iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 12 Issue: I Month of publication: January 2024

DOI: https://doi.org/10.22214/ijraset.2024.57886

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 12 Issue I Jan 2024- Available at www.ijraset.com

An Artificial Intelligence Mechanism for the Prediction of Signal Strength in Drones to IoT Devices in Smart Cities

Ronald Chiwariro[1], Martin Muduva[2], Austin Makate[3]
[1]Jain University, India
[2]Midlands State University, Zimbabwe
[3]University of Zimbabwe, Zimbabwe

Abstract: Smart cities are comprised of intelligent objects that can collectively and automatically improve living standards, preserve lives, and function as a sustainable environment. Drones or Unmanned aerial vehicles (UAV), robotics, cognitive computing, and the Internet of Things (IoT) are mandatory to enhance the intellectual ability of smart cities by enhancing connectivity, energy efficiency, and Quality of Signal (QoS). Consequently, the integration of drones with IoT plays a crucial part in enabling a vast array of smart-city applications. Drones are undeniably the technology of the future. They glide in the air, keeping an eye on things in their metropolis. They do not need human control or operation. They capture data based on visuals and sounds by employing a variety of sensors, webcams, and mics, and then transfer it to a gateway for processing and retrieving information. Drones will let us gather vast volumes of data for processing, while also enhancing the intelligence of smart cities. The drone's signal is vulnerable to absorption, refraction, diffraction, and attenuation. Therefore, it is essential to predict the signal from the drone. This study presents an intelligent method using Deep Learning to predict the signal strength for enhancing network connectivity and delivering the desired QoS of IoTs and drone integration. This enables effective data transmission, boosts QoS for end-users/devices, and reduces data transmission power consumption.
Keywords: Drone, Signal, Deep Learning, Wireless, Smart City, Signal Prediction.

I. INTRODUCTION

The combination of Artificial Intelligence (AI), communication, and robots has the potential to drastically alter our world and way of life. Recent years have seen an increase in the prevalence of robotic communication in a range of workplaces, including homes, hospitals, hotels, and businesses. To enable robots to share information with people, it is necessary to create preferred communication channels. The environmental repercussions have an impact on the construction of a communication link between robots and humans. When enhancing a communication link, signal strength, channel dispersion, elevation angle, and radiation power should all be considered [1]. Atmospheric and environmental effects like scattering, diffraction, reflection, and shadowing of electromagnetic waves can have a substantial impact on signal strength during transmission. Additionally, large and small fading reduce the dependability and quality of drone-to-ground communications. Consequently, the communication link between the drones and other robots on the ground fades and weakens. Numerous research has been performed to develop satellite and terrestrial communication networks [2]. However, communication links for UAVs are still in their infancy and differ from satellite and terrestrial connectivity. The primary distinction is between the mobility of the UAV (transmitter) in a homogenous environment and the movement of reception agents on the ground in various surroundings. Drones have recently gained appeal in the scientific and industrial sectors as a result of their adaptability and flexibility to be utilized in a vast array of applications, including security, control, monitoring, and exploration of hard-to-reach locations. The most significant characteristic of an unmanned aerial vehicle is its line of sight. This function increases the signal rate effectively, provides communication services to a vast coverage area, and deploys to improve the QoS [3]. Drones can be used to provide services for temporary events such as sports, deliver packages in high-traffic locations, and stadiums, and monitor traffic, among other applications. When conducting these operations, signal intensity must be taken into account. This necessitates the development of the most precise and effective method for predicting the volume of communications between drones and IoT devices. Consequently, we examine the effect of a small number of signal intensity observations on estimations of prediction accuracy and propagation parameters. Listed below are some past efforts on signal strength prediction.

The author of the paper [4] presents a unique model-assisted deep learning approach for predicting path loss using top-view geographic imagery of the receiver's position. In a full examination, they apply the suggested technique to a huge real-world data set consisting of five distinct circumstances and over 125 thousand individual measurements. The novel solution achieves a root-mean-squared error of 6 dB across fundamentally heterogeneous data sources, reducing the average prediction error by up to 53 percent compared to ray-tracing techniques. The journal [5] discusses the building of ANN models for four VHF broadcast stations using measured meteorological conditions to calculate received signal intensity (RSS). Using the LMBP back-propagation method, the network was trained. Several activation functions, the number of neurons in the hidden layer, and several data normalization techniques were utilized in a methodical training strategy. The mean and variance of the MSE (mean square error) calculations for each network were compared over ten iterations. The fact that the estimated signal strength values matched the observed signal strength values implies that the ANN model performed adequately. UAV and the IoT can be linked through the use of a creative technique that maximizes network connectivity while providing the proper QoS [6]. The QoS for end-users/devices can be enhanced by predicting signal strength and fading channel conditions, which reduces data transmission power consumption. UAVs can collect data in locations where humans cannot or are reluctant to do so. Diminished, more reflective, diffraction, scattering, and darker conditions impair the UAV's signal. In addition, the capacity of ANN to predict the signal intensity and channel propagation from a drone in addition to the physical environment was evaluated. Despite this, the results indicate that signal distortion can be decreased and enhanced greatly. SNR and PDR are predicted using a Neural Network (NN) in the publication [7]. Even when trained with only 10% of the data, the NN can predict signal-to-intervention noise ratio (SNR) and Packet Delivery Ratio (PDR) with up to 96 and 98 percent accuracy, respectively, using an actual dataset. A subset of attributes that is useful for predicting both SNR and PDR should be considered simultaneously for both measurements. When the SNR and PDR are predictable, transmission power can be regulated dynamically and adaptively to meet reliability standards while conserving energy. This can aid in the development of an eco-friendly communication system. The research [8] provides a rapid and accurate method for calibrating deep interior environments. In determining the signal strength of a mobile device, it has been demonstrated that the calibration model is more accurate than any other prediction model. They also confirmed that the model significantly reduced calibration time while keeping accuracy comparable to the conventional way of calibrating real-time locating devices. With more prediction points and an improved process for reference point distribution, we anticipate that our model will be able to produce even higher-quality location estimates for future investigations. Accuracy and efficiency in network estimate are crucial to the successful deployment of 5G networks. According to the study [9], the error of the observation points was used as optimization objectives, and features were extracted from both a model analysis and a data analysis perspective. Based on these characteristics, a NN for multi-objective learning and radio wave signal strength prediction is developed. The radio wave signal strength prediction model based on deep learning currently has an MSE of 8.59, which is a significant practical reference value in engineering practice. By an article in [10], it is possible to predict future signals using prior signal samples. Forecasting improves customer service when amplitude and non-systematic phase signals are applied in real-world signal processing settings. The Elliot wave theory method was tested in the actual world with 60 kph-travelling pedestrians and autos. Consequently, the projected outcome comprises signal strength based on expanding distribution utility, SNR, and instability in their future period. The final output of the algorithm displays a 68 percent success rate. The paper is done to identify the signal strength from drones to IoT devices. This helps to collect the data from the drone at the appropriate time and with minimum loss. The paper is written in the following ways, the first chapter details the innovation of drones and a literature survey on recent papers to analyse the problem statement and available solutions. The necessity of drones in the smart city is detailed in Chapter 2, the signal strength and the technical terms are described in Chapter 3, the workflow of the research is detailed in Chapter 4 and in Chapter 5 the DL technique used to predict the signal is explained with the architecture. Finally, chapters 6 and 7 discuss the result obtained by the trained DL model.

II. IMPORTANCE OF DRONES IN SMART CITY

Information is shared by the drone effectively and efficiently in compliance with modern technology collaboration criteria. The paper [11] discusses the benefits and prospective applications of drones in wireless telecommunications. It is thus possible to improve the precision of data gathering by using similarities in data collection from diverse IoT devices. According to the authors [12], there are benefits and drawbacks to using drones in smart cities. Confidentiality, safety, and morality use were only a few of the questions raised. A drone has unique features. It is the best instrument for the city monitoring task because it is flexible, repairable, quick to set up, and effective in assessing a range of factors anywhere at a particular time. Data can be gathered and given to intelligent frameworks that can perform data analysis at a low cost (image, audio, or video). As a result, drones have a significant influence on social relationships as well as the overall well-being of people who live in smart cities.

The number of drones in use is expected to expand rapidly in the future. Drones' ability to carry out complex activities quickly and efficiently in real-time opens up a range of new opportunities for defence, industrial, corporate, and commercial applications. Figure 1 demonstrates the use of drones in smart cities.

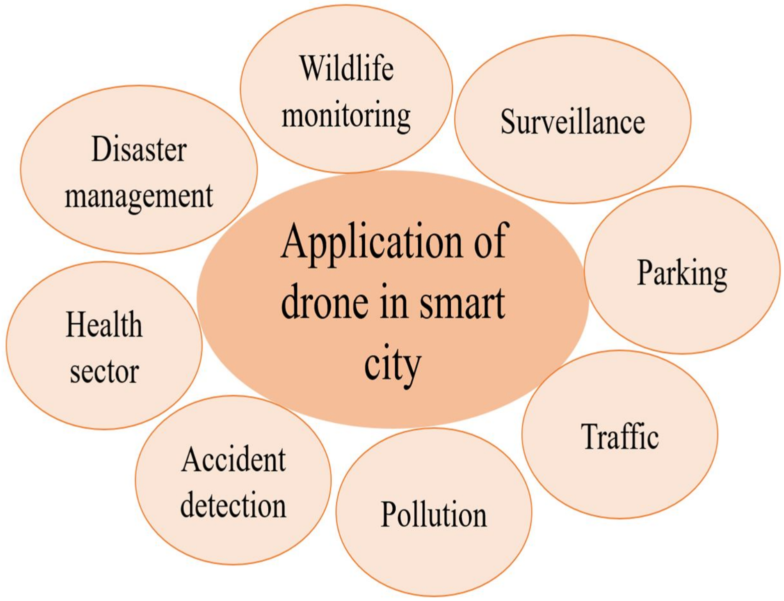


Fig. 1. Drone application in smart city

The Internet of Drones can easily be stated as a subset of the IoT. IoT is its backbone, it provides controlled and coordinated access to supervised airspace for UAVs [13], also known as drones. With the continued decrease in the size of the sensors, processors, camera units, digital memory, and ubiquitous wireless connectivity, these drones are rapidly finding several new and productive uses in enhancing the way of living. The drones add an extra layer for data processing and reduce the load on the cloud server. They enable faster transmission of data and at the same time reduce the load on the gateways.

III. SIGNAL STRENGTH

Wireless Multimedia Sensor Networks (WMSN) have emerged in response to the growing demand for imaging and video sensors in wireless sensor network (WSN) equipped smart cities. WMSNs may capture and wirelessly transfer multimedia data from their environment. For WMSN applications to effectively communicate event details, multimedia elements such as audio, photographs, and videos are required. WMSN must address similar issues as WSN, including dependability, QoS, and high bandwidth demands [14]. Consequently, new protocols must be created to accommodate the transmission requirements of multimedia data in real-time, while minimizing energy usage in data processing and communication. WMSNs have different QoS standards than conventional networks. Signal strength is essential during transmission. Controlled drones can maintain a predetermined course, receive signals from ground agents that allow them to follow their movements and identify specific objects, and locate the precise spot they are seeking. A signal travelling over space is prone to several occurrences. These incidents diminish the signal strength between UAVs and agents or IoT devices on the ground, resulting in a signal that is extremely faint when it reaches the destination. In constructing transmission and receiving systems, these phenomena must be taken into account. Each application demands various network services. These are the prerequisites for the required level of service quality. The QoS for wireless sensor multimedia networks consists of timeliness, dependability, and power. The capacity to transmit data within a specific timeframe is known as "timeliness." When we discuss reliability, we are referring to the ability to receive trustworthy data with low to no loss. Measurements of QoS include packet loss, accuracy, and overall coverage. Coverage refers to the total number of sensors necessary to obtain a comprehensive view of the target region. In other words, accuracy quantifies the difference between the information detected and the information received by the end-user. Any node with sufficient energy can transmit all data. Several factors affect the communication channel between drones and ground agents or IoT devices, including fading, radiation power, and signal strength. The coverage area and surrounding environment influence fading, signal strength, and radiation power. UAVs are also employed to offer wireless communication coverage.

IV. RESEARCH FLOW

The research flow of AI Mechanism for the Prediction of Signal Strength in Drones is detailed in this section with the help of Figure 2. To predict the signal strength by AI model the data is important. The data is collected by the experimental method. To collect the data the drone was allowed to fly at different distances and various amplitudes. Then the data like distance and amplitude of the drone from the land, frequency, path loss, and its respective signal strength using the conventional instruments. The signal strength is taken as the target variable and other parameters are considered features. The data recorded is used to train the ANN model. After training the ANN model is deployed to predict the signal strength. In the prediction phase, parameters like distance, the amplitude of the drone, frequency, and path loss of signal are given to the ANN model and asked to predict the signal. Finally, the result of the ANN model is compared with the original signal strength to analyse the efficiency of the designed ANN model.

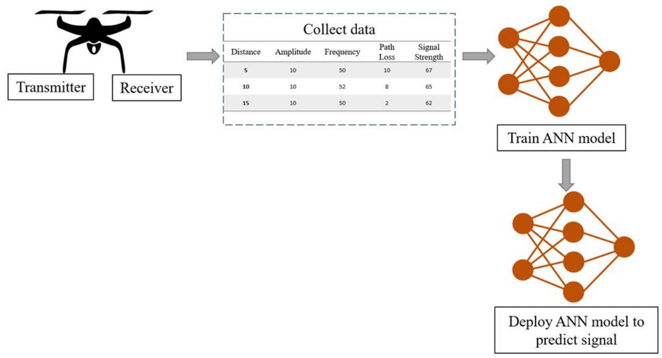


Fig. 2. Research flow

V. ARTIFICIAL NEURAL NETWORK (ANN)

To enhance receiver and transmitter performance, it is necessary to accurately estimate signal strength. We developed an ANN method to predict the precise signal at different heights and distances.

Research on the brain and nervous system is used to develop ANN. These networks are comparable to biological NN but employ a limited number of biological principles [15]. A mathematical model that replicates the electrical impulses of the neurons, as well as others, is known as an ANN model. There are connections among processing components (neurode or a perceptron). Typically, neurode layers are employed, with the result of one layer serving as the input for the next or succeeding layers. For instance, a neuron may be connected to another neuron in the layer, or it may be connected to a subset of such neuronal connections. Weighted data signals can be utilized to simulate the electric stimulation of a nerve cell and the subsequent information transfer inside a network of the brain. To replicate the strengthening of NN in the brain, the input parameters of a processing system are assigned a connection weight. ANNs approximate learning by modifying the strength of the connections. To use a transfer function, the input values are computed, and the output is obtained (input signals to the further layer). The transfer function modifies the input value of the neuron. Typically, a nonlinear function, including a sigmoid, tangent, hyperbolic, or SoftMax is employed in this conversion. The NN produces a final output value, a vector of values by continuing the algorithm between successive layers of processing units. If the ANN is to mimic the asynchronous functioning of the nervous system, then its processing units must be triggered asynchronously with the weighted input signal. In contrast, ANN often adopts a more discretised methodology in which each processing node is active only once per vector representation [16].

The ANN, which is modelled after the human nervous system, uses representative data to learn by example about physical occurrences or decision-making processes. ANN is capable of identifying relationships between variables and extracting sophisticated knowledge from representative data sets. It is possible to establish connections between variables if no assumptions are made about how events are mathematically represented. ANN models, for instance, maybe more equipped to handle noisy data than conventional regression models. One or more layers of hidden nodes connect a layer of input nodes to a layer of output nodes. Nodes in the input layers execute activation functions, whereas nodes in the concealed layer, depending on the evidence, either execute or remain inactive. In the hidden layers, the evidence is weighted, and when the value of a node or collection of nodes in the hidden layer reaches a specific threshold, a value is transferred to one or more nodes in the output layer. To train ANNs, an enormous number of cases are required (data). Rare or severe incidents cannot be modelled with ANNs since the available data is insufficient for training the model. In an ANN, qualitative data cannot be substituted for human experience (expert opinion). ANNs can incorporate uncertainty by assessing the probability of each output node.

However, the most probable assumption for each scenario cannot be determined. Despite this, NN is black boxes (i.e., NN are black boxes). Since hidden layer nodes have no physical significance, the output cannot be conveyed directly to the process. In NN, judgments must be made beforehand regarding which data to analyse (inputs) and how to classify it (outputs). Using ANN, predictive models for signal strength have been developed to address nonlinearity difficulties. They can be used for signal optimization, signal control, and signal strength evaluation. It will also aid in making sound decisions based on the signal from the drone. Figure 3 illustrates a design illustration for the ANN. Distance, altitude, frequency, and route loss are inputs. The output is the sum of the concealed layer's summation. The output measures and calculates the perceived signal strength. The ANN model is designed with four nodes in the input layer and one node in the output layer. Next, a total of three hidden layers are employed with various counts of nodes. First, the input parameters like distance, altitude, frequency, and path loss are given to each node of the input layer. Next, the hidden layers are extracting the important features from the input features. And finally, the output layer is responsible for estimating signal strength.

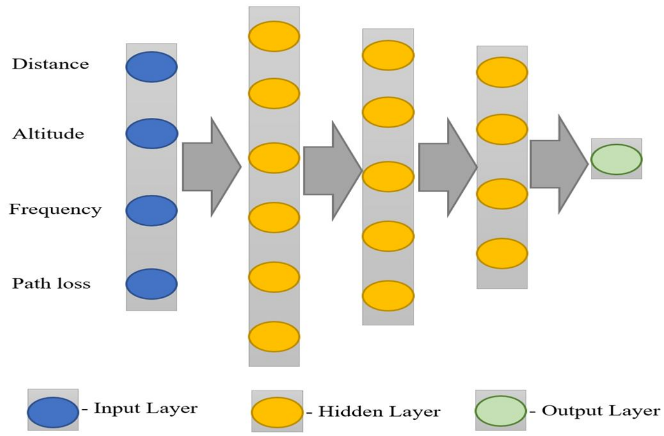


Fig. 3. ANN architecture

VI. RESULTS AND DISCUSSION

The signal strength prediction is very important to collect the data more effectively from the drone which is employed to monitor the city. The proper acquisition of data helps the specialists, and government to analyse the condition of the city and take the decision to enhance the economy, wealth, healthcare, and reduce crime in the city. The QoS plays an important role in data acquisition. The QoS should be high for proper communication. But practically it is not possible to maintain the QoS at the desired level due to environmental and technical issues. But this issue can be solved, by predicting the drone QoS in the future. Based on this prediction we take some necessary steps to maintain the signal strength. For prediction in this research, the ANN algorithm is used. Collecting the parameters which affect the QoS is sued to train the ANN. After getting a good accuracy rate in the training phase the model is deployed in real-time for the prediction of QoS in drones. Next, the developed ANN is tested by placing the drone at different positions. First, the drone is placed at different heights and in the atmospheres and the QoS is measured using the hardware, which also makes the ANN predict the QoS. The placement of drones at different heights and the transmission of signals are shown in Figure 4.

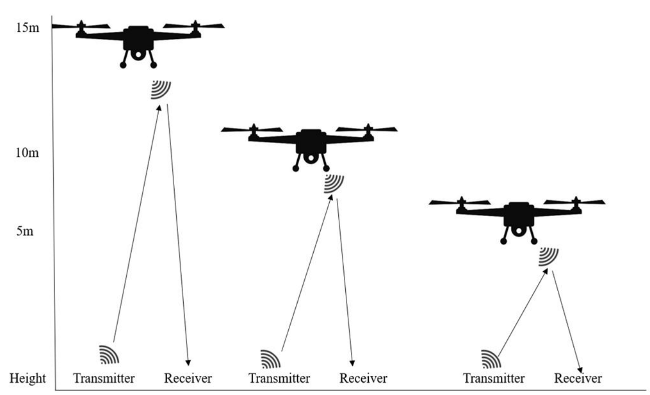


Fig.4. Signal prediction at different heights

Second, the drone is placed at fixed heights in the atmosphere and signal transmission and reception device position is varied. Similarly, as discussed in the previous condition, the QoS is measured using the hardware and also makes the ANN predict the QoS. The placement of drones at fixed heights and the transmission of signals at various distances are shown in Figure 5.

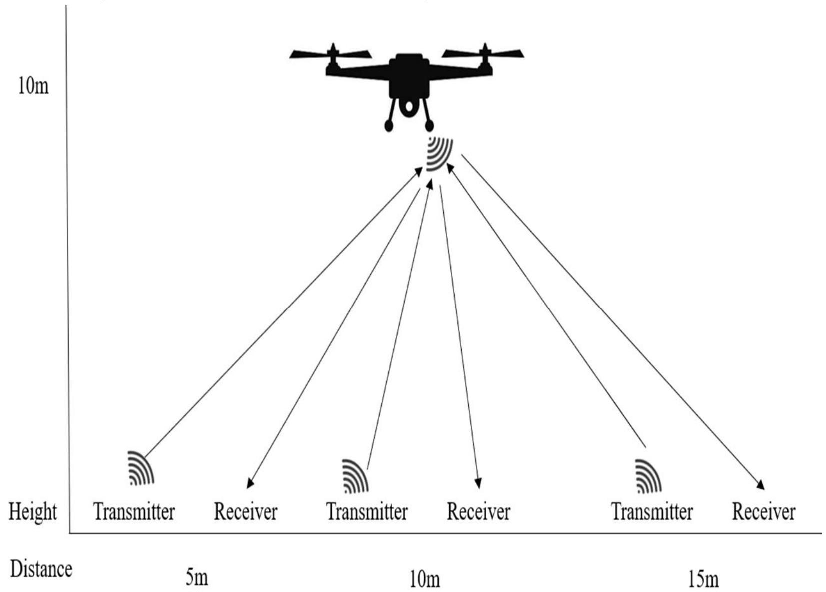


Fig. 5. Signal prediction at different distances

The QoS measured from the device and the ANN predicted QoS are compared to find the effectiveness of the designed model. Figure 6 shows the actual signal and predicted signal when the drone is placed at various heights. The x-axis guides locating the height of the drone in meters and the y-axis represents the signal values in dBm. Both actual and predicted signals are plotted in the figure and they are differentiated with the help of colours. The actual signal value is indicated in blue colour and the predicted signal value is indicated in orange colour. The figure proves that the designed ANN predicts the QoS near to the actual value. And there is not much deviation in the estimation of QoS.

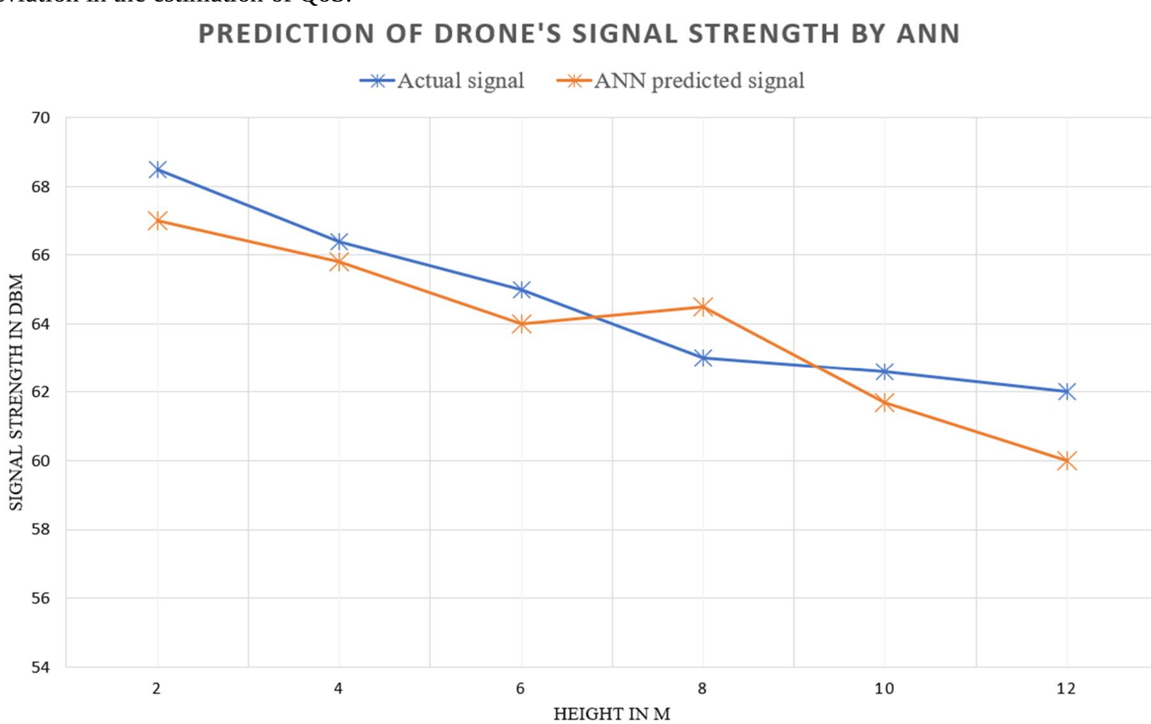


Fig. 6. Signal prediction at different heights

For various installation distances of the receiving unit from the drone, the actual signal and anticipated signal are shown in Figure 7. Drones' distance from the reception unit is measured in meters, and the signal strength is measured in decibels (dBm) and these values are taken on the x and y-axis of the plot. In the figure, the real signal and the anticipated signal are both plotted, and the colours are used to differentiate them. Signal values in blue and projected signal values in green are shown in the graphs. The graph shows that the ANN's predicted QoS is close to the actual value. In addition, the QoS estimation shows little variation.

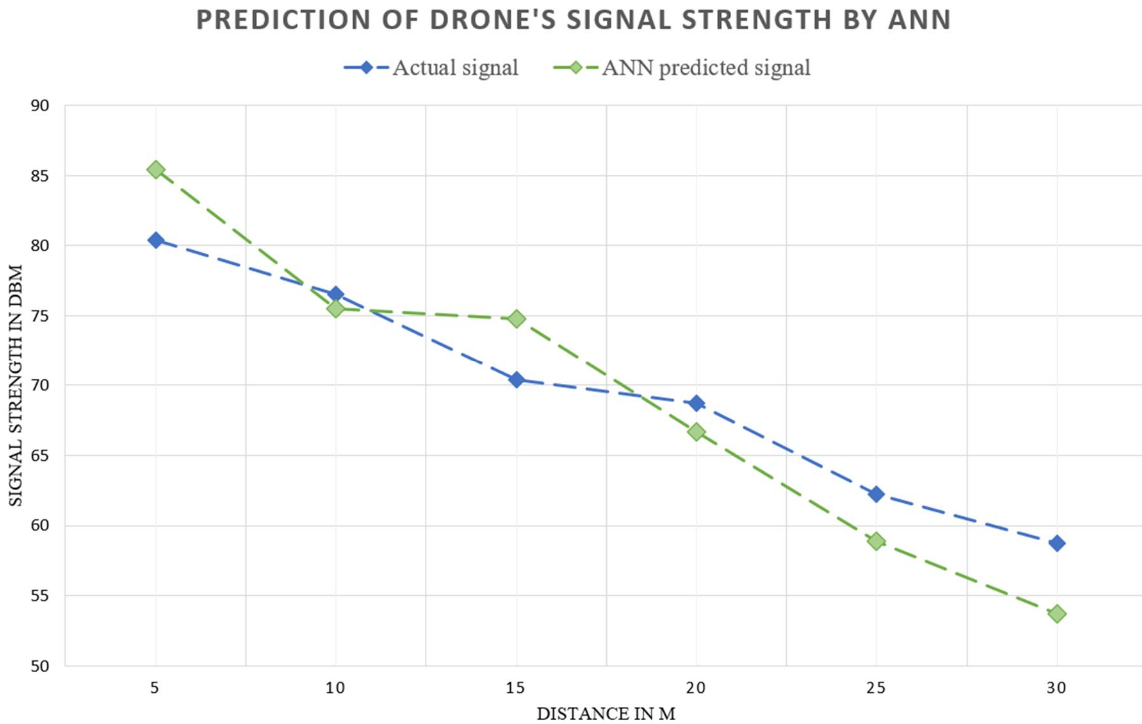


Fig. 7. Signal prediction at different distances

VII. CONCLUSION

By combining ANN, drones and IoT can be leveraged to address today's most difficult challenges. It is already being utilized to displace the wired sensors in stationary sites, as an advancement in IoT. The data collected by IoT devices cannot be transmitted across long distances. The integration of drones and IoT devices provided a solution to this problem. Through the deployment of IoT devices, drones can be utilized to enhance public life and also to safeguard the environment in several ways. The decreasing energy usage, and maintaining a high level of QoS by integrating drones with the IoT. A smart drone collects data from multiple IoT devices and decides to transmit the data to its final destination. The environmental condition influences a smart drone's capacity to communicate. So, determining signal strength with good accuracy would be challenging. Thus, the environmental factors are taken into account while constructing the transmitter and receiver. When constructing a reception device, the potential to appropriately predict the signal is critical. Signal strength estimation, in particular, is a difficult problem to tackle. The signal strength is affected by wireless channel dynamic changes and geographical considerations. To determine the accurate and efficient signal strength, ANN is used. To train the ANN height, path loss, elevation angle, and distances are considered important features. From the simulation result, ANN predicts the signal strength accurately with tolerable error limits.

REFERENCES

[1] Alsamhi, Saeed & Ma, Ou & Ansari, Samar. (2018). Predictive Estimation of the Optimal Signal Strength from Unmanned Aerial Vehicle over the Internet of Things Using ANN.

[2] M. Jia, X. Gu, Q. Guo, W. Xiang, and N. Zhang, "Broadband Hybrid Satellite-Terrestrial Communication Systems Based on Cognitive Radio toward 5G," IEEE Wireless Communications, vol. 23, pp. 96-106, 2016.

[3] S. Alsamhi and N. Rajput, "An Efficient Channel Reservation Technique for Improved QoS for Mobile Communication Deployment Using High Altitude Platform," Wireless Personal Communications, vol. 91, pp. 1095-1108, 2016.

[4] J. Thrane, B. Sliwa, C. Wietfeld and H. L. Christiansen, "Deep Learning-based Signal Strength Prediction Using Geographical Images and Expert Knowledge," GLOBECOM 2020 - 2020 IEEE Global Communications Conference, 2020, pp. 1-6, DOI: 10.1109/GLOBECOM42002.2020.9322089.

[5] K.C.Igwe, O.D.Oyedum, A.M.Aibinu, M.O.Ajewole, A.S.Moses, "Application of artificial neural network modelling techniques to signal strength computation," Heliyon, Volume 7, Issue 3, March 2021, e06047, DOI: 10.1016/j.heliyon.2021.e06047

[6] Madhavi Gogula, Beer Pal Singh, "Unmanned Aerial Vehicles Estimation of IoT using Artificial Neural Network", Science, Technology and Development, Volume VIII, Issue IV, pp. 206, APRIL 2019

[7] Ateeq, Muhammad & Afzal, Muhammad & Naeem, Muhammad & Shafiq, Muhammad & Choi, Jin-Ghoo. (2020). Deep Learning-Based Multiparametric Predictions for IoT. Sustainability. 12. 7752. 10.3390/su12187752.

[8] Narzullaev, Anvar & Park, Yongwan & Jung, Ho-Youl. (2008). Accurate signal strength prediction based on positioning for indoor WLAN systems. 685 - 688. 10.1109/PLANS.2008.4569989.

[9] M. Wu, C. Li and C. Song, "Research On Wireless Intelligent Propagation Model Based On Deep Learning," 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), 2020, pp. 1119-1123, DOI: 10.1109/ITAIC49862.2020.9339171.

[10] Balasubramaniam, P.M. & S, Arivoli & N, Prabhakaran. (2020). Performance of Signal Strength prediction in Data transmission Using Elliott wave Theory. International Journal of Computer Communication and Informatics. 2. 62-69. 10.34256/ijcci2017.

[11] Mohammad Mozaffari, Walid Saad, Mehdi Bennis, Young-Han Nam, and MÃl'rouane Debbah. A tutorial on UAVs for wireless networks: Applications, challenges, and open problems. arXiv preprint arXiv:1803.00680, 2018

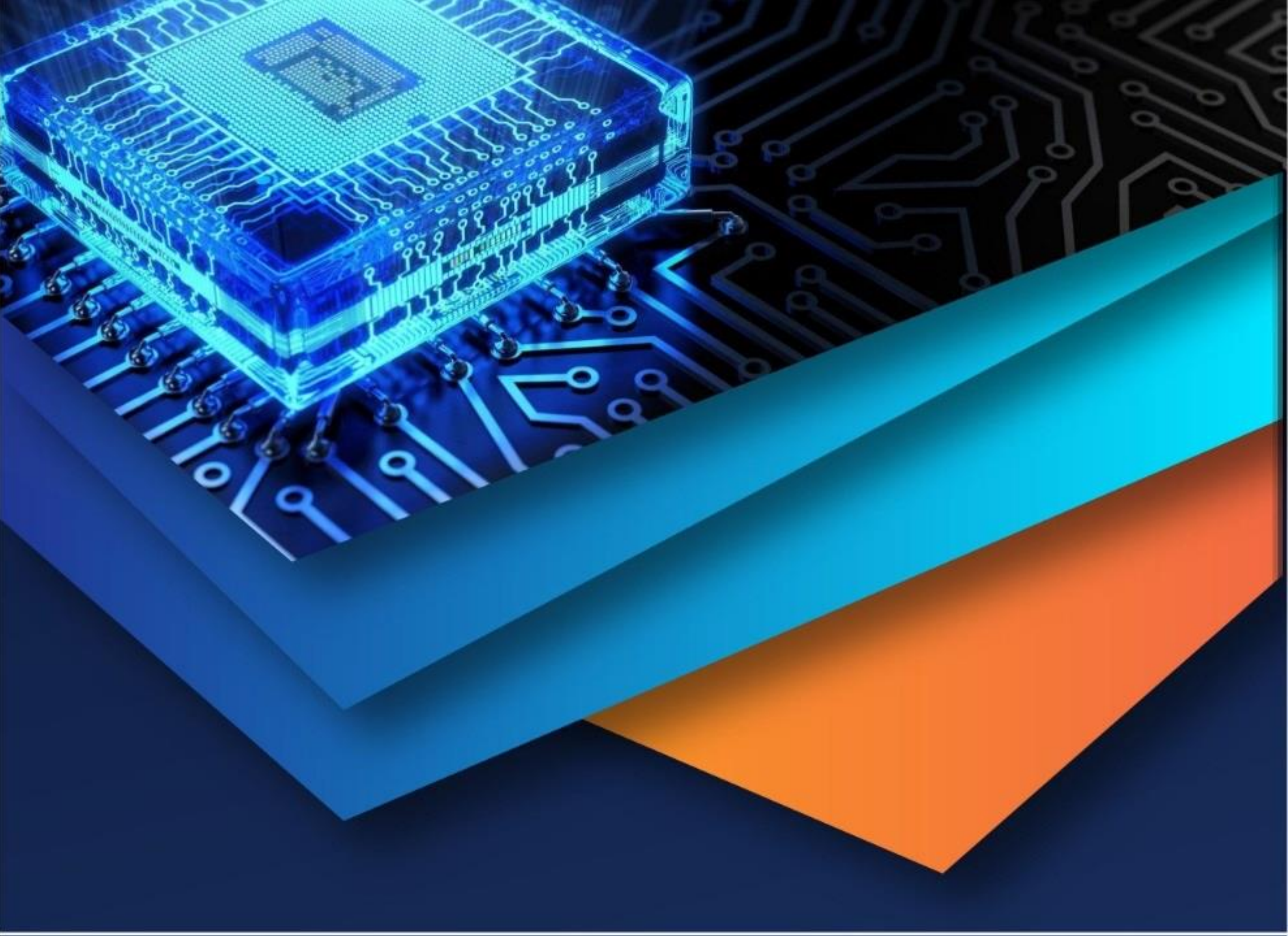
[12] Farhan Mohammed, Ahmed Idries, Nader Mohamed, Jameela AlJaroodi, and Imad Jawhar. UAVs for smart cities: Opportunities and challenges. 2014 International Conference on Unmanned Aircraft Systems (ICUAS), pages 267–273, 2014.

[13] A. Cavoukian, "Privacy and Drones: Unmanned Aerial Vehicles," Information and Privacy Commissioner of Ontario, Ontario, Canada, pp. 1-30, 2012.

[14] Choong, Khong & Yee, Y. & Low, A. & Chien, Sf & Ng, S.. (2006). QoS provisioning for multimedia wireless networks. BT Technology Journal. 24. 10.1007/s10550-006-0048-3.

[15] Grossi, Enzo & Buscema, Massimo. (2008). Introduction to artificial neural networks. European journal of gastroenterology & hepatology. 19. 1046-54. 10.1097/MEG.0b013e3282f198a0.

[16] Li, E. Y. (1994). "Artificial neural networks and their business applications," Infor. Management, 27 (5), 303–313



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY