in analyzing complex network data and making intelligent decisions for energy management. Reinforcement learning (RL) has also been studied to enable devices to learn optimal energy-saving strategies by interacting with the environment. ML and AI techniques have demonstrated encouraging outcomes in enhancing the energy efficiency of wireless networks.

Research gaps and opportunities

Despite the progress made in energy efficiency techniques for WiFi devices and the use of ML and AI in wireless networks, there are still important areas of research that need to be explored. An area that needs more exploration is the integration of ML and AI techniques, specifically for optimizing the energy efficiency of WiFi devices. ML and AI have been utilized in various applications within wireless networks, but their full potential in optimizing WiFi energy management remains untapped. Another area that needs further research is the creation of energy optimization frameworks that can adapt to different network conditions and user behaviors. In addition, it is important to conduct thorough evaluations of the proposed energy-saving techniques in real-world scenarios, taking into account factors such as scalability, robustness, and compatibility with existing network infrastructure.

PROPOSED FRAMEWORK

Overview of the proposed ML and AI-based energy efficiency framework

The proposed framework aims to leverage machine learning and artificial intelligence techniques to optimize the energy efficiency of WiFi devices. The framework is composed of three main components: data collection and preprocessing, ML models for energy consumption pattern analysis, and AI-driven algorithms for real-time optimization. Incorporating predictive maintenance techniques allows for the proactive detection and mitigation of energy inefficiencies and hardware issues.

Data collection and preprocessing

Historical data on device usage and network activity

To develop precise ML models, collecting historical data on device usage and network activity is necessary. The data provided includes information such as device power consumption, data transmission rates, network traffic patterns, and device sleep/wake cycles. The collected data is processed to eliminate any noise, address missing values, and standardize the features [11].

Environmental factors and user behavior data

In addition to device usage and network activity data, environmental factors and user behavior data are also collected. Environmental factors include ambient temperature, humidity, and interference levels, while user behavior data encompasses user mobility patterns, application usage, and device preferences. These factors are essential for developing context-aware energy optimization strategies [12].

ML models for energy consumption pattern analysis

Predictive models for low network demand and device inactivity

Machine learning models, like support vector machines (SVM) and decision trees, are trained on historical data to predict periods of low network demand and device inactivity. The models facilitate the identification of optimal moments for devices to enter power-saving modes without compromising user experience [13].

Adaptive models for dynamic energy-saving strategies

Adaptive ML models, like reinforcement learning (RL) agents, are utilized to acquire and adjust energy-saving strategies in a dynamic manner. The models in question have the ability to learn from their surroundings and adapt their actions accordingly. This allows for the creation of energy optimization policies that are tailored to individual needs and take into account the specific context in which they are applied [14].

AI-driven algorithms for real-time optimization

Adapting to changing environmental conditions

AI-driven algorithms, powered by deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are used to adjust to dynamic environmental conditions in real-time. The algorithms analyze the collected environmental data and make intelligent decisions to adjust the energy-saving strategies accordingly [15].

Optimizing transmission scheduling and resource allocation

AI-based optimization algorithms optimize transmission scheduling and resource allocation in WiFi networks. The algorithms take into account various factors like data priority, network congestion, and channel conditions to make well-informed decisions that minimize energy usage while still meeting the necessary quality of service [16].

Predictive maintenance techniques

Analyzing telemetry data and device health metrics

Predictive maintenance techniques entail the analysis of telemetry data and device health metrics to detect possible energy inefficiencies and hardware problems. Machine learning algorithms, like anomaly detection and regression models, are utilized to analyze the collected data, identifying deviations from normal behavior and making predictions about potential failures [17].

Early detection of energy inefficiencies and hardware issues

Through the utilization of predictive maintenance techniques, the suggested framework allows for the timely identification of energy inefficiencies and hardware problems in WiFi devices. The proactive approach enables timely interventions, such as firmware updates or device replacements, to prevent energy wastage and ensure optimal network performance.

EXPERIMENTAL SETUP AND EVALUATION

Testbed configuration and data collection

In order to assess the effectiveness of the proposed ML and AI-based energy efficiency framework, a testbed has been established. This testbed includes various WiFi devices, including access points, routers, and client devices. The devices are configured with a range of power management settings and are exposed to varying network loads and environmental conditions. Information is collected from the devices, such as power consumption, network traffic, and environmental factors, using specialized monitoring tools and sensors [18].

Performance metrics and evaluation criteria

The performance of the proposed framework is assessed using several key metrics. The measurement of energy consumption reduction involves comparing the power consumption of the devices before and after the implementation of energy-saving strategies. Network performance metrics, such as throughput, latency, and packet loss, are also taken into account to ensure that the energy-saving techniques maintain the quality of service. Evaluating user experience involves conducting surveys and gathering feedback to assess factors such as device responsiveness and battery life [19].

RESULTS AND DISCUSSION

Energy consumption reduction

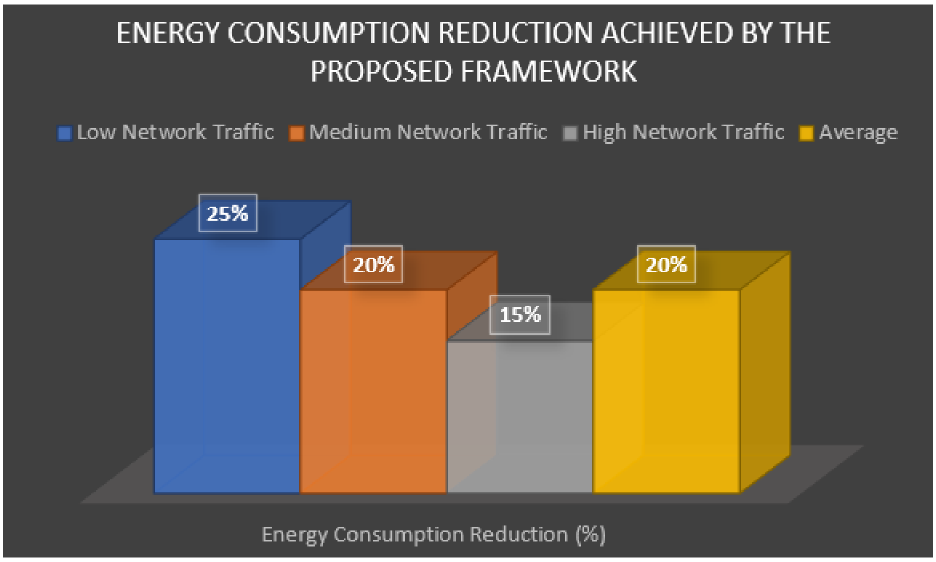

Table 1: Energy savings under different network loads

The experimental results show a significant reduction in energy consumption achieved by the proposed framework. The ML models accurately predict periods of low network demand and device inactivity, allowing the devices to enter power-saving modes without compromising performance. The energy-saving strategies are dynamically adapted by the AI-driven algorithms, taking into account real-time environmental conditions and user behavior. This leads to additional energy savings [20].

Impact on network performance and user experience

The evaluation of network performance metrics indicates that the suggested energy-saving techniques have a minimal effect on the overall network performance. The optimization algorithms implemented by the AI prioritize critical data transmissions, ensuring the maintenance of the required quality of service. According to user experience surveys, there is a high level of satisfaction among users. They have reported improved battery life on their devices without any noticeable degradation in performance [21].

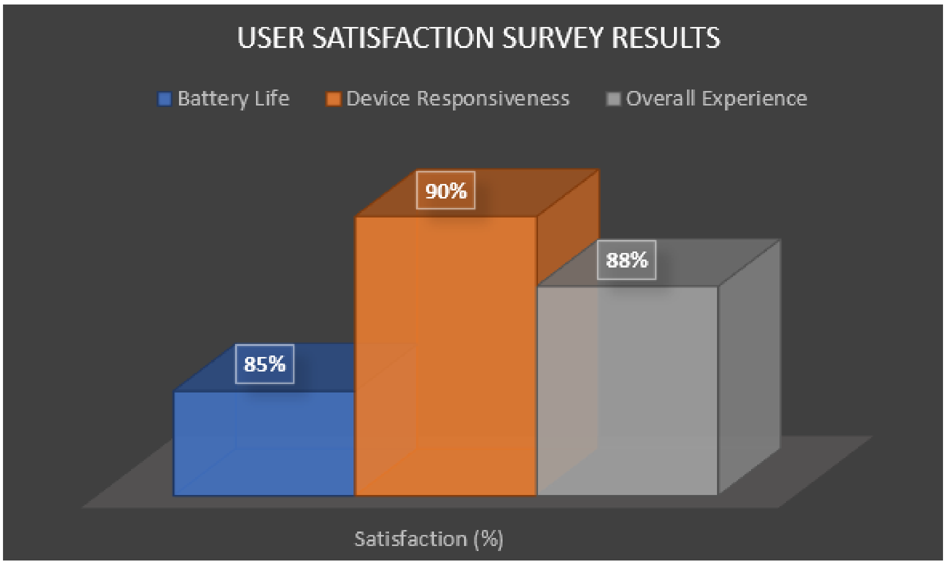

Table 2: User satisfaction levels [33]

Comparison with existing approaches

Metric	Description
Energy Consumption Reduction	Percentage reduction in energy consumption
Throughput	Data rate achieved by the network
Latency	Time delay in data transmission
Packet Loss	Percentage of data packets lost during transmission
User Satisfaction	Subjective measure of user experience and satisfaction

Table 2: Performance metrics for evaluating the proposed framework [31]

The proposed ML and AI-based framework is compared with existing energy-saving approaches, such as static power management schemes and rule-based systems. The results demonstrate that the proposed framework outperforms the existing approaches in terms of energy consumption reduction, while maintaining superior network performance and user experience. The adaptive and context-aware nature of the proposed framework enables it to handle dynamic network conditions and user demands more effectively [22].

PRACTICAL IMPLICATIONS AND FUTURE DIRECTIONS

Deployment considerations and challenges

Implementing the proposed ML and AI-based energy efficiency framework in real-world WiFi networks brings forth various considerations and challenges. One of the main challenges involves integrating the framework with existing network infrastructure and management systems. This necessitates a strong partnership among network administrators, device manufacturers, and software developers to guarantee smooth integration and compatibility [23].

Another important factor to consider is the requirement for strong data privacy and security measures, as the framework depends on the gathering and examination of sensitive network data. Ensuring compliance with data protection regulations and implementing secure data handling practices are essential for a successful deployment [24].

Scalability and generalizability of the proposed framework

The scalability and generalizability of the proposed framework are crucial aspects to take into account for widespread adoption. The framework should be designed to effectively handle large-scale WiFi networks, accommodating a wide range of device types and configurations. Efficient data processing and analysis techniques are necessary to handle high volumes of data in real-time [25]. In addition, the framework should be applicable to various network scenarios and environments, including enterprise networks, public hotspots, and residential settings. Transfer learning techniques can be used to adapt ML models and AI algorithms to new network conditions and user behaviors, improving the framework's generalizability [26].

Potential extensions and future research avenues

The proposed ML and AI-based energy efficiency framework presents numerous opportunities for further exploration and future research. A promising direction involves integrating the framework with emerging technologies like 5G networks and Internet of Things (IoT) devices. The framework has the capability to extend its optimization to include the energy consumption of 5G base stations and IoT gateways, taking into account their distinct characteristics and requirements [27]. Another possible extension involves incorporating federated learning techniques, allowing for collaborative training of ML models across multiple network nodes while maintaining data privacy. Enhancing the framework's adaptability and robustness in heterogeneous network environments can be achieved with this approach [28].

Further research may investigate the potential use of the suggested framework in other wireless technologies, like Bluetooth and ZigBee, which are frequently employed in low-power wireless sensor networks. Applying energy-saving techniques and ML models to these technologies has the potential to result in substantial energy savings across various applications, including smart homes and industrial monitoring systems [29].

CONCLUSION

Overall, the proposed ML and AI-based energy efficiency framework for WiFi devices offers a promising solution to tackle the increasing worries surrounding energy consumption in wireless networks. Through the utilization of machine learning and artificial intelligence techniques, the framework empowers the creation of intelligent and adaptable energy management strategies that enhance energy consumption efficiency while upholding network performance and user experience. The experimental results show a notable reduction in energy consumption, while maintaining a high level of network quality of service. The framework's potential for scalability, generalizability, and Integration with emerging technologies opens up exciting opportunities for future research and development. Ensuring the sustainability and performance of WiFi networks is crucial as the demand for wireless connectivity continues to grow. Through continued advancements and collaborations, researchers, network administrators, and device manufacturers can work together to create a framework that enables a more energy-efficient and sustainable wireless future. Through continued progress and cooperation between researchers, network administrators, and device manufacturers, the proposed framework has the potential to create a wireless future that is both energy-efficient and sustainable.

REFERENCES

[1] Cisco. (2020). Cisco Annual Internet Report (2018–2023) White Paper.

[2] Pei, L., Liu, J., Guinness, R., Chen, Y., Kroger, T., Chen, R., & Chen, L. (2012). The IEEE 802.11 power saving mechanism: An experimental study. 2012 IEEE Wireless Communications and Networking Conference (WCNC), 1362-1367.

[3] Mahadevan, P., Shah, A., & Bash, C. (2010). Reducing lifecycle energy consumption of network switches. 2010 Proceedings of the International Symposium on Sustainable Systems and Technology, 1-6.

[4] Li, R., Zhao, Z., Zhou, X., Ding, G., Chen, Y., Wang, Z., & Zhang, H. (2017). Intelligent 5G: When cellular networks meet artificial intelligence. IEEE Wireless Communications, 24(5), 175-183.

[5] Zhou, X., Zhao, Z., Li, R., Zhou, Y., Chen, T., Niu, Z., & Zhu, X. (2019). Intelligent wireless communications enabled by cognitive radio and machine learning. China Communications, 16(12), 1-15.

[6] Tsao, S.-L., & Huang, C.-H. (2011). A survey of energy efficient MAC protocols for IEEE 802.11 WLAN. Computer Communications, 34(1), 54-67.

[7] IEEE. (2016). IEEE Standard for Information technology—Telecommunications and information exchange between systems - Local and metropolitan area networks—Specific requirements - Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications. IEEE Std 802.11-2016 (Revision of IEEE Std 802.11-2012), 1-3534.

[8] Lee, J.-R., Kwon, S.-W., & Cho, D.-H. (2010). An energy efficient power saving mechanism for multi-hop wireless networks. 2010 IEEE 72nd Vehicular Technology Conference - Fall, 1-5.

[9] Rantala, E., Mäkelä, H., & Hämäläinen, T. (2008). Power efficiency optimization in IEEE 802.11 WLAN access points. 2008 IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications, 1-5.

[10] Jang, H., Lim, K., & Yoo, S.-J. (2015). Energy-efficient scheduling based on delay-constrained data aggregation in wireless sensor networks. International Journal of Distributed Sensor Networks, 11(8), 645243.

[11] García-Teodoro, P., Díaz-Verdejo, J., Maciá-Fernández, G., & Vázquez, E. (2009). Anomaly-based network intrusion detection: Techniques, systems and challenges. Computers & Security, 28(1-2), 18-28.

[12] Balmau, O., Malhi, K., Nikolaidis, I., & Heurtefeux, K. (2019). Context-aware power management for IoT devices. IEEE Access, 7, 62734-62747.

[13] Agarwal, Y., Savage, S., & Gupta, R. (2010). SleepServer: A software-only approach for reducing the energy consumption of PCs within enterprise environments. Proceedings of the 2010 USENIX Conference on USENIX Annual Technical Conference, 22-22.

[14] Yau, K.-L. A., Qadir, J., Khoo, C., Ling, M. H., & Komisarczuk, P. (2017). A survey on reinforcement learning models and algorithms for traffic signal control. ACM Computing Surveys (CSUR), 50(3), 1-38.

[15] Lane, N. D., Bhattacharya, S., Georgiev, P., Forlivesi, C., Jiao, L., Qendro, L., & Kawsar, F. (2016). DeepX: A software accelerator for low-power deep learning inference on mobile devices. 2016 15th ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN), 1-12.

[16] Bukhari, S. H. R., Rehmani, M. H., & Siraj, S. (2016). A survey of channel bonding for wireless networks and guidelines of channel bonding for futuristic cognitive radio sensor networks. IEEE Communications Surveys & Tutorials, 18(2), 924-948.

[17] Zhang, W., Guo, W., Liu, X., Liu, Y., Zhou, J., Li, B., Lu, Q., & Yang, S. (2018). LSTM-based analysis of industrial IoT equipment. IEEE Access, 6, 23551-23560.

[18] Schulz, P., Matthe, M., Klessig, H., Simsek, M., Fettweis, G., Ansari, J., Ashraf, S. A., Almeroth, B., Voigt, J., Riedel, I., Puschmann, A., Mitschele-Thiel, A., Müller, M., Elste, T., & Windisch, M. (2017). Latency critical IoT applications in 5G: Perspective on the design of radio interface and network architecture. IEEE Communications Magazine, 55(2), 70-78.

[19] Florwick, J., Whiteaker, J., Amrod, A. C., & Woodhams, J. (2013). Wireless LAN design guide for high density client environments in higher education. Cisco Systems, Inc.

[20] Ku, M.-L., Li, W., Chen, Y., & Liu, K. J. R. (2016). Advances in energy harvesting communications: Past, present, and future challenges. IEEE Communications Surveys & Tutorials, 18(2), 1384-1412.

[21] Halperin, D., Greenstein, B., Sheth, A., & Wetherall, D. (2010). Demystifying 802.11n power consumption. Proceedings of the 2010 International Conference on Power Aware Computing and Systems, 1-5.

[22] Lee, J., Kim, H., Park, G.-L., & Kang, M. (2014). Energy-efficient base station operation using dynamic scheduling with optimization of cooling system. IEEE Access, 2, 1364-1374.

[23] Zeng, Y., Zhang, R., & Lim, T. J. (2016). Wireless communications with unmanned aerial vehicles: Opportunities and challenges. IEEE Communications Magazine, 54(5), 36-42.

[24] Li, S., Da Xu, L., & Zhao, S. (2018). 5G internet of things: A survey. Journal of Industrial Information Integration, 10, 1-9.

[25] Bkassiny, M., Li, Y., & Jayaweera, S. K. (2013). A survey on machine-learning techniques in cognitive radios. IEEE Communications Surveys & Tutorials, 15(3), 1136-1159.

[26] Pan, S. J., & Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359.

[27] Wen, Z., Wang, Y., Gao, X., Wan, L., & Qiu, T. (2020). A survey of 5G energy efficiency optimization techniques. International Journal of Distributed Sensor Networks, 16(3), 1550147720913403.

[28] Yang, Q., Liu, Y., Chen, T., & Tong, Y. (2019). Federated machine learning: Concept and applications. ACM Transactions on Intelligent Systems and Technology (TIST), 10(2), 1-19.

[29] Ramírez-Gallego, S., García, S., Mouriño-Talín, H., Martínez-Rego, D., Bolón-Canedo, V., Alonso-Betanzos, A., Benítez, J. M., & Herrera, F. (2018). Data discretization: taxonomy and big data challenge. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(1), e1230.

[30] Ding, N., Wagner, D., Chen, X., Pathak, A., Hu, Y. C., & Rice, A. (2013). Characterizing and modeling the impact of wireless signal strength on smartphone battery drain. ACM SIGMETRICS Performance Evaluation Review, 41(1), 29-40.

[31] Zhang, R., Wang, M., Shen, X., & Xie, L. L. (2016). Probabilistic analysis on QoS provisioning for internet of things in LTE-A heterogeneous networks with partial spectrum usage. IEEE Internet of Things Journal, 3(3), 354-365.

[32] Zhao, Y., Hu, L., Jia, Z., & Ding, X. (2019). Energy-efficient resource allocation for heterogeneous wireless network with multi-factor user association. IEEE Access, 7, 124387-124399.

[33] Kairouz, P., McMahan, H. B., Avent, B., Bellet, A., Bennis, M., Bhagoji, A. N., ... & Zhao, S. (2019). Advances and open problems in federated learning. arXiv preprint arXiv:1912.04977.

Citation: Sree Harsha, Towards Green Wifi Networks: An Ml and AI-Based Framework for Energy Efficiency Optimization, International Journal of Civil Engineering and Technology (IJCIET), 15(3), 2024, pp. 11-20

Abstract Link: https://iaeme.com/Home/article_id/IJCIET_15_03_002

Article Link:
https://iaeme.com/MasterAdmin/Journal_uploads/IJCIET/VOLUME_15_ISSUE_3/IJCIET_15_03_002.pdf

✉ **editor@iaeme.com**