Mobility Prediction Algorithms for Handover Management in Heterogeneous LiFi and RF Networks: An Ensemble Approach

Jaafaru Sanusi
Department of Electrical and Electronics Engineering, Nile University of Nigeria, Abuja, Nigeria
jafarsanusiliman@nileuniversity.edu.ng (corresponding author)

Steve Adeshina
Department of Computer Engineering, Nile University of Nigeria, Abuja, Nigeria
steve.adeshina@nileuniversity.edu.ng

Abiodun Musa Aibinu
Department of Mechatronics Engineering, Summit University Offa, Nigeria
maibinu@gmail.com

Omotayo Oshiga
Department of Electrical and Electronics Engineering, Nile University of Nigeria, Abuja, Nigeria
ooshiga@nileuniversity.edu.ng

Rajesh Prasad
Department of Computer Science and Engineering, Ajay Kumar Garg Engineering College, Ghaziabad, India
prasadrajesh@akgec.ac.in

Abubakar Dayyabu
Department of Civil Engineering, Nile University of Nigeria, Abuja, Nigeria
adayyabu@nileuniversity.edu.ng

Received: 1 September 2024 | Revised: 16 September 2024 | Accepted: 22 September 2024

ABSTRACT

Light Fidelity (LiFi) is a communication technology that operates in the Visible Light (VL) region, using light as a medium to enable ultra-high-speed communication. The spectrum occupied by LiFi does not overlap with the Radio Frequency (RF) spectrum. Thus, they can be used in a hybrid manner to enhance the Quality of Service (QoS) for users. However, in a heterogeneous LiFi and RF network, users experience constant handovers due to the small coverage area of the LiFi and their frequent movement. This study proposes an intelligent handover scheme, where the network parameters of the users are used to train four machine learning models, namely an Artificial Neural Network (ANN), an Adaptive Neurofuzzy Inference System (ANFIS), a Support Vector Machine (SVM), and a Regression Tree (RT), to predict the mobility of the users, so that the central network can have a priori mobility information to ensure seamless connectivity. Furthermore, the performance of the standalone models was enhanced by integrating ensemble learning techniques such as the Simple Averaging Ensemble (SAE), Weighted Averaging Ensemble (WAE), and a Meta-Learning Ensemble (MLE). The results show that the ensemble algorithms improved prediction performance, with an average error decrease of 44.40%, 53.53%, and 61.03% for SAE, WAE, and MLE, respectively, which further demonstrated the effectiveness and robustness of using ensemble algorithms to predict user mobility.

Keywords-light fidelity; visible light; radio frequency; machine learning; ensemble learning

I. INTRODUCTION

Recently, Cisco Systems published a visual networking index, in which it predicts that more than 70% of all IP traffic will come from mobile data traffic and more than 80% of this will take place indoors [1]. This will make short-range wireless communication technologies such as WiFi a part of the 5G and beyond era. Moreover, another report estimated that there would be more than 628 million Wi-Fi hotspots by 2023 and that data demand is growing exponentially, making it difficult for the RF spectrum to meet up with [2, 3]. To free up the demands of the RF spectrum and to address spectrum shortages, LiFi, a form of Visible Light Communication (VLC), has been proposed to meet the ever-increasing demands of users [4]. LiFi is license-free, as it operates in the visible light spectrum, and has a bandwidth that is more than 10,000 times higher than that of the RF spectrum. It uses an existing Light Emitting Diode (LED) both for illumination and as a transmitter, while a photodiode receiver is used to provide up to 1 Gbps continuous high-speed Internet services to users [5, 6]. In addition, it is more secure than RF wireless communication, as light cannot penetrate walls, hence it can be used in a confined area making it difficult for signals to be intercepted. LiFi communication technology can be used for communication between vehicles and traffic infrastructure for traffic management purposes [4-6]. Furthermore, LiFi technology is safe for human health. It can also be used in areas where RF usage is restricted, such as nuclear plants, hospitals, and airplanes, and it is energy efficient since the same source used to transmit signals is also used for illumination [7].

As RF and LiFi technology operate on different spectrums of electromagnetic waves, they can be combined to form hybrid networks without interference to achieve better network performance, due to the huge bandwidth of the VLC spectrum, and enhanced QoS for users regardless of their position within a given coverage area [8]. Users in a combined Li-Fi and WiFi network experience constant handovers due to their frequent mobility and the small coverage area of a single Access Point (AP), which considerably degrades QoS. Therefore, as constant handover will be experienced in combined WiFi-LiFi networks, effective and efficient handover decision algorithms must be designed to address the problem [8-11]. Handover is the process of transferring an ongoing wireless communication from one network to another [12]. The handover is divided into vertical and horizontal handover. Horizontal handover is a type of handover between similar networks, while vertical handover is the type of handover between different network technologies [4]. The following handover decision parameters should be considered to enable handover [12-23]: network load, monetary service cost, Received Signal Strength Indicator (RSSI), handover delay/latency, handover failure probability, throughput, Signal-to-Noise Ratio (SNR), security control, number of unnecessary handovers, and user preferences.

This study proposes an intelligent handover scheme where the network parameters of the users are used to train machine learning models to predict their mobility so that the central network can have priori mobility information of the users to ensure seamless connectivity, as shown in Figure 1.

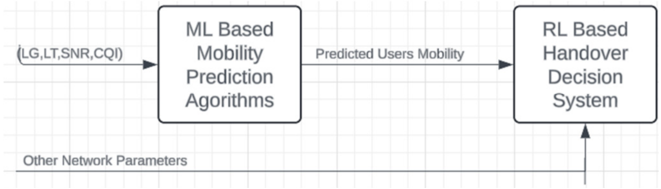

Fig. 1. The proposed handover decision system.

II. METHODOLOGY

A. Data Preprocessing

This study used simple averaging, weighted averaging, and meta-learning ensemble learning techniques to improve the prediction performance of the developed models, namely, ANN, ANFIS, SVR, and RT. The dataset used in this study is from an Irish operator that collected user traces for different mobility patterns [24] (train, bus, car, pedestrian, and static), which could be used for wide areas of applications. The collected data were standardized in the range of 0 to 1 to enhance learning and performance using:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x_n denotes the normalized data, x is the data to be normalized, and x_{min} and x_{max} are the minimum and maximum values.

When designing prediction models, some input variables may have extreme effects or more impact on the output than others. Therefore, it is necessary to determine the best sets of input variables to obtain an ideal solution. Subsequently, the Longitude (LG), Latitude (LT), SNR, and Channel Quality Indicator (CQI) were chosen to arrive at the three input combinations, as shown in (2). Each combination was used with ANN, ANFIS, SVR, and RT to predict user mobility.

$$MB = \begin{cases} M1 = LG + LT \\ M2 = LG + LT + SNR \\ M3 = LG + LT + SNR + CQI \end{cases} \quad (2)$$

The performance of the standalone models, namely ANN, ANFIS, SVR, and REG, was further improved by ensemble optimization. The flowchart of the method is given in Figure 2.

B. Artificial Neural Network (ANN)

ANNs learn from experience, by example, and by analogy, and have been applied to solve real-world problems such as pattern recognition, system processing, systems identification, prediction, optimization, control systems, modeling, etc. [4, 17]. The adopted ANN architecture has three layers: the input that is fed into the system, the output layer that obtains data after combining and passing the inputs into the activation function, and lastly the hidden layers that connect the input and output layers.

C. Support Vector Regression (SVR)

SVR is a supervised machine learning algorithm that falls under the family of support vector classification and Support Vector Machine (SVM) algorithms. SVM is one of the most important machine learning algorithms and is suitable for linear or nonlinear regression, classification, detection of outliers, etc.

SVMs have a wide range of applications, such as handwriting recognition, image classification, text classification, spam detection, gene expression analysis, anomaly detection, face detection, etc. [24]. SVRs are very powerful and effective, especially when dealing with high-dimensional data and nonlinear relationships [25].

D. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS was introduced in the early 1990s and is an artificial neural network structured on the Sugeno-Takagi-based fuzzy system [26]. ANFIS integrates the principles of the fuzzy logic system and neural networks and combines the benefits of these systems. The ANFIS architecture is basically composed of five layers [26, 27].

E. Regression Tree (RT)

A decision tree is an important supervised learning technique that can be used for either regression or classification tasks. When the target values are discrete, the tree model is said to be a classification tree, while if the target values are continuous (real), is said to be an RT. A decision tree has a tree-like structure, consisting of internal nodes representing a test on an attribute, a branch representing the test outcome, and a leaf or terminal node holding a class label [28-31].

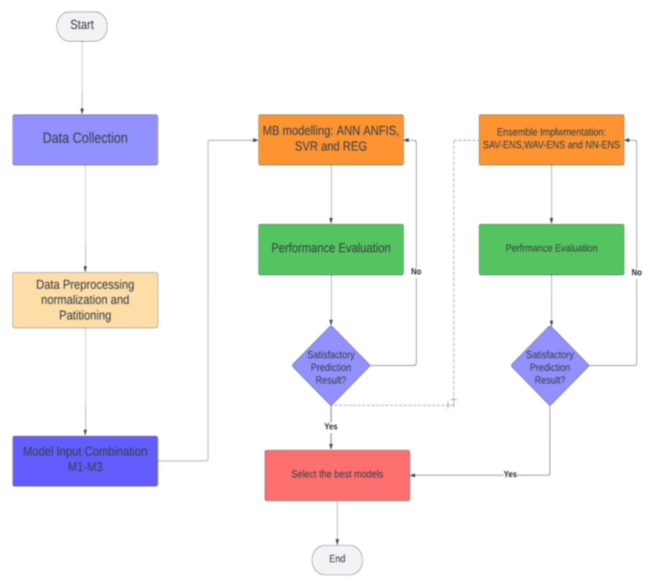

Fig. 2. Study flowchart.

F. Ensemble Learning

Ensemble learning is used in supervised learning. It is a technique that uses machine learning algorithms to obtain improved predictive performance by combining their results. Ensemble methods use inducers or base learners, such as ANNs, DT, neuro-fuzzy, regression models, etc. to make a final judgment. Ensemble learning is very important, as it helps improve prediction performance by addressing overfitting, class imbalance, concept drift, and dimensionality problems associated with other learning techniques to compensate for poor-performing algorithms [32, 33].

1) Simple Averaging Ensemble (SAE)

SAE is one of the most popular, and easily implementable and utilizable ensemble techniques. This technique has demonstrated improved performance for prediction models, having been applied to numerous machine learning algorithms [28, 34]. SAE is widely applied in real-life problems due to its simplicity, effectiveness, and robustness. In (3), the proposed SAE technique takes the average of the outputs of the trained standalone models (ANN, ANFIS, SVR, and RT).

$$MB_{(t)} = \frac{1}{n}\sum_{i=1}^{n} MB_{(t)i} \tag{3}$$

2) Weighted Averaging Ensemble (WAE)

WAE assigns a specific weight to each distinct output, according to each output's relative importance, to obtain the predicted results. This technique is considered to offer better prediction, training, and testing effectiveness compared to unweighted ensembles, as weights try to minimize the error between the actual and ensemble output [28, 34]. The correlation and the determination coefficients are mostly used to determine the standalone relative weights of the models. The WAE adopted in this study was based on the determination coefficient, given as:

$$MB_{(t)} = \sum_{i=1}^{n} w_i \,.\, MB_{(t)i} \tag{4}$$

where w_i is denoted by:

$$w_i = \frac{\Delta C_i}{\sum_{i=1}^{n} C_i} \tag{5}$$

where w_i is the weight assigned to the corresponding i^{th} model, $MB_{(t)}$ is the i^{th} output of a standalone model (ANN, SVR, ANFIS, and DTR), n shows the total number of individual models ($n = 4$), and ΔC_i is the coefficient of determination of the i^{th} standalone models' output. Figure 3 shows the block diagram of WAE.

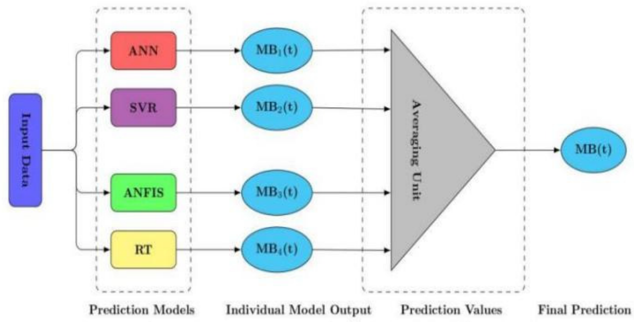

Fig. 3. Proposed WAE.

3) Meta-Learning Ensemble (MLE)

MLE is a technique that learns from other learning methods or algorithms. In other words, it is a machine-learning technique that combines predictions of algorithms by learning from the outputs of other ML algorithms. In the MLE adopted in this study, the outputs from the standalone models (ANN, SVR, ANFIS, and RT) are used as the input to the meta-learner, which is another ML model that produces a final output. This technique is very effective, especially when base models make errors in classifying instances [34]. In this study, the predictions from the standalone models (ANN, SVR, ANFIS, and RT) were used as inputs and trained by the Neural Network (NN). NN was used as a meta-learner due to its reliability, effectiveness, and wide use [33-36]. Figure 4 shows the schematic diagram of the proposed MLE.

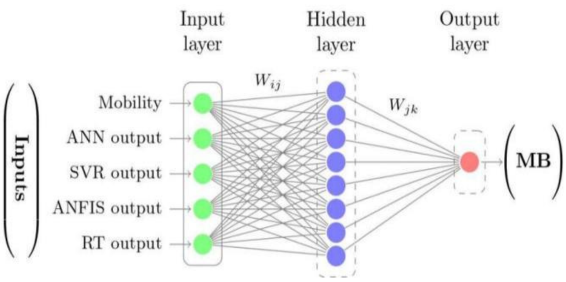

Fig. 4. Proposed MLE.

III. RESULTS

The dataset was split into 70% for training and 30% for testing. The performance of the standalone ANFIS, ANN, SVR, and RT models was evaluated using r, R^2, MSE, and RMSE, as shown in Table I. The Pearson correlation coefficient is between 0 to 1, and the closer to 1, the better the model's prediction capability. MSE should be as close to zero as possible because the idea is to minimize the error between the actual and the predicted value. Table II shows the performance evaluation of the ensemble models.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2} \quad (7)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y_i}\right)^2} \quad (8)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(Y_i - Y_p\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y_i}\right)^2}} \quad (9)$$

TABLE I. PERFORMANCE EVALUATION OF THE STANDALONE MODELS

	Training				Testing			
Models	**R**	**R^2**	**MSE**	**RMSE**	**R**	**R^2**	**MSE**	**RMSE**
ANN-M1	0.5831	0.3400	0.0545	0.2335	0.2791	0.0779	0.0343	0.1851
ANN-M2	0.8429	0.7104	0.0239	0.1548	0.643	0.4135	0.0221	0.1486
ANN-M3	0.9166	0.8401	0.0132	0.1149	0.8426	0.71	0.0109	0.1043
ANFIS-M1	0.6119	0.3744	0.0516	0.2272	0.3673	0.1349	0.0322	0.1795
ANFIS-M2	0.7512	0.5643	0.036	0.1896	0.6045	0.3654	0.0237	0.1538
ANFIS-M3	0.833	0.6939	0.0253	0.159	0.7511	0.5641	0.0162	0.1273
SVM-M1	0.6823	0.4656	0.0442	0.2101	0.6509	0.4236	0.0214	0.1465
SVM-M2	0.7223	0.5217	0.0396	0.1989	0.6609	0.4368	0.0211	0.1452
SVM-M3	0.7439	0.5534	0.0371	0.1925	0.7903	0.6246	0.0144	0.1198
RT-M1	0.9873	0.9748	0.0021	0.0456	0.9986	0.9971	1.06E-04	0.0103
RT-M2	0.9919	0.9838	0.0013	0.0365	0.9986	0.9971	1.06E-04	0.0103
RT-M3	0.9914	0.9828	0.0014	0.0377	0.9984	0.9969	1.16E-04	0.0108

A. *Prediction Performance of the Mobility-based Standalone Models*

The M3 performance of the ANN was the best in terms of prediction capability among the ANN models. The combination of LG, LT, CQI, and SNR in M3 provided better prediction performance in both training and testing phases compared to M2 (LG, LT, SNR) and M1 (LG, LT), respectively. The ANN-M3 model is preferred among the ANN models due to its Pearson coefficient performance of 0.9166 in the testing phase compared to ANN-M2 and ANN-M1 with 0.8429 and 0.5831, respectively. Furthermore, ANN-M3 proved its robustness among the other models by having an MSE value of 0.0109 in testing compared to ANN-M2 and ANN-M1 with 0.0221 and 0.0343, respectively. The results of the ANFIS models were also encouraging. ANFIS-M3, which considered LG, LT, CQI, and SNR, had an MSE of 0.0162 in the testing phase compared to M2 and M1 with 0.0237 and 0.0322, respectively. Moreover, a good correlation between actual and predicted mobility was observed in both training and testing the ANFIS models.

In the SVR, it was noticed that the M3 had optimal performance in predicting user mobility both in terms of errors and goodness of fit in the training and testing stages. M3, which combined LG, LT, CQI, and SNR had an R of 0.7903 and an MSE of 0.0144 in the testing stage, while M2 (LG, LT, and SNR) had 0.6609 and 0.0211, and M1 (LG and LT) had 0.6509 and 0.0214, respectively. This could be interpreted as M1 with fewer inputs than M2 could also be used to make mobility predictions with lower computational complexity.

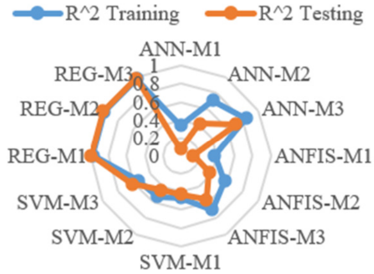

Fig. 5. Radar plot of the standalone models.

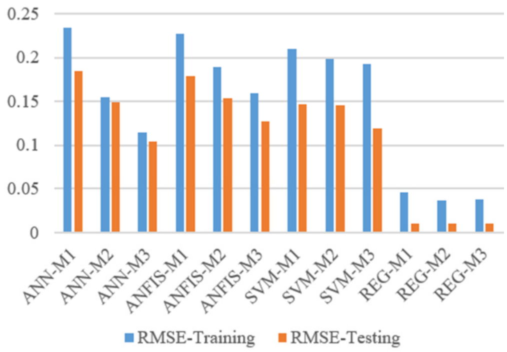

Fig. 6. Error plot of the standalone models.

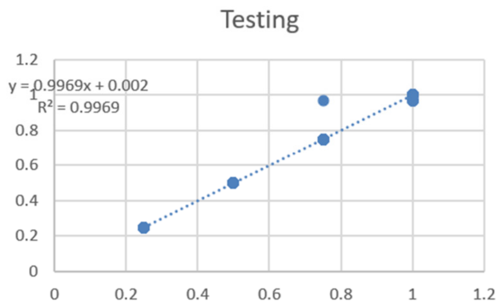

Fig. 7. Scatter plot of the RT-M3 model.

Figures 5 and 6 present the performance of all the standalone models using a radar plot, with RT-M2 being the optimal. Figure 7 shows the error plots of the standalone models. Figure 7 shows the scatter plot of the best model. Scatter plots are very handy in analyzing the assessing the precision of the proposed models. In RT-M3, most data points lie around the $y=x$ line. These results demonstrate the model's reliability and robustness in prediction accuracy.

B. Performance of the Ensemble Models

The idea behind ensembles is to aggregate the performance of multiple learners to achieve better predictions. In most cases, the performance of a standalone model is improved by ensemble models because they help address the shortcomings of a single standalone model, such as overfitting, underfitting, bias, and variance reduction. This is the reason why they gained popularity and are applied in a lot of machine learning problems. SAE, WAE, and MLE techniques were adopted in this work with the dataset divided into 70% for training and 30% for testing. Table II presents the results obtained from the ensemble-based models. Performance improvement was achieved by integrating ensemble models. For instance in M2, SAE was found to improve the predictive performance of the standalone ANN, ANFIS, and SVM by 40.93%, 49.91%, and 37.12%, respectively. WAE was found to improve the predictive performance of the standalone ANN, ANFIS, and SVM models by 46.86%, 56.21%, and 42.88%, respectively. MAE improved the prediction performance of the ANN, ANFIS, SVM, and RT models by 55.38%, 65.28%, 51.17%, and 5%, respectively. The MLE model was more effective and robust compared to WAE and SAE. Meanwhile, the prediction accuracy of the RT models is very similar to that of the MLE and better than that of the WAE and SAE.

TABLE II. RESULTS OF ENSEMBLE MODELS

	Training				Testing			
Ensemble models	**R**	**R^2**	**MSE**	**RMSE**	**R**	**R^2**	**MSE**	**RMSE**
SAE-M1	0.8552	0.7314	0.0278	0.1668	0.8708	0.7582	0.0202	0.142
SAE-M2	0.911	0.83	0.0166	0.1288	0.9062	0.8213	0.0136	0.1166
SAEM3	0.9446	0.8923	0.0106	0.1028	0.9279	0.861	0.0061	0.0784
WAE-M1	0.936	0.8761	0.0156	0.1248	0.9615	0.9245	0.0103	0.1014
WAE-M2	0.9386	0.881	0.0122	0.1103	0.9443	0.8917	0.01	0.0999
WAE-M3	0.9577	0.9171	0.0082	0.0907	0.9436	0.8903	0.0049	0.0702
MLE -M1	0.9867	0.9737	0.0022	0.0467	0.998	0.9961	1.49E-04	0.0122
MLE-M2	0.9939	0.9878	9.04E-04	0.0301	0.9991	0.9982	7.90E-05	0.0089
MLE-M3	0.995	0.9899	7.50E-04	0.0274	0.9989	0.9978	1.11E-04	0.0106

The ensemble models reduced the errors of the standalone models, proving their superiority and justifying the need for their adoption. For example, in M1, SAE reduced the RMSE of the standalone ANN, ANFIS, and SVM models by 28.57%, 26.58%, and 20.61%, respectively. Similarly, in M2, WAE reduced the RMSE of the standalone ANN, ANFIS, and SVM models by 28.75%, 41.82%, and 44.541%, respectively. In M3, MAE reduced the RMSE of the standalone ANN, ANFIS, SVM, and RT models by 76.15%, 82.77%, 85.77%, and 27.32%, respectively. Figure 8(a) shows the performance of the ensemble models in the testing stage using R. A value to the outermost gridline indicates a better predictive performance. Based on this criterion, the best models were SAE-M3, WAE-M2, and MLE-M2. Figure 8(b) shows a graphical comparison between the best ensemble models and related works [37], with MLE-M2 having the optimum predictive performance.

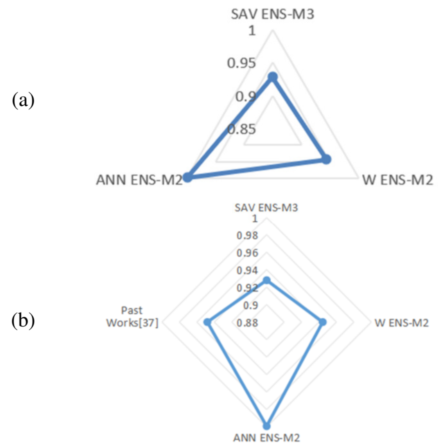

Fig. 8. Radar plots of the ensemble models: (a) Best ensemble models in this study, (b) Comparison with related works.

IV. CONCLUSION

This study considered a hybrid LiFi-WiFi network to meet the ever-increasing demand for data services because the RF communication spectrum seems over-saturated. Frequent handover was considered a problem in a LiFi-WiFi hybrid network due to the movement of users coupled with the fact that a single AP covers a small service area. Therefore, an intelligent handover scheme was proposed, in which user network parameters (LT, LG, SNR, and CQI) were used to train machine learning models to predict their mobility so that the central network can have a priori mobility information to ensure seamless connectivity. The results show that the four proposed ML techniques can be relied upon for user mobility prediction. Furthermore, the proposed ensemble learning techniques enhanced the prediction performance of the proposed mobility algorithms, thus proving superiority and effectiveness in handover decision applications. The proposed techniques can be applied extensively to address handover problems in heterogeneous networks for 5G and beyond communications where operations are intelligence-driven.

ACKNOWLEDGMENT

The authors acknowledge the Department of Electrical Engineering of the Nile University of Nigeria, Abuja, for their support toward this research.

REFERENCES

[1] M. Grayson, "Cisco Vision 5G: Thriving Indoors," Cisco, 2024.

[2] "Products - 5G Enterprise Radio Access Networks White Paper," *Cisco*. https://www.cisco.com/c/en/us/products/collateral/wireless/nb-06-radio-access-networks-cte-en.html.

[3] A. Zubow *et al.*, "Hybrid-Fidelity: Utilizing IEEE 802.11 MIMO for Practical Aggregation of LiFi and WiFi," *IEEE Transactions on Mobile Computing*, vol. 22, no. 8, pp. 4682–4697, Dec. 2023, https://doi.org/10.1109/TMC.2022.3157452.

[4] J. Sanusi, S. Idris, S. Adeshina, A. M. Aibinu, and I. Umar, "Development of Handover Decision Algorithms in Hybrid Li-Fi and Wi-Fi Networks," in *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)*, Thoothukudi, India, Dec. 2020, pp. 1232–1239, https://doi.org/10.1109/ICISS49785.2020.9316116.

[5] A. B. Ozyurt and W. O. Popoola, "Mobility management in multi-tier LiFi networks," *Journal of Optical Communications and Networking*, vol. 13, no. 9, pp. 204–213, Sep. 2021, https://doi.org/10.1364/JOCN.423925.

[6] A. B. Ozyurt and W. O. Popoola, "Mobility management in multi-tier LiFi networks," *Journal of Optical Communications and Networking*, vol. 13, no. 9, pp. 204–213, Sep. 2021, https://doi.org/10.1364/JOCN.423925.

[7] J. Sanusi, S. Idris, A. M. Aibinu, S. Adeshina, and A. N. Obadiah, "Handover in Hybrid LiFi and WiFi Networks," in *2019 15th International Conference on Electronics, Computer and Computation (ICECCO)*, Abuja, Nigeria, Dec. 2019, pp. 1–6, https://doi.org/10.1109/ICECCO48375.2019.9043251.

[8] R. Ahmad and A. Srivastava, "Sequential Load Balancing for Link Aggregation Enabled Heterogeneous LiFi WiFi Network," *IEEE Open Journal of Vehicular Technology*, vol. 3, pp. 138–148, 2022, https://doi.org/10.1109/OJVT.2022.3165537.

[9] R. Ahmad, M. D. Soltani, M. Safari, and A. Srivastava, "Reinforcement Learning-Based Near-Optimal Load Balancing for Heterogeneous LiFi WiFi Network," *IEEE Systems Journal*, vol. 16, no. 2, pp. 3084–3095, Jun. 2022, https://doi.org/10.1109/JSYST.2021.3088302.

[10] X. Wu, M. D. Soltani, L. Zhou, M. Safari, and H. Haas, "Hybrid LiFi and WiFi Networks: A Survey," *IEEE Communications Surveys & Tutorials*, vol. 23, no. 2, pp. 1398–1420, 2021, https://doi.org/10.1109/COMST.2021.3058296.

[11] P. H. Pathak, X. Feng, P. Hu, and P. Mohapatra, "Visible Light Communication, Networking, and Sensing: A Survey, Potential and Challenges," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2047–2077, 2015, https://doi.org/10.1109/COMST.2015.2476474.

[12] A. Ahmed, L. M. Boulahia, and D. Gaïti, "Enabling Vertical Handover Decisions in Heterogeneous Wireless Networks: A State-of-the-Art and A Classification," *IEEE Communications Surveys & Tutorials*, vol. 16, no. 2, pp. 776–811, 2014, https://doi.org/10.1109/SURV.2013.082713.00141.

[13] A. M. Vegni and T. D. C. Little, "Handover in VLC systems with cooperating mobile devices," in *2012 International Conference on Computing, Networking and Communications (ICNC)*, Maui, HI, USA, Jan. 2012, pp. 126–130, https://doi.org/10.1109/ICCNC.2012.6167395.

[14] Y. Wang, D. A. Basnayaka, X. Wu, and H. Haas, "Optimization of Load Balancing in Hybrid LiFi/RF Networks," *IEEE Transactions on Communications*, vol. 65, no. 4, pp. 1708–1720, Apr. 2017, https://doi.org/10.1109/TCOMM.2017.2654249.

[15] X. Wu and H. Haas, "Handover Skipping for LiFi," *IEEE Access*, vol. 7, pp. 38369–38378, 2019, https://doi.org/10.1109/ACCESS.2019.2903409.

[16] Y. Wang, X. Wu, and H. Haas, "Fuzzy logic based dynamic handover scheme for indoor Li-Fi and RF hybrid network," in *2016 IEEE International Conference on Communications (ICC)*, Kuala Lumpur, Malaysia, May 2016, pp. 1–6, https://doi.org/10.1109/ICC.2016.7510823.

[17] G. Ma, R. Parthiban, and N. Karmakar, "An Artificial Neural Network-Based Handover Scheme for Hybrid LiFi Networks," *IEEE Access*, vol. 10, pp. 130350–130358, 2022, https://doi.org/10.1109/ACCESS.2022.3228570.

[18] G. Ma, R. Parthiban, and N. Karmakar, "Novel Handover Algorithms Using Pattern Recognition for Hybrid LiFi Networks," in *2022 IEEE Symposium on Computers and Communications (ISCC)*, Rhodes, Greece, Jun. 2022, pp. 1–7, https://doi.org/10.1109/ISCC55528.2022.9912760.

[19] X. Wu and D. C. O'Brien, "A Novel Machine Learning-Based Handover Scheme for Hybrid LiFi and WiFi Networks," in *2020 IEEE Globecom Workshops (GC Wkshps*, Taipei, Taiwan, Dec. 2020, pp. 1–5, https://doi.org/10.1109/GCWkshps50303.2020.9367577.

[20] J. Yang, Z. Xiao, H. Cui, J. Zhao, G. Jiang, and Z. Han, "DQN-ALrM-Based Intelligent Handover Method for Satellite-Ground Integrated Network," *IEEE Transactions on Cognitive Communications and Networking*, vol. 9, no. 4, pp. 977–990, Dec. 2023, https://doi.org/10.1109/TCCN.2023.3262239.

[21] G. Ma, R. Parthiban, and N. Karmakar, "An Adaptive Handover Scheme for Hybrid LiFi and WiFi Networks," *IEEE Access*, vol. 10, pp. 18955–18965, 2022, https://doi.org/10.1109/ACCESS.2022.3151858.

[22] X. Wu and H. Haas, "Load Balancing for Hybrid LiFi and WiFi Networks: To Tackle User Mobility and Light-Path Blockage," *IEEE Transactions on Communications*, vol. 68, no. 3, pp. 1675–1683, Mar. 2020, https://doi.org/10.1109/TCOMM.2019.2962434.

[23] W. Ma and L. Zhang, "QoE-Driven Optimized Load Balancing Design for Hybrid LiFi and WiFi Networks," *IEEE Communications Letters*, vol. 22, no. 11, pp. 2354–2357, Aug. 2018, https://doi.org/10.1109/LCOMM.2018.2869388.

[24] D. Raca, J. J. Quinlan, A. H. Zahran, and C. J. Sreenan, "Beyond throughput: a 4G LTE dataset with channel and context metrics," in *Proceedings of the 9th ACM Multimedia Systems Conference*, Amsterdam, The Netherlands, Jun. 2018, pp. 460–465, https://doi.org/10.1145/3204949.3208123.

[25] F. Elmaz, Ö. Yücel, and A. Y. Mutlu, "Predictive modeling of biomass gasification with machine learning-based regression methods," *Energy*, vol. 191, Jan. 2020, Art. no. 116541, https://doi.org/10.1016/j.energy.2019.116541.

[26] U. A. Dodo, E. C. Ashigwuike, J. N. Emechebe, and S. I. Abba, "Prediction of energy content of biomass based on hybrid machine

learning ensemble algorithm," *Energy Nexus*, vol. 8, Dec. 2022, Art. no. 100157, https://doi.org/10.1016/j.nexus.2022.100157.

[27] B. Mohammadi *et al.*, "Adaptive neuro-fuzzy inference system coupled with shuffled frog leaping algorithm for predicting river streamflow time series," *Hydrological Sciences Journal*, vol. 65, no. 10, pp. 1738–1751, Jul. 2020, https://doi.org/10.1080/02626667.2020.1758703.

[28] M. Aqil, I. Kita, A. Yano, and S. Nishiyama, "Analysis and prediction of flow from local source in a river basin using a Neuro-fuzzy modeling tool," *Journal of Environmental Management*, vol. 85, no. 1, pp. 215–223, Oct. 2007, https://doi.org/10.1016/j.jenvman.2006.09.009.

[29] N. Baig, S. I. Abba, J. Usman, M. Benaafi, and I. H. Aljundi, "Ensemble hybrid machine learning to simulate dye/divalent salt fractionation using a loose nanofiltration membrane," *Environmental Science: Advances*, vol. 2, no. 10, pp. 1446–1459, 2023, https://doi.org/10.1039/D3VA00124E.

[30] Md. M. Hassan *et al.*, "Machine Learning-Based Rainfall Prediction: Unveiling Insights and Forecasting for Improved Preparedness," *IEEE Access*, vol. 11, pp. 132196–132222, 2023, https://doi.org/10.1109/ACCESS.2023.3333876.

[31] F. F. Fadoul, A. A. Hassan, and R. Çağlar, "Assessing the Feasibility of Integrating Renewable Energy: Decision Tree Analysis for Parameter Evaluation and LSTM Forecasting for Solar and Wind Power Generation in a Campus Microgrid," *IEEE Access*, vol. 11, pp. 124690–124708, 2023, https://doi.org/10.1109/ACCESS.2023.3328336.

[32] I. D. Mienye and Y. Sun, "A Survey of Ensemble Learning: Concepts, Algorithms, Applications, and Prospects," *IEEE Access*, vol. 10, pp. 99129–99149, 2022, https://doi.org/10.1109/ACCESS.2022.3207287.

[33] E. Eldesouky, M. Bekhit, A. Fathalla, A. Salah, and A. Ali, "A Robust UWSN Handover Prediction System Using Ensemble Learning," *Sensors*, vol. 21, no. 17, Jan. 2021, Art. no. 5777, https://doi.org/10.3390/s21175777.

[34] E. Kim and I. Joe, "Handover Triggering Prediction with the Two-Step XGBOOST Ensemble Algorithm for Conditional Handover in Non-Terrestrial Networks," *Electronics*, vol. 12, no. 16, Jan. 2023, Art. no. 3435, https://doi.org/10.3390/electronics12163435.

[35] V. Nourani, G. Elkiran, and S. I. Abba, "Wastewater treatment plant performance analysis using artificial intelligence – an ensemble approach," *Water Science and Technology*, vol. 78, no. 10, pp. 2064–2076, Nov. 2018, https://doi.org/10.2166/wst.2018.477.

[36] A. G. Armaki, M. F. Fallah, M. Alborzi, and A. Mohammadzadeh, "A Hybrid Meta-Learner Technique for Credit Scoring of Banks' Customers," *Engineering, Technology & Applied Science Research*, vol. 7, no. 5, pp. 2073–2082, Oct. 2017, https://doi.org/10.48084/etasr.1361.

[37] K. Smolak, W. Rohm, and K. Sila-Nowicka, "Explaining human mobility predictions through a pattern matching algorithm," *EPJ Data Science*, vol. 11, Dec. 2022, Art. no. 45.