International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-14 Issue-5, January 2026

Machine-Learning-Driven 3D Antenna Design for Energy-Efficient HAPS in Smart Cities

Kholod D Alsufiani, Eman S. Alkhalifah

Abstract: ***The development of smart sustainable cities increasingly relies on advanced communication infrastructures to support intelligent transportation systems, energy management, and data-intensive urban services. The rapid expansion of Internet of Everything networks has led to rising energy consumption, posing a critical challenge for sustainable urban development. This research was conducted to address the need for energy-efficient, high-performance wireless communication solutions capable of supporting large-scale, innovative city applications. In particular, High Altitude Platform Systems have emerged as promising communication enablers due to their wide coverage and deployment flexibility; however, their effectiveness is constrained by the energy efficiency and performance of antenna systems. This study investigates the application of Machine Learning techniques for the optimisation of 3D antenna structures to enhance communication efficiency. The 3D intelligent Microstrip Patch Multiple Input Multiple Output antenna operating at 28 GHz was designed and optimised using a Machine Learning-driven framework. The antenna design process was carried out using 3D digital Computer Simulation Technology software, enabling precise electromagnetic modelling and performance evaluation. Machine Learning algorithms were employed to systematically adjust antenna parameters, allowing the identification of optimal design configurations beyond conventional trial-and-error methods. The performance of the optimised antenna was evaluated using Quality of Service parameters for power efficiency and last-mile connectivity. Comparative analysis with non-optimised antenna designs demonstrated substantial performance gains. The results reveal an improvement of up to 31% in power efficiency, accompanied by enhanced connectivity performance. These findings indicate that Artificial Intelligence-driven antenna design is a practical approach to developing sustainable, energy-efficient communication infrastructure for future, innovative city environments.***

Keywords: 3D Digital Design, AI, ML, Optimisation, Smart Cities.

Nomenclature:
ICTs: Information and Communication Technologies
ITU: International Telecommunication Union
SDGs: Sustainable Development Goals
ML: Machine Learning
AI: Artificial Intelligence
IoE: Internet of Everything
HAPs: High-Altitude Platforms
IoV: Internet of Vehicles
SOA: Swarm Optimisation Algorithm
MILP: Mixed-Integer Linear Programming
RF: Radio Frequency
ADCs: Analogue-to-Digital Converters
RIS: Reconfigurable Intelligent Surface
4IR: Fourth Industrial Revolution
M2M: Machine-to-Machine
EEUD: Energy-Efficient Unmanned Aerial Vehicle Deployment
EPOS: Economic Planning and Optimized Selections
MIMO: Multiple Input Multiple Output
PECM: Propulsion Energy Consumption Model
AO: Alternative Optimization
SCA: Successive Convex Approximation
HFL: Heterogeneous Federated learning
CST: Computer Simulation Technology
BER: Bit Error Rate
QoS: Quality of Service
VSWR: Voltage Standing Wave Ratio
MAPL: Maximum Allowable Path Loss
AWGN: Additive White Gaussian Noise
MSE: Mean Squared Error

Manuscript received on 08 December 2025 | First Revised Manuscript received on 18 December 2025 | Second Revised Manuscript received on 01 January 2025 | Manuscript Accepted on 15 January 2026 | Manuscript published on 30 January 2026.
*Correspondence Author(s)

Kholod D Alsufiani*, Department of Computer Sciences Program, Turabah University College, Taif University, Taif, Saudi Arabia. Email ID: K.kholod@tu.edu.sa , ORCID ID: 0009-0001-8881-9912

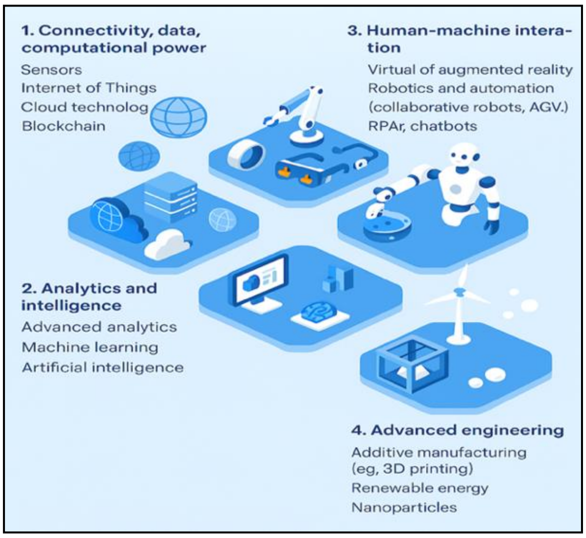
Eman S. Alkhalifah, Department of Graphic Design and Digital Media, College of Arts and Design, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia. Email ID: ealkhalifah@pnu.edu.sa

I. INTRODUCTION

The world's population continues to grow; urbanisation remains one of the most pressing challenges facing humanity. Smart sustainable cities offer a promising way to meet this challenge by creating more livable, equitable, and environmentally friendly urban environments. Smart sustainable cities are urban areas that use information and communication technologies (ICTs) to improve the quality of life, the efficiency of urban operations and services, and competitiveness, while ensuring they meet the needs of present and future generations across economic, social, environmental, and cultural aspects.

Smart sustainable cities can play a significant role in achieving the Sustainable Development Goals (SDGs) by using technology to improve the efficiency of urban systems and services. For instance, goal 11 (sustainable cities and communities), where smart cities can help to make cities more inclusive, safe, resilient, and sustainable by improving infrastructure, transportation, waste management, and responsible power consumption [1, 2]. According to the International Telecommunication Union (ITU), the revised the concept of "Smart City" is "Smart Sustainable City", which can be defined as “A Smart Sustainable City is an innovative city that uses Information and Communication Technologies (ICTs) and other means to improve quality of life, efficiency of urban operation and services, and competitiveness, while ensuring that it meets the needs of present and future generations with respect to economic, social, environmental as well as cultural aspects” [3]. Thus, according to McKinsey, the Fourth Industrial Revolution (4IR) has a significant impact on smart, sustainable cities, where the combination of Machine Learning (ML) with communication systems can open new possibilities for innovation.

Figure 1 shows the main pillars of the 4IR that support smart cities [4, 5]. Two main pillars of the 4IR that support smart cities are ML and Internet of Everything (IoE), which have the potential to revolutionise the way we live, work, and interact with the world around us. Where the IoE is the concept of connecting any device with an on/off switch to the Internet and/or to other devices, this includes everything from cellphones, coffee makers, washing machines, headphones, wearable devices, and smart cities. At the same time, ML is a form of artificial intelligence (AI) that enables software applications to become more accurate at predicting outcomes without being explicitly programmed to do so. ML algorithms use historical data as input to predict new output values [6, 7].



[Fig.1: The Main Pillars of the 4IR that Support Smart Cities]

Interest in unamended, helium-filled solar-powered platforms, such as High-Altitude Platforms (HAPs) that operate in the stratosphere, up to 20km above ground, is growing. They have many merits, such as satellite systems, but without the distance penalty. The combination of IoE and ML connected to the HAPs system would enable a wide range of smart city solutions. For example, the IoE can be used to collect data from sensors throughout the city, and ML can be used to analyse this data to identify patterns and trends with aerial support from HAPs' wireless network. This information can then be used to make informed decisions about improving the efficiency and sustainability of urban systems [8, 9]. In the context of smart sustainable cities, both ML and IoE can be used to:

- Collect data from sensors and devices throughout the city. This data can be used to monitor and improve a wide range of urban systems, such as transportation, energy, and waste management.
- Enable real-time communication between devices. This can be used to improve coordination and efficiency in areas such as traffic management and emergency response.
- Provide citizens with access to information and services. This can be used to improve civic engagement and make cities more responsive to residents' needs.

Some specific examples of how the IoE is being used to create smart sustainable cities include: smart grids, smart buildings and streets, intelligent transportation systems, and innovative waste management systems. The IoE has the potential to make a significant contribution to achieving the SDGs. By improving the efficiency of urban systems and services, the IoE can help to reduce energy consumption, emissions, and waste [10, 11].

The IoE can also improve the quality of life for urban residents by providing access to information and services that enable them to live more sustainably. As the IoE continues to develop, we can expect to see even more innovative solutions that help to create more sustainable cities. The IoE and ML are potent tools for building more sustainable cities. By using these technologies to collect and analyse data, cities can make informed decisions to improve the efficiency and sustainability of urban systems [12]. Moreover, the upcoming 6G network generation is being designed to meet the stringent requirements of smart cities in terms of quality of service, availability, and dependability.

The rest of this paper is organized as follows: Section 2 presents literature review. Section 3 describes the proposed model along with the mathematical calculations. Section 4: The simulations, validation, and highlight the main findings. Section 5, the paper concludes.

II. LITERATURE REVIEW

This section shows articles that collectively provide insights into the key technologies, applications, and challenges in the context of smart cities. This section presents representative literature reviews related to our research that highlight research gaps, thereby allowing our research motivations to emerge.

This section also highlights the importance of energy efficiency and sustainability, and the transformative potential of these technologies in creating more innovative and efficient urban environments. The articles also emphasize the role of AI in empowering wireless networks and enabling innovative applications such as digital twins and immersive realities. Overall, these recent articles contribute to our understanding of the advancement of smart cities in the era of 6G, ML, and IoE, thereby clarifying our motivations.

Articles in [12-14] emphasize the importance of HAPs in supporting last-mile connectivity and empower smart cities in various aspects. Authors in [15] introduced a collaborative, efficient energy management network using a smart grid and an IoT framework for sustainable management in smart cities. The obtained results confirm that utilising such an advanced concept in the current digital era would reduce energy consumption and hence support a sustainable smart city.

The use of IoT and the Internet of Vehicles (IoV) for waste management in smart cities was presented in [16]. An IoV-based data collection architecture for waste management in a sustainable smart city has been considered, relying on static and mobile sensor nodes; however, data can also be collected using mobile vehicles and fixed base stations.

A multipath propagation channel with Doppler frequency shift is discussed in [17] for a digital twin in an urban vehicular environment, using both conventional and dynamic channel estimation schemes. Results were promising, yet

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

geometry-based areas could increase computation load. As a recommendation, channel optimisation for future smart cities is pioneering work that could open new research opportunities for connected autonomous vehicles.

Researchers in [18] emphasis that Machine-to-Machine (M2M) communication applications, which support IoE, requiring low data rates are now endorsed by innovative satellite communication technologies. IoT devices in rural areas can benefit from backup connectivity thanks to satellite technology. A recent study presented a technique for integrating solar and wind turbine power generation systems with satellite communication technologies into a smart grid.

To convey data swiftly between communication channels and receivers with reasonable energy usage, an optimization approach is recommended in [19], which can help improve energy grids for a sustainable smart city. IoT and ML are discussed as possible solutions to smart cities' farming in [20]. Where various parameters can be monitored in an optimized LoRa network. Results indicate low power consumption of the proposed work.

In [21], researchers are moving towards smart sustainable cities using Li-Fi technology due to its high bandwidth. Power consumption and continuous wireless connectivity remain open challenges. The nested cells distribution of the beehive multilayer architecture for 6G in Futuristic Sustainable Smart Cities was presented in [22]. Results indicate a noticeably high level of computational power on the ground, due to the nature of the terrestrial network. Thus, an aerial network, such as HAPs or satellites, would mitigate this issue. Channel modelling for IoT and smart cities was intensively reviewed in [23] with highlights of the challenges and opportunities. Where optimizing propagation models for power consumption reduction is recommended to support smart sustainable cities.

A decentralized energy-aware coordination model was used in [24] for spatio-temporal sensing via a swarm of 10 drones. Accuracy and efficiency were obtained using the proposed model. Authors in [25] present a study to maximise the energy efficiency of a UAV system by jointly optimising the UAV trajectory and IoT communication resources. The proposed framework suggested an improvement in energy efficiency.

Further, similar work presented in [26] considers an air-to-ground propagation model and jointly optimises the UAV trajectory with reconfigurable intelligent surface (RIS) phase shifts. The proposed AI framework used an energy-efficient unmanned aerial vehicle deployment (EEUD) algorithm. Yet, it is recommended as future work to investigate further propagation models that consider the Rician factor and elevation angle.

A combined optimization of task segmentation and UAV with resource allocation with intelligent reflecting surfaces (IRS) for wireless powered mobile edge computing networks in smart cities was discussed in [27]. The IoT devices exhibited reduced energy consumption. Researchers in [28] used a swarm of intelligent UAVs for distributed sensing to enhance power consumption using Economic Planning and Optimized Selections (EPOS) for the testbed. This approach can effectively support innovative applications in cities and farms.

A framework introduced in [29] to compute UAV swarm placement and task scheduling for better energy consumption. A tethered UAV coverage over innovative environments was introduced in [30] using flexible beamforming. The proposed work aims to maximise the number of users while minimising energy waste. Another approach to noticeably reduce energy consumption while utilising UAVs is to optimise task offloading, as presented in [31].

A method discussed in [32] that combined a deep learning-based energy optimization and an adaptive adjustment for UAV-aided communication. The method shows a decent improvement in energy consumption. However, considering LoS and NLoS conditions in complex environments is needed as future work. Authors in [33] worked on reducing the energy consumption of UAVs via a swarm optimisation algorithm (SOA) by enhancing UAV routes for disaster management in smart cities.

In [34], energy consumption and task delays of the UAV system were optimised using differential evolution and ant colony techniques. The obtained results supported the designated aims. Further energy optimisation for UAV path planning was discussed in [35] using particle swarm optimisation. The obtained results indicate that the proposed work has reduced non-essential energy consumption during UAV flight operations.

Path planning for a swarm of UAVs is presented in [36] to reduce power consumption in industrial IoT. The proposed work uses a ground-air propagation model along with Multiple Input Multiple Output (MIMO) antenna and double-loop iterative for optimization. More optimization in terms of UAV trajectory planning for an innovative IoT environment is discussed in [37].

A Mixed-Integer Linear Programming (MILP) optimisation model was used in [38] to optimise the energy efficiency of offloading Cloud-Fog via a trajectory-based UAV. Results show visible energy efficiency. Authors in [39] discussed optimising energy for device-to-device UAV communications for smart industrial IoT. The proposed system used a directive antenna for propagating RF signals. Recourse allocation and multi-UAV scenarios are recommended as future work.

A deep reinforcement learning solution was proposed in [40] to maximizes data rate of UAV communication in smart cities. Results show enhancement in data rate and convergence time. Energy consumption optimisation should be addressed in future work. To enhance the received signal patterns in a 5G smart city UAV network, the authors of [41] used a deep residual learning-based cognitive model. Results show a modest improvement that slightly affects the energy consumption of IoT devices and sensors.

A generalized propulsion energy consumption model (PECM) was proposed in [42, 43] to minimize power consumption and maximize throughput for multi-UAV enabled IoT. Where Alternative optimization (AO) and successive convex approximation (SCA) techniques were applied. The obtained results showed that the UAV trajectory has reduced the energy consumption and resource management.

A multi-objective optimization for the trajectory discussed in [44] for energy efficiency in Multi-UAV-enabled communication systems. Approximating the LoS

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

propagation channel model is recommended for future work to suit complex environments. More multi-objective optimization was presented in [45] to improve throughput and energy efficiency in UAV-enabled IoT. Where LoS propagation was used with an omnidirectional antenna, there was a noticeable improvement in throughput and energy, but additional transmission conditions warrant further testing and enhancement.

A joint optimization of energy and delay parameters was tested in [46] in a cluster-based UAV network. By relaying tasks between UAVs using free-space propagation, the aim of the proposed work was pursued. Optimizing energy allocation for a space-based system of CubeSats has studied in [47] using serious gaming approach. Performance indicators suggest decent improvements in power consumption. Table 1. Summary of the related study in relation to the proposed work, so the motivation of our work can be drawn. There is a need of an optimization framework that could enhance propagation model that include the full range of link budget parameters. The optimised model can be evolved from a MIMO antenna design. Therefore, this paper aims to develop an intelligent MIMO antenna to optimise the wireless connectivity of HAPs in smart, sustainable cities using a machine learning approach, thereby achieving the goal of power consumption. This is the main contribution of this work, a noticeable improvement over exciting work.

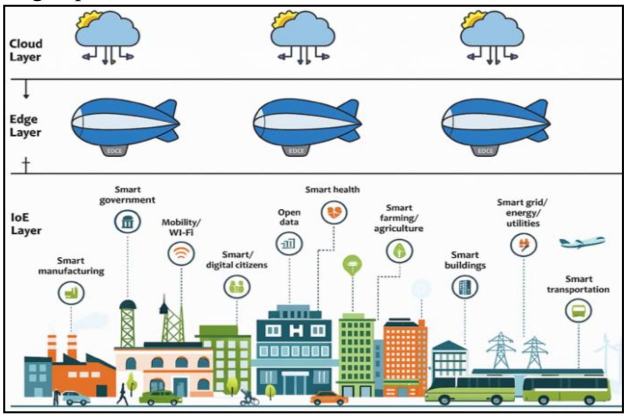
Table I: Summary of the Related Study

Ref.	Platform Type	AI Framework	Propagation Model	Antenna Type	Scope of Optimization	Issues
[25]	Drone	Dinkelbach algorithm	Free space	Omnidirectional	Jointly optimize trajectory & IoT comms. resources	Antenna constraints lead to more power consumption
[26]	Drone	EEUD algorithm	Air-to-ground	Directional	Jointly optimize trajectory with RIS phase shifts	Antenna constraints lead to more power consumption
[27]	Drone	Mixed integer & non-convex	Free space with IRS	Directional	Combined optimize of UAV placement and task segmentation with IRS	Antenna constrains lead to more power consumption
[28]	UAV	EPOS algorithm	Free space	Omnidirectional	Swarm of intelligent UAVs and sensing map	Channel modelling to enhance connectivity
[29]	Airborne	Multi-objectives algorithm	Multi-ray Propagation	Omnidirectional	Convergence of airborne swarm and task scheduling	Antenna constrains lead to more power consumption
[30]	Tethered UAV	x	Air-to-ground	MIMO	Optimizing bandwidth and power allocations	No AI optimization
[31]	UAV	Three-layer game algorithm	Free space	Omnidirectional	Optimizing tasks offloading	Deep learning is suggested as future work
[32]	Drone	Deep Learning	Free space	Omnidirectional	Optimizing for edge device	Beyond LoS is not considered
[33]	UAV	SOA	Radio propagation	Omnidirectional	Optimize UAV route	Antenna constrains lead to more power consumption
[34]	UAV	differential evolution & ant colony	Free space	Omnidirectional	Optimizing tasks offloading	Ground users' mobility can be considered as future work
[35]	UAV	Particle swarm optimization	Free space	Omnidirectional	Optimizing path planning of UAV	Environmental factors have to be considered
[36]	UAV	Double loop iterative	Channel attenuation	MIMO	Swarm path planning & tasks offloading optimization	Channel modeling constrains
[37]	UAV	multi-objective optimization	Free space	Omnidirectional	UAV trajectory planning	An enhanced air-ground channel model is recommended as future work
[38]	Drone	MILP optimization	Free space	Omnidirectional	UAV trajectory planning & tasks offloading optimization	Design heuristic algorithms for multi-UAV scenarios
[39]	Drone	Mulitiobjective evolutionary algorithm	Free space	MIMO	Enhance transmission	Channel modeling constrains
[40]	UAV	Deep Q-Learning	Air-to-ground	Directional	Enhance small cells communication	Energy consumption optimization should be addressed
[41]	UAV	Deep residual learning	Rayleigh channel	Directional	Develop connectivity	Channel modeling constrains
[42] [43]	UAV	(AO) & (SCA)	LoS channel	Directional	Jointly optimizing scheduling & UAV trajectory variables	Antenna constrains lead to more power consumption
[45] [46]	UAV	multi-objective optimization	Air-to-ground	Omnidirectional	Jointly optimizing throughput & UAV trajectory	Deep learning is suggested as future work
[47]	CubeSats	Serious gaming	Free space	MIMO	Optimizing propagation model	Channel modeling constrains
Proposed	HAP	Machine learning	Log-normal shadowing	Intelligent MIMO	Optimizing beams, gains, and power consumption	Complexity

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

III. 3D PROPOSED MODEL

The proposed model aims to develop an intelligent MIMO antenna to optimise the wireless connectivity of HAPs in smart, sustainable cities using a machine learning approach, thereby achieving the goal of power consumption. Figure 2 shows an outline of the proposed structure, which consists of three layers: 1) Cloud layer, which has the cloud for storage and processing tasks. 2) Edge layer, which has the HAP network that includes the HAP platforms with their communication payload, including MIMO antenna. 3) IoE layer, which has the ground control station, ground sensors, and mobile devices. The remainder of the section will cover the mathematical analysis of the proposed work and the design specifications of the smart MIMO antenna.



[Fig.2: Outline of the Proposed Structure]

Log Normal Shadowing is the propagation model considered here, together with its link budget parameters, which help predict the behaviour of electromagnetic waves as they propagate through various environments and under shadowing conditions. This propagation model is associated with MIMO intelligent antenna, enabling spatial multiplexing or diversity techniques that exploit multi-path propagation characteristics [48, 49].

A. The Proposed ML Model

Figure 3 shows the proposed intelligent MIMO system for a 6G network using an ML model. Radio Frequency (RF) chains and Analogue-to-Digital Converters (ADCs) are integrated into an ML model, thereby enhancing beam patterns for improved wireless connectivity and reducing power consumption. Thanks to the adaptivity of the ML framework, which helps adopt the geomatic channel model for the HAP network [52-55]. The equations for an intelligent MIMO system using Heterogeneous Federated learning (HFL), which is one of the advanced collaborative ML techniques, as per equations (1) to (4):

$$\sqrt{FL}(\widetilde{w}) = \sum_{k=1}^{k} \frac{mk}{M} L_k(\widetilde{w}) \quad \dots \quad (1)$$

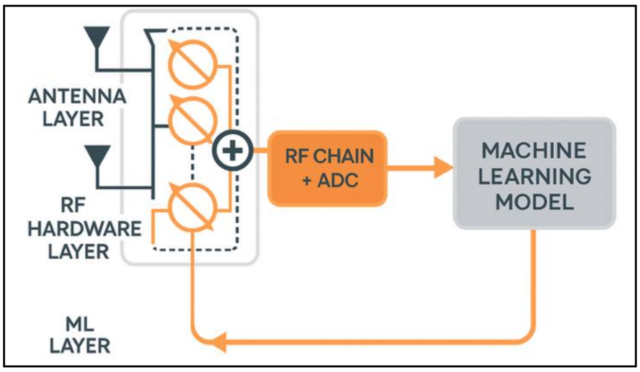
$$L_k(\widetilde{w}) = \frac{1}{mk} \sum_{k=1}^{k} L\left(\widetilde{y}_k^{(i)}, y_k^{(i)}\right) \quad \dots \quad (2)$$

$$\widetilde{w}_k := \widetilde{w}_k - \alpha \frac{\delta L_k}{\delta \widetilde{w}_k} \quad \dots \quad (3)$$

$$\widetilde{w} := \widetilde{w} - \sum_{k=1}^{k} \frac{mk}{M} \widetilde{w}_k \quad \dots \quad (4)$$

where $J_{FL}(\widetilde{w})$ refers to the FL objective function, $L_k(\widetilde{w})$ refers to the loss function of k clients, $\widetilde{w}_k$ refers to the updated global state, mk refers to local training samples.

The objective function of the proposed HFL model is based on user distributions, in which intelligent MIMO beams and gains are clustered and optimised according to connectivity (LoS or NLoS) scenarios to achieve high beamforming performance. Therefore, thus optimizing power consumption.



[Fig.3: The Proposed ML Model]

The log-normal shadowing propagation model that is considered in this work is modified by evolving the elevation angle factor (θ) when calculating the distance, which is a noticeable improvement that suits the nature of space-based communication systems like HAP. Further, the link budget parameters represent a comprehensive accounting of all the gains and losses that a communication signal experiences as it travels from the HAP transmitter to the terrestrial receiver. This analysis is vital to ensure the efficiency and reliability of the wireless connectivity via the HAP system. THE received signal power is sufficient for reliable communication. The analysis is crucial in the design and optimization of wireless communication systems. The link budget parameters include RSSI (Received Signal Strength Indicator, in dBm), SINR (Signal-to-Interference-plus-Noise Ratio, in dB), and T (Throughput, in b/s) [50, 51].

The equations for the log-normal shadowing model and the link budget parameters as per equations (5) to (9):

$$\mathrm{PL} = \mathrm{PL}(\mathrm{d0}) + 10 * \mathrm{n} * \log\left(\frac{\mathrm{d}}{\mathrm{d0}}\right) + \mathrm{X} \quad \dots \quad (5)$$

$$\mathrm{d} = 2\mathrm{E_r}\left[\cos^{-1}\left(\frac{\mathrm{Er}}{\mathrm{Er} + \mathrm{ht}} * \cos(\theta)\right) - \theta\right] \quad \dots \quad (6)$$

$$\mathrm{RSSI} = \mathrm{pt} + \mathrm{gt} + \mathrm{gr} - \mathrm{PL} - \mathrm{L} \quad \dots \quad (7)$$

$$\mathrm{SINR} = \frac{\mathrm{RSs}}{\mathrm{N} + 1} \quad \dots \quad (8)$$

$$\mathrm{T} = \mathrm{B}.* \log 2\left(1 + \left(10.^{\frac{SNIR}{10}}\right)\right) \quad \dots \quad (9)$$

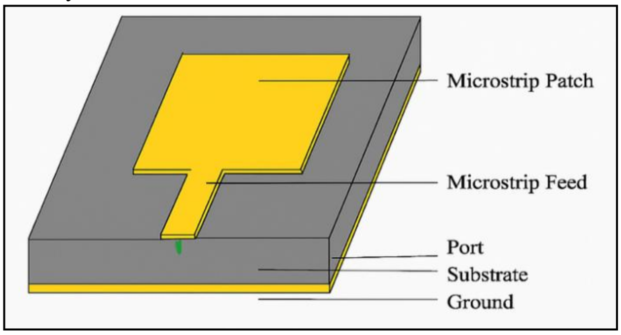
Where PL refers to the path loss of the log-normal shadowing propagation

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

model, $PL(d0)$ refers to path loss in dB at a distance d0; χ is a zero-mean Gaussian-distributed random variable (in dB) with standard deviation (σ). This variable is used only when a shadowing effect is present; otherwise, it is set to 0. n denotes the path-loss exponent for various environments. E_r refers to Earth's radius at 6,378 km, ht refers to the altitude of HAP, and θ refers to the minimum elevation angle from a receiver and/or user's location.

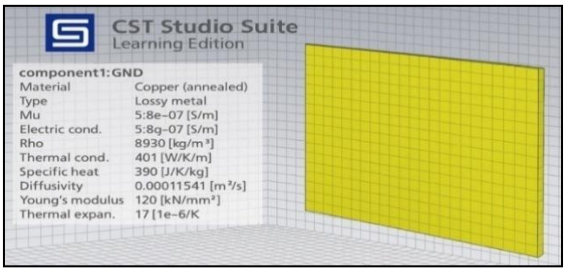
B. The 3D Digital Antenna Design

In this proposed work, a Microstrip Patch intelligent MIMO antenna is designed using Computer Simulation Technology (CST) software to achieve long-range wireless communication across different environments with the highest possible efficiency. Figure 4 shows the Microstrip Patch intelligent MIMO antenna using CST at 28 GHz. Further, the 3D Patch Microstrip intelligent MIMO antenna enables us to analyse electromagnetic components through its three layers.

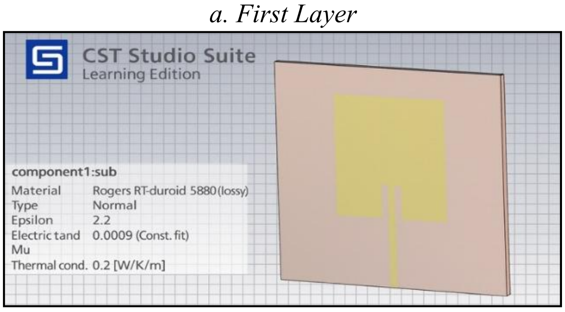


[Fig.4: 3D Design of the Microstrip Patch Intelligent MIMO Antenna Using CST]

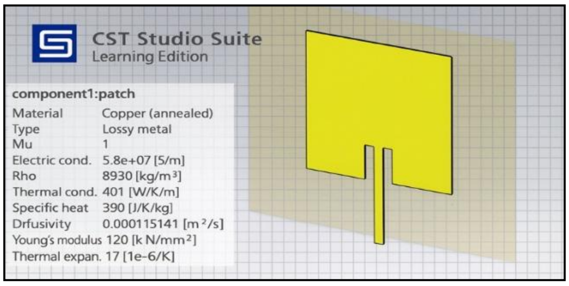
Figure 5 displays. The first layer is the ground layer, made of copper, which improves radiation efficiency and protects it from unwanted signals. The second layer, the Substrate layer made of Rogers RT5880, provides desirable properties that make it well-suited for antenna substrates, such as thermal conductivity and dimensional stability, thereby improving the antenna's performance and reliability. The third layer is the patch layer made of copper. The Inset-fed type was adopted in this design because it provides a strong bandwidth for resistance and is easy to integrate, making it a better option for HAP use.



a. First Layer



b. Second Layer



c. Third Layer

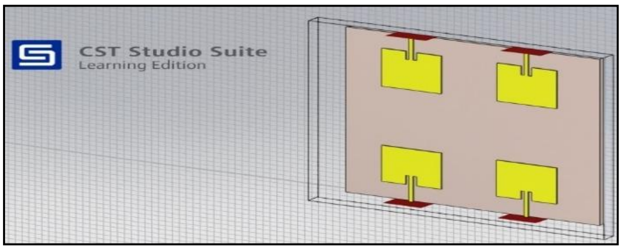
[Fig.5: The three Layers of the 3D Patch Microstrip Smart MIMO Antenna in CST Software]

Table II: Measurements of the Three Layers of the Optimised Antenna

The Ground Layer		
Parameter	**Symbol**	**Value (mm)**
Width	WGr	40
Length	LGr	40.61
Thickness	hG	0.035
The Substrate Layer		
Parameter	Symbol	Value (mm)
Width	W_s	40
Length	L_s	40.61
Thickness	h_s	0.508
The Patch Layer		
Parameter	Symbol	Value (mm)
Width	W_p	9.9
Length	L_p	9.7
Thickness	h_p	0.035
The Gap Dimensions		
Parameter	Symbol	Value (mm)
Width	W_G	0.5
Length	L_G	2.4
The Feed Line Dimensions		
Parameter	Symbol	Value (mm)
Width	W_F	0.7
Length	L_F	4.75

The simulation specifications is considered in this work a 5G MIMO that obtained ITU Radiocommunication Study as follows: frequency [28 GHz], transmitter power [43 dBm], modulation type [256 QAM], bandwidth [20 MHz], noise figure [7 dBm], transmitter altitude [20 km], transmitter antenna gain with diversity [20 dBi], received altitude [1.5 m], receiver antenna gain with diversity gain [5 dBi], receiver power [27 dBm], transmitter sensitivity [-88 dBm], interference margin loss [5 dB], losses [1.2 dB], receiver sensitivity [-87.3 dBm].

Figure 6 shows the optimised antenna shape for a 4x4 microstrip patch MIMO intelligent antenna, while Table 2 presents measurements of the three layers of the optimised antenna.



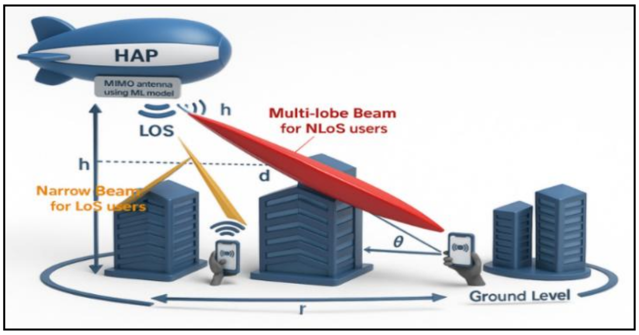
[Fig.6: The Optimized Antenna Shape Using a 4x4 Microstrip Patch MIMO Antenna in CST Software]

Figure 7 displays the beam patterns of the learned codebook using the HFL model of an intelligent MIMO

Retrieval Number: 100.1/ijrte.E832514050126
DOI: 10.35940/ijrte.E8325.14050126
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

antenna. It shows how the ML-driven MIMO antenna adaptively optimises beamforming: focusing energy for LoS users while flexibly shaping beams to overcome blockage for NLoS users. This enables improved connectivity, spectral efficiency, and energy savings, which are essential for HAP-based communication systems in smart, sustainable cities.



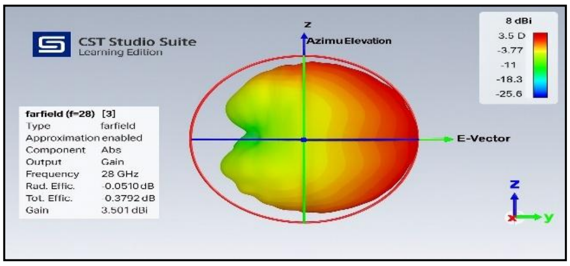
[Fig.7: The Proposed Beam Patterns of the Learned Codebook Using the HFL Model of an Intelligent MIMO Antenna]

IV. RESULTS AND DISCUSSION

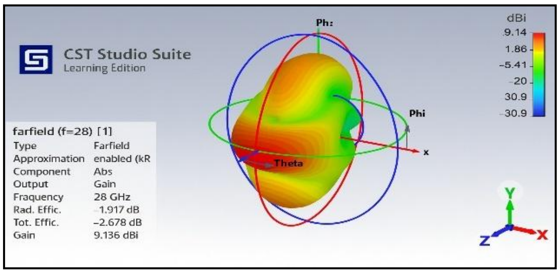
This section presents the predicted results and highlights the main features of the proposed solution, starting with connectivity and link-budget parameters, then progressing to MIMO antenna design, and finally to the optimised results of the intelligent MIMO antenna using the HFL model. The proposed framework was validated using Energy per Bit to Noise Spectrum Density (Eb/No) and Bit Error Rate (BER), two well-known Quality of Service (QoS) parameters, to assess the effectiveness of the wireless system from the perspective of smart IoE devices.

Understanding gain and directivity is crucial for selecting and using MIMO intelligent antennas effectively in various wireless communications, let alone when they are optimised and enhanced. Figures 8 and 9 show the gain and directivity of the proposed Microstrip Patch MIMO intelligent antenna in non-optimized and optimized scenarios using CST toolbox, respectively. Clearly, higher gain and directivity indicate that the antenna is more focused in its radiation, which has an excellent impact on receiving signals in the desired direction over longer distances with greater efficiency, as in the optimised antenna scenario.

From these figures, it can be concluded that, in an optimised antenna scenario, the proposed Microstrip Patch MIMO intelligent antenna improves signal quality, capacity, interference-rejection capabilities, radiation-pattern flexibility, and spectral efficiency. Another notable point is that the coverage footprint and connectivity were better in the optimised antenna scenario, with parallel transmission and reception of independent data streams, supporting IoE applications in smart, sustainable cities.

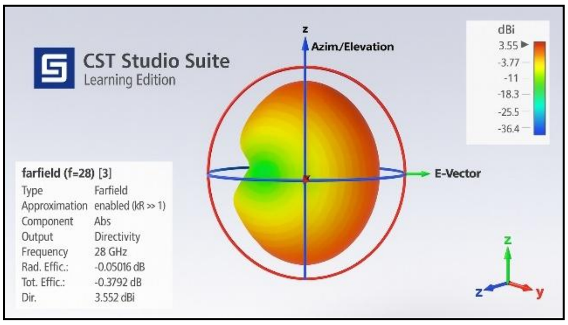


a. Non-optimised Scenario

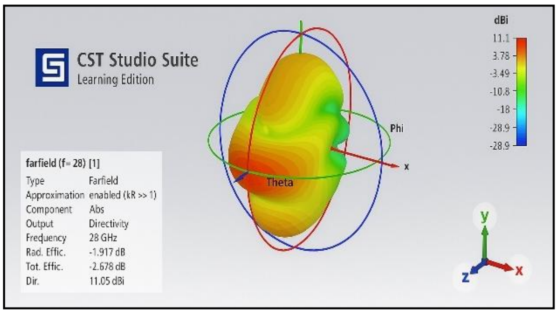


b. Optimised Scenario

[Fig.8: Gain of the Microstrip Patch MIMO Intelligent Antenna Using the CST Toolbox]



a. Non-optimized Scenario



b. Optimized Scenario

[Fig.9: Directivity of the Microstrip Patch MIMO Intelligent Antenna Using CST Toolbox]

In addition to gain and directivity, there are vibrant parameters by which to evaluate the performance of the microstrip patch MIMO intelligent antenna, as demonstrated in Figure 10. The parameters under consideration are as follows: reflection coefficient (S11), bandwidth, voltage standing wave ratio (VSWR), and efficiency. As illustrated in Figure 10, the graphs demonstrate the parameters in both optimised and non-optimised scenarios. The S11 optimized The value indicates good impedance matching and efficient power transfer, which, in turn, improves antenna performance.

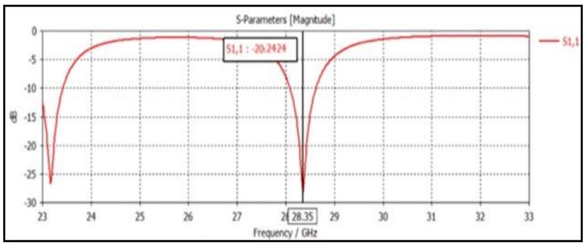
The optimised bandwidth indicates a wider bandwidth that can operate effectively over a broader frequency range, making it versatile for a variety of applications. The optimised VSWR for a microstrip patch MIMO intelligent antenna is less than 2, which is acceptable. The efficiency of a system is measured by the ratio of the radiated power to the total input power. A higher efficiency indicates that the antenna is less lossy and can radiate more of the power that is fed into it. The optimised antenna demonstrated an efficiency of 90.08%, indicating a notable performance enhancement.

Table 3 shows numerical

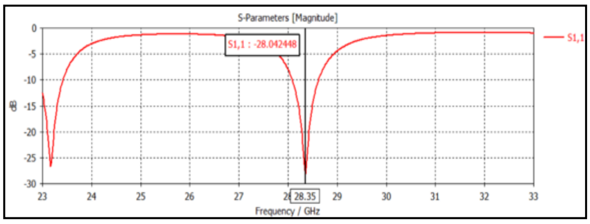
results for the evaluation parameters of the Microstrip Patch MIMO intelligent antenna in non-optimised and optimised scenarios. Overall, it is evident that there is a noticeable improvement of the optimized Microstrip Patch MIMO intelligent antenna in relation to non-optimized version.

Table III: Numerical Results of the Evaluation Parameters of the Microstrip Patch MIMO Intelligent Antenna

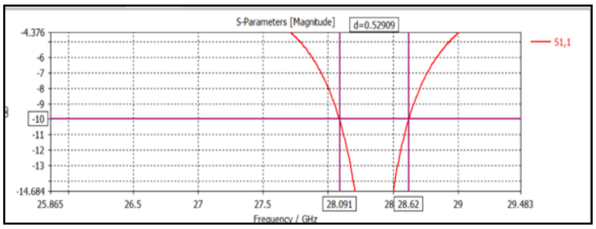
Parameter	Values of a Non-Optimised Antenna	Values of Optimize Antenna
Gain (dB)	3.501	9.136
Directivity(dBi)	3.552	11.05
S11 (dB)	-20.2424	-28.042448
BW (GHz)	3.1459	0.52909
VSWR	1.5375576	1.0825024
Efficiency (%)	83.74%	94.08%



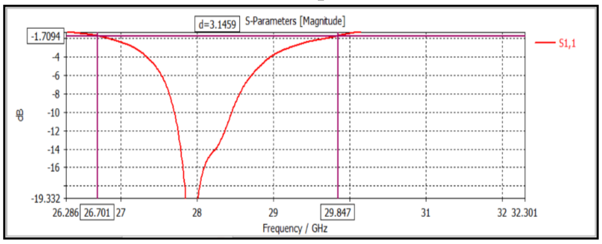
a. Reflection Coefficient (S11) - Non-Optimized Scenario



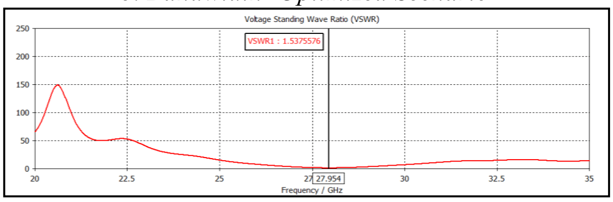
a. Reflection Coefficient (S11) - Optimized Scenario



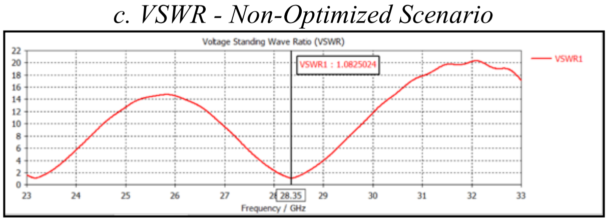
b. Bandwidth- Non-Optimized Scenario



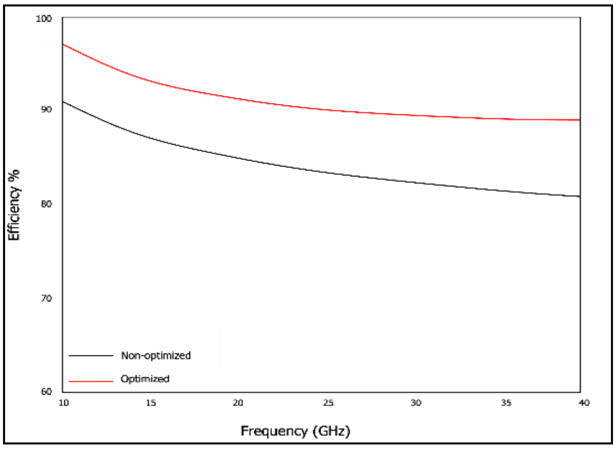
b. Bandwidth- Optimized Scenario



c. VSWR - Non-Optimized Scenario

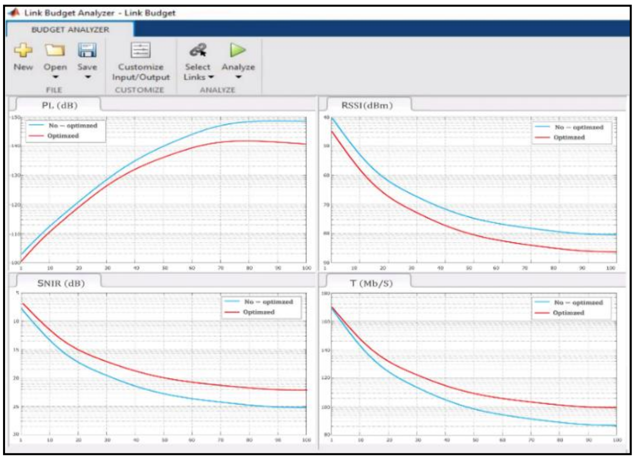


c. VSWR - Optimized Scenario



d. Efficiency

[Fig.10: Evaluating Parameters of the Microstrip Patch MIMO Intelligent Antenna in Optimized Scenario Using CST Toolbox]



[Fig.11: The Predicted Results of the Link Budget Parameters]

Figure 11 shows the predicted link budget parameters for the modified log-normal shadowing propagation model, with θ included in both non-optimised and optimised scenarios, using MATLAB. In the stratosphere, the HAP altitude is set to 20km above ground. PL predicted results of the log-normal shadowing model show values below the maximum allowable path loss (MAPL) value of 150dB. Indeed, the PL increases gradually as the footprint converges. The standard deviation of the log-normal random variable is called the shadowing margin.

The shadowing margin is a measure of RSSI variability. Where the RSSI is aligned with PL predictions, it shows similar characteristics, with a peak value of -88 dBm. SNIR ranges between the upper and lower bounds of 6-25 dB. T falls with distance and with higher PL. Network footprint coverage is affected by transmitter and receiver antenna specifications, geomorphology, and a moderate θ of 15°. Therefore, the HAP convergence reaches 100km at a HAP altitude of 20 km.

After optimisation, the predicted link budget results have shown a noticeable improvement. This suggests that the signal has become stronger, resulting. in better communication quality at all distances. Further, these improvements collectively

Retrieval Number: 100.1/ijrte.E832514050126
DOI: 10.35940/ijrte.E8325.14050126
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

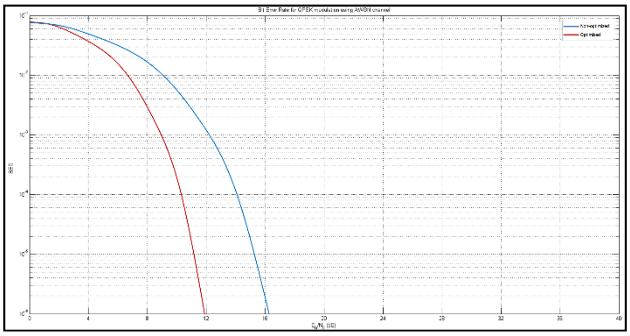
enhance the system's performance. Furthermore, optimized link budget results not only lead to better connectivity, but also strengthen power consumption, which enhance the IoE sensors and devices in sustainable smart city.

To validate the performance of the proposed Microstrip Patch MIMO intelligent antenna from a power consumption perspective, the two QoS parameters (Eb/No and BER) are evaluated. Figure 12 shows a comparison of the predicted Eb/No and BER values of an Additive white Gaussian noise (AWGN) channel of the proposed Microstrip Patch MIMO intelligent antenna in non-optimised and optimised scenarios using the “semilogy” function in MATLAB.

Evidently, the optimized scenario shows better Eb/No performance at the lowest BER achieved of $1x10^{-6}$ with around a 4dB difference. Another observed point is that as the Eb/No and BER values decrease, wireless link performance enhances. This means that a channel with low error rates is used, and minimum transmission power is used. Thanks to the optimized diversity gain and collaborative beamforming of the proposed Microstrip Patch MIMO intelligent antenna. This maximises link budget, capacity, and coverage without consuming more transmission power between the HAP and the ground IoE nodes.

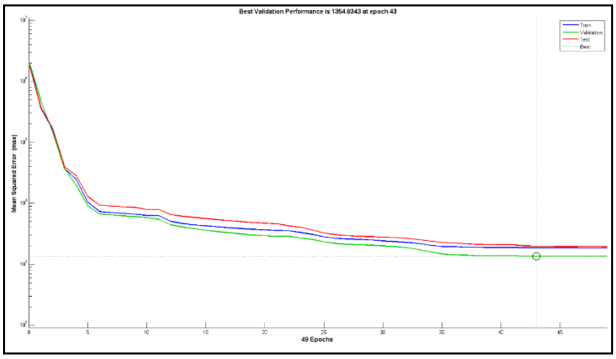
Bearing in mind that enhancing the power consumption of IoE nodes is an essential matter in the context of smart, sustainable cities. Optimizing how these devices sip, rather than guzzle, electricity is crucial for both sustainability and cost efficiency. The benefits of optimizing energy use in these complex ecosystems are manifold:

- Less energy use equals a lower carbon footprint, aligning with global sustainability goals.
- Extended IoE devices' lifetime, where batteries in remote sensors last longer, minimising maintenance and device replacements.
- Cost savings via reducing energy bills for individuals and businesses, making IoE more accessible and attractive.
- Economic optimization, where Smart energy grids and optimized resource allocation save city budgets and enable investments in other crucial areas like education and healthcare.



[Fig.12: Qos Parameters of Eb/No and BER to Validate the Proposed Work]

Figure 13 shows the Mean Squared Error (MSE) performance of the HFL model. The graph shows the training, testing, and validation process, with error rates gradually decreasing up to 43 iterations. Then, the training stops as the error rate increases. The achieved result seems rational, as no significant overfitting has occurred. Also, the ultimate MSE is low, and the test-set and validation-set errors are similar.



[Fig.13: The MSE Performance of the HFL Model]

V. CONCLUSION AND FUTURE WORK

The future of smart, sustainable cities depends on leveraging 4IR technologies to build interconnected, data-driven, and eco-efficient urban systems. Integrating IoE with intelligent MIMO antennas offers significant potential to enhance these cities. This study focuses on optimising energy efficiency in IoE devices by developing an intelligent microstrip patch MIMO antenna to improve HAPs’ wireless connectivity and power consumption using the HFL model. Simulations were performed in CST at 28 GHz, and MATLAB was used for HFL and validation through Eb/No and BER parameters. Results showed a 31% reduction in power use and improved last-mile connectivity. Future work will include real-world testing to compare simulated and experimental outcomes.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

- **Conflicts of Interest/ Competing Interests:** Based on my understanding, this article has no conflicts of interest.
- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted with objectivity and without any external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author’s Contributions:** The authorship of this article is contributed equally to all participating individuals.

REFERENCES

1. J. Shao and B. Min, “Sustainable development strategies for Smart Cities: Review and development framework,” Cities, vol. 158, p. 105663, Dec. 2024, DOI: https://doi.org/10.1016/j.cities.2024.105663
2. S. H. Alsamhi et al., “Machine Learning for Smart Environments in B5G Networks: Connectivity and QoS,” Computational Intelligence and Neuroscience, vol. 2021, pp. 1–23, Sep. 2021,

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

DOI: https://doi.org/10.1155/2021/6805151.
3. H. Gaber, A.M. Othman, A.H. Fahad, Future of connected autonomous vehicles in smart cities. Solving Urban Infrastructure Problems Using Smart City Technologies, Elsevier, 2021, pp. 599–611, DOI: https://doi.org/10.1016/B978-0-12-816816-5.00027-9
4. F. A. Almalki and M. C. Angelides, "Integrating machine learning with a positioning mechanism for managing interference and power consumption in a multilayer fleet of unmanned aerial platforms," Cluster Computing, vol. 28, no. 6, Jun. 2025, DOI: https://doi.org/10.1007/s10586-024-05044-8
5. M. Agrawal, K. Eloot, M. Mancini, and A. Patel, "Industry 4.0: Reimagining manufacturing operations after COVID-19 | McKinsey," www.mckinsey.com, Jul. 29, 2020. https://www.mckinsey.com/capabilities/operations/our-insights/industry-40-reimagining-manufacturing-operations-after-covid-19, Accessed Dec. 21, 2023)
6. S. Tanwar, A. Popat, P. Bhattacharya, R. Gupta, and N. Kumar, "A taxonomy of energy optimization techniques for smart cities: Architecture and future directions," Expert Systems, Apr. 2021, DOI: https://doi.org/10.1111/exsy.12703
7. F.A. Almalki, S.H. Alsamhi, M.C. Angelides, Internet of X-Enabled Intelligent Unmanned Aerial Vehicles Security for Hyper-connected Societies, Springer Nature Singapore, Singapore: 75–100, 2022, DOI: http://10.1007/978-981-19-1960-2_5
8. S. H. Alsamhi et al., Survey on Collaborative Smart Drones and Internet of Things for Improving Smartness of Smart Cities. IEEE Access 2019, 7, 128125–128152, DOI: http://10.1109/access.2019.2934998
9. Alhusayni S.A. et al., "Experimental Study of a Tethered Balloon Using 5G Antenna to Enhance Internet Connectivity". In: Arai K. (eds) Intelligent Computing. Lecture Notes in Networks and Systems, vol 285. Springer, Cham. DOI: https://doi.org/10.1007/978-3-030-80129-8_46
10. Z. Qadir, K. N. Le, N. Saeed, and H. S. Munawar, "Towards 6G internet of things: Recent advances, use cases, and open challenges," ICT Express, vol. 9, no. 3, Jun. 2022, DOI: https://doi.org/10.1016/j.icte.2022.06.006
11. S. H. Alsamhi et al., "Predictive Estimation of Optimal Signal Strength from Drones over IoT Frameworks in Smart Cities," IEEE Transactions on Mobile Computing, DOI: http://10.1109/TMC.2021.3074442
12. Almalki, F.A.; Angelides, M.C. A machine learning approach to evolving an optimal propagation model for last mile connectivity using low altitude platforms. Comput. Commun. 2019, 142–143, 9–33, DOI: http://doi:10.1016/j.comcom.2019.04.001
13. E. S. Alkhalifah and F. A. Almalki, "Developing an Intelligent Cellular Structure Design for a UAV Wireless Communication Topology," Axioms, vol. 12, no. 2, p. 129, Jan. 2023, DOI: https://doi.org/10.3390/axioms12020129
14. F. A. Almalki and M. C. Angelides, "Deployment of an aerial platform system for rapid restoration of communications links after a disaster: a machine learning approach," Computing, vol. 102, no. 4, pp. 829–864, Nov. 2019, DOI: https://doi.org/10.1007/s00607-019-00764-x
15. B. Li, "Effective energy utilization through economic development for sustainable management in smart cities," Energy Reports, vol. 8, pp. 4975–4987, Nov. 2022, DOI: https://doi.org/10.1016/j.egyr.2022.02.303
16. G. K. Ijemaru, K. L.-M. Ang, and J. K. P. Seng, "Transformation from IoT to IoV for waste management in smart cities," Journal of Network and Computer Applications, p. 103393, Apr. 2022, DOI: https://doi.org/10.1016/j.jnca.2022.103393
17. C. Ding and Ivan Wang-Hei Ho, "Digital-Twin-Enabled City-Model-Aware Deep Learning for Dynamic Channel Estimation in Urban Vehicular Environments," IEEE Transactions on Green Communications and Networking, vol. 6, no. 3, pp. 1604–1612, Sep. 2022, DOI: https://doi.org/10.1109/tgcn.2022.3173414
18. P. Mishra and G. Singh, "Energy Management Systems in Sustainable Smart Cities Based on the Internet of Energy: A Technical Review," Energies, vol. 16, no. 19, p. 6903, Jan. 2023, DOI: https://doi.org/10.3390/en16196903
19. M. Humayun, M. S. Alsaqer, and N. Jhanjhi, "Energy Optimisation for Smart Cities Using IoT," Applied Artificial Intelligence, pp. 1–17, Feb. 2022, DOI: https://doi.org/10.1080/08839514.2022.2037255
20. D. K. Singh, R. Sobti, A. Jain, P. K. Malik, and D. Le, "LoRa-based intelligent soil and weather condition monitoring with Internet of Things for precision agriculture in smart cities," IET Communications, vol. 16, no. 5, pp. 604–618, Feb. 2022, DOI: https://doi.org/10.1049/cmu2.12352
21. Lamya Albraheem et al., "Towards smart sustainable cities using Li-Fi technology: geo-location infrastructure utilising LED street lights," Peerj Computer Science, vol. 8, Jul. 2022, DOI: https://doi.org/10.7717/peerj-cs.1009
22. M. Farooq et al., "Nested Bee Hive: A Conceptual Multilayer Architecture for 6G in Futuristic Sustainable Smart Cities," Sensors, vol. 22, no. 16, pp. 5950–5950, Aug. 2022, DOI: https://doi.org/10.3390/s22165950
23. H. A. H. Alobaidy, M. Jit Singh, M. Behjati, R. Nordin, and N. F. Abdullah, "Wireless Transmissions, Propagation and Channel Modelling for IoT Technologies: Applications and Challenges," IEEE Access, vol. 10, pp. 24095–24131, 2022, DOI: https://doi.org/10.1109/access.2022.3151967
24. C. Qin and E. Pournaras, "Coordination of drones at scale: Decentralised energy-aware swarm intelligence for spatio-temporal sensing," Transportation Research Part C: Emerging Technologies, vol. 157, pp. 104387–104387, Dec. 2023, DOI: https://doi.org/10.1016/j.trc.2023.104387
25. X. Tang, W. Wang, H. He, and R. Zhang, "Energy-efficient data collection for UAV-assisted IoT: Joint trajectory and resource optimization," Chinese Journal of Aeronautics, vol. 35, no. 9, pp. 95–105, Sep. 2022, DOI: https://doi.org/10.1016/j.cja.2021.09.017
26. Y. Yao, Ke Lv, S. Huang, X. Li, and X. Wang, "UAV Trajectory and Energy Efficiency Optimization in RIS-Assisted Multi-User Air-to-Ground Communications Networks," Drones, vol. 7, no. 4, pp. 272–272, Apr. 2023, DOI: https://doi.org/10.3390/drones7040272
27. M. Ahmed et al., "Joint optimization of UAV-IRS placement and resource allocation for wireless powered mobile edge computing networks," Journal of King Saud University - Computer and Information Sciences, vol. 35, no. 8, pp. 101646–101646, Sep. 2023, DOI: https://doi.org/10.1016/j.jksuci.2023.101646
28. C. Qin, Fethi Candan, Lyudmila Mihaylova, and E. Pournaras, "3, 2, 1, Drones Go! A Testbed to Take off UAV Swarm Intelligence for Distributed Sensing," arXiv (Cornell University), Aug. 2022, DOI: https://doi.org/10.48550/arxiv.2208.05914
29. Kadhim Hayawi et al., "Airborne Computing: A Toolkit for UAV-Assisted Federated Computing for Sustainable Smart Cities," IEEE Internet of Things Journal, vol. 10, no. 21, pp. 18941–18950, Nov. 2023, DOI: https://doi.org/10.1109/jiot.2023.3292308
30. A. Saif et al., "Flexible Beamforming in B5G for Improving Tethered UAV Coverage over Smart Environments," arXiv (Cornell University), Jul. 2023, DOI: https://doi.org/10.48550/arxiv.2307.07395
31. S. Alhelaly, A. Muthanna, and I. A. Elgendy, "Optimizing Task Offloading Energy in Multi-User Multi-UAV-Enabled Mobile Edge-Cloud Computing Systems," Applied Sciences, vol. 12, no. 13, p. 6566, Jun. 2022, DOI: https://doi.org/10.3390/app12136566
32. C. Chen et al., "Deep Learning-Based Energy Optimization for Edge Device in UAV-Aided Communications," Drones, vol. 6, no. 6, p. 139, Jun. 2022, doi: https://doi.org/10.3390/drones6060139
33. W. Alawad, N. B. Halima, and L. Aziz, "An Unmanned Aerial Vehicle (UAV) System for Disaster and Crisis Management in Smart Cities," Electronics, vol. 12, no. 4, p. 1051, Feb. 2023, DOI: https://doi.org/10.3390/electronics12041051
34. M. H. Mousa and M. K. Hussein, "Efficient UAV-based mobile edge computing using differential evolution and ant colony optimization," PeerJ Computer Science, vol. 8, p. e870, Feb. 2022, DOI: https://doi.org/10.7717/peerj-cs.870
35. Young-Jong Na et al., "Optimal Energy Consumption Path Planning for Unmanned Aerial Vehicles Based on Improved Particle Swarm Optimization," Sustainability, vol. 15, no. 16, pp. 12101–12101, Aug. 2023, DOI: https://doi.org/10.3390/su151612101.
36. Y. Miao, K. Hwang, D. Wu, Y. Hao, and M. Chen, "Drone Swarm Path Planning for Mobile Edge Computing in Industrial Internet of Things," IEEE Transactions on Industrial Informatics, vol. 19, no. 5, pp. 6836–6848, May 2023, DOI: https://doi.org/10.1109/TII.2022.3196392
37. A. Banerjee, A. Sufian, K. K. Paul, and S. K. Gupta, "EDTP: Energy and Delay Optimized Trajectory Planning for UAV-IoT Environment," Computer Networks, vol. 202, p. 108623, Jan. 2022, DOI: https://doi.org/10.1016/j.comnet.2021.108623
38. H. A. Alharbi, B. A. Yosuf, M. Aldossary, Jaber Almutairi, and Jaafar, "Energy Efficient UAV-Based Service Offloading Over Cloud-Fog Architectures," IEEE Access, vol. 10, pp. 89598–89613, Jan. 2022, DOI: https://doi.org/10.1109/access.2022.3201112
39. Z. Su et al., "Energy Efficiency Optimization for D2D Communications Underlaying UAV-assisted Industrial IoT Networks with SWIPT," IEEE Internet of Things Journal, pp. 1–1, 2022, DOI: https://doi.org/10.1109/jiot.2022.3142026
40. N. Parvaresh and B. Kantarci, "A Continuous Actor–Critic Deep Q-Learning-Enabled Deployment of UAV Base Stations: Toward 6G Small Cells in the Skies of Smart Cities," IEEE Open Journal of the Communications Society, vol. 4, pp.

700–712, 2023, DOI: https://doi.org/10.1109/ojcoms.2023.3251297
41. R. Ahmed, Y. Chen, and B. Hassan, "Deep residual learning-based cognitive model for detection and classification of transmitted signal patterns in 5G smart city networks," Digital Signal Processing, vol. 120, p. 103290, Jan. 2022, DOI: https://doi.org/10.1016/j.dsp.2021.103290
42. X. Dai, Bin Duo, X. Yuan, and W. Tang, "Energy-Efficient UAV Communications: A Generalized Propulsion Energy Consumption Model," IEEE Wireless Communications Letters, vol. 11, no. 10, pp. 2150–2154, Oct. 2022, DOI: https://doi.org/10.1109/lwc.2022.3195787
43. X. Liu, Z. Liu, B. Lai, B. Peng, and T. S. Durrani, "Fair Energy-Efficient Resource Optimization for Multi-UAV Enabled Internet of Things," IEEE Transactions on Vehicular Technology, pp. 1–11, 2022. DOI: https://doi.org/10.1109/tvt.2022.3219613
44. N. Lin et al., "GREEN: A Global Energy Efficiency Maximization Strategy for Multi-UAV Enabled Communication Systems," IEEE TRANSACTIONS ON MOBILE COMPUTING, vol. 22, no. 10, pp. 1–18, Jan. 2022, DOI: https://doi.org/10.1109/tmc.2022.3207791
45. L. Liu, A. Wang, G. Sun, and J. Li, "Multiobjective Optimization for Improving Throughput and Energy Efficiency in UAV-Enabled IoT," IEEE Internet of Things Journal, vol. 9, no. 20, pp. 20763–20777, Oct. 2022, DOI: https://doi.org/10.1109/jiot.2022.3175712
46. S. Mokhtari, N. Nouri, J. Abouei, A. Avokh, and K. N. Plataniotis, "Relaying Data with Joint Optimization of Energy and Delay in Cluster-based UAV-assisted VANETs," IEEE Internet of Things Journal, vol. 9, no. 23, pp. 1–1, 2022, DOI: https://doi.org/10.1109/jiot.2022.3188563
47. F. A. Almalki and M. C. Angelides, "A serious gaming approach for optimization of energy allocation in CubeSats," Multimedia Tools and Applications, Jun. 2023, DOI: https://doi.org/10.1007/s11042-023-15795-y
48. R. Mandal, S. Sharma, M. I. Hasan, A. Chauhan and S. Singh, "Spectral Efficiency of Different Diversity Combiners Under Log-Normal Shadowing Channels- A Review," International Conference on Computer, Electronics & Electrical Engineering & their Applications (IC2E3), Srinagar Garhwal, India, 2023, pp. 1-5, DOI: https://doi.org/10.1109/ic2e357697.2023.10262509
49. F. A. Almalki and M. C. Angelides, "An enhanced design of a 5G MIMO antenna for fixed wireless aerial access," Cluster Computing, Jul. 2021, DOI: https://doi.org/10.1007/s10586-021-03318-z
50. F. A. Almalki and M. C. Angelides, "Empirical evolution of a propagation model for low altitude platforms," IEEE Computing Conference, London, UK, 2017, pp. 1297-1304, DOI: https://10.1109/SAI.2017.8252258
51. Faris. A. Almalki, "Developing an Adaptive Channel Modelling using a Genetic Algorithm Technique to Enhance Aerial Vehicle-to-Everything Wireless Communications," International Journal of Computer Networks & Communications, vol. 13, no. 2, pp. 37–56, Mar. 2021, DOI: https://doi.org/10.5121/ijcnc.2021.13203
52. Y. Zhang, M. Alrabeiah and A. Alkhateeb, "Learning Beam Codebooks with Neural Networks: Towards Environment-Aware mmWave MIMO," IEEE 21st International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), Atlanta, GA, USA, 2020, pp. 1-5, DOI: https://doi.org/10.1109/spawc48557.2020.9154320
53. S. Wang, M. Lee, S. Hosseinalipour, R. Morabito, M. Chiang and C. G. Brinton, "Device Sampling for Heterogeneous Federated Learning: Theory, Algorithms, and Implementation," IEEE INFOCOM 2021 - IEEE Conference on Computer Communications, Vancouver, BC, Canada, 2021, pp. 1-10, DOI: https://10.1109/INFOCOM42981.2021.9488906
54. Adeb Salh et al., "Deep Reinforcement Learning-Driven Hybrid Precoding for Efficient Mm-Wave Multi-User MIMO Systems," Journal of Sensor and Actuator Networks, vol. 14, no. 1, pp. 20–20, Feb. 2025, DOI: https://doi.org/10.3390/jsan14010020
55. S. Kavaiya, H. Mewada, S. Patel, D. Chauhan, F. A. Almalki, and H. M. Mujlid, "Physical Layer Security of 6G Vehicular Networks with UAV Systems: First Order Secrecy Metrics, Optimization, and Bounds," Computers, Materials & Continua, vol. 80, no. 3, pp. 3685–3711, 2024, DOI: https://doi.org/10.32604/cmc.2024.053587

AUTHOR'S PROFILE

Kholod Alsufiani holds a BSc degree with honours in Computer Science from Taif University, followed by an MSc in Computer Science from Middlesex University in London, which she obtained in 2013. In 2020, she completed her PhD in Computer Science from Middlesex University. Currently serving as an Assistant Professor at Turaba University College, Taif University. Kholod's research interests are centred on information visualisation, human-centred artificial intelligence, and human-centred design.

Eman S. Alkhalifah holds a PhD in Marketing from Alliance Manchester Business School, University of Manchester, UK, and a PhD in Art and Design from Princess Nourah bint Abdulrahman University, Saudi Arabia. With over 20 years of academic and leadership experience, she has combined creative design and strategic business thinking across teaching, research, and institutional initiatives. Her expertise spans multiple disciplines, including design, marketing, entrepreneurship, sustainability, and artificial intelligence, enabling her to offer integrated perspectives that unite creativity, impact, and technology. Dr Alkhalifah has contributed to national initiatives that support educational quality, innovation, and the development of creative industries. She has also played a leading role in organising conferences and exhibitions that highlight Saudi talent and promote women's leadership in design and entrepreneurship. Her work reflects a strong commitment to fusing cultural identity with innovation in both design and business, aiming to build sustainable ecosystems that nurture local creatives and contribute to the growth of the creative economy in Saudi Arabia.