Patient Localization using RFID in Wireless Insite Propagation & Neural Network

Prince Okoto Siaw[1], Ebenezer Adjei[1], Ahmad Aldelemy[1,2] and Claudia Barbosa[1,3]
{p.o.siaw@bradford.ac.uk, e.adjei@bradford.ac.uk, a.aldelemy@bradford.ac.uk, cbarbosa@av.it.pt}

[1]Department of Engineering & Digital Technologies, University of Bradford, UK.
[2]Basrah University College of Science and Technology, Basrah 61004, Iraq
[3] The Instituto de Telecomunicações, Campus Universitário de Santiago, Aveiro 3810-193, Portugal

Abstract. Due to strains on healthcare and staff shortages, longer lifespans and improved quality of life have led to inadequate healthcare, especially for individuals with epileptic seizures, particularly those living alone. To address this, engineers are focusing on wireless communication and technology to develop tools that alleviate pressure on healthcare. This study concentrates on monitoring patients during and after certain major or minor surgeries using wireless sensors (RFID) and an application in a smart room setup. The system relies on two sophisticated power measurement models for location detection, including lying down and falling. A neural network in MATLAB learns power transmission variations for accurate prediction. Simulations replicate empty room scenarios for lying down and falling positions. Data is stored in cloud databases and accessible through a real-time app using APIs and IoT technology. This research aims to enhance patient monitoring and response during incidents while lessening strain on healthcare systems.

Keywords: remote access, epilepsy, seizure, wireless, sensors, neural network.

1. Introduction

The global population of older individuals is increasing significantly, with projections indicating a rise from 1 billion to 1.4 billion people over 60 years between 2020 and 2030. In England alone, it is expected to reach nearly 2.1 billion by 2050, representing more than 1 in 5 of the population [1]. In the UK, the number of people over 60 is estimated to grow from 14.9 million in 2014 to 18.5 million in 2025 [2],[3]. This demographic shift is leading to a growing demand for social and healthcare services, particularly for patients with various health conditions, including mobility issues, chronic illnesses, post-surgery recovery, and disabilities [4]. Providing support for older individuals to enhance their quality of life is a fundamental aspect of healthcare [5]. In advanced countries like the UK, a significant portion of government healthcare spending, over 40%, is directed towards the elderly, especially those above 65 years [6]. Healthcare costs are projected to increase annually, and expenditures on adult social care have already risen, reflecting a 4.8% increase in real terms and an 11.8% increase in cash terms between 2019 and 2021 [8]. The healthcare sector in advanced countries is grappling with financial challenges and labour shortages in meeting the rising demand for at-home care for the elderly, who often face common health issues such as falls, reduced mobility, incontinence, and cognitive decline [9]. Additionally, psychological, and social factors complicate care for older

IMDC-IST 2023, October 25-27, Yola, Nigeria

DOI 10.4108/eai.25-10-2023.2348738

individuals [10]. Various medical conditions affect both older and younger generations, impacting cognitive skills [11].

Traditional assessment methods like the Bethel Index, I-ADL scales, and functional independence measure (FIM) scales rely on questionnaires, self-reports, or subjective judgments, leading to accuracy and consistency challenges, as well as patient reluctance to provide accurate information. These issues can result in delayed diagnosis and treatment [12].

2 Methodology

This research finding is based on a simulated environment created to experiment and obtain sufficient data from proposed six transmitters (Tx) and six receivers (Rx) within Wireless Insite propagation software to determine the possible position of a model human with mobility issues with the risk of falling. It does not include a real person but instead a model of a human which makes it easier to facilitate this research since questionnaires and possible forms would be challenging to obtain physically from individuals. It involves different type of materials and programmes used to obtain and analyse results with the aid of a machine learning algorithm for qualitative results.

2.1. System Design Brief

A receiver, antenna, smart home, location Windows server, and a mobile application are among the parts of the system architecture. Each room has reader devices attached at specified locations to generate electromagnetic radiations that the antenna picks up. Then, using the amount of power received and the time it took for it to arrive (time delays and arrival), these radiations are broadcast back to the reader and evaluated to pinpoint the location of the person.
Each receiver in the smart home receives radio waves, which are then transformed into digital data and sent to the local Windows server for quick processing. These location data are converted into useful digital information by the location windows server and stored in the Responder database for evaluation and further analysis.

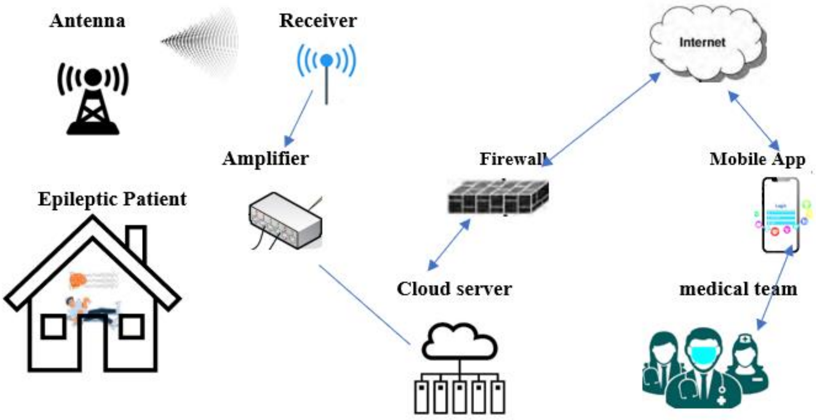


Figure 1. Architecture of a typical RFID sensor module

2.2. Data Collection Model

Data was gathered for this investigation from a simulated smart home. At first, measurements were taken in a simulated empty room and expressed as decibels (dB). After that, an Excel file containing these measurements was exported for analysis. Then, simulations were performed while a human model was introduced into various rooms of the smart home while standing and lying down. The standing and lying down postures were replicated in each area of the house, including the living room, kitchen, bathroom, and bedroom. For additional research, the gathered data was finally divided into categories depending on several conditions (empty room, sitting, and standing).

This model used in collecting the data to be used as deduced from the popular equation by Herald T. Friis equation based on Figure 2 and seen in the equations below,

$$P_{rx} = P_{tx} G_{tx} G_{rx} \left(\frac{c}{4\pi D_r f_0}\right)^2. \qquad (1)$$

Where,
P_{rx} is the receiving antenna power
P_{tx} is the transmitting antenna power
G_{rx} is the receiving power gain
G_{tx} is the transmitting power gain
4π spherical area coverage of signal
c is the velocity of light
f_0, the frequency of both signals
(Transmitter & Receivcer)

The Above equation can also be written as

$$P_r = \frac{P_t G_t G_r \lambda^2}{(4\pi R)^2}. \qquad (2)$$

λ = Wavelength
R= Distance between the two antennas

$$\text{RSSI} = N_{total} + P_r + I_{total}. \qquad (3)$$

Where Noise =N, Interference =I, Cell power received Pr

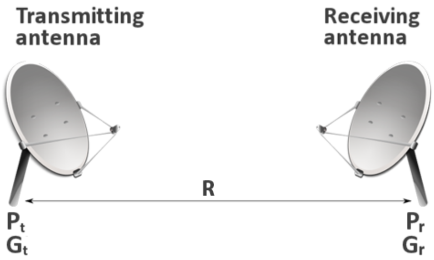


Figure 2. Herald T. Friis equation module

2.3. Transmitter and Receiver Properties

The simulation procedure used a single transmitter set with cartesian coordinates and a linear dipole antenna as shown in Figure 3 and Table 1. The propagation employed six receiver and transmitter units. Each receiver and transmitter set are spaced apart from each room. The transmitter and receiver sets' antenna characteristics for an RFID application are shown in the table below.

Table 1. A table showing the antenna properties of the Wireless Insite simulation.

Antenna	Linear dipole
Transmitter Set (Tx)	6 points
Receiver Set (Rx)	6 points
Waveform	Sinusoid
Maximum gain (dBi)	0.0000
Polarization	Vertical
Length(m)	1.0000
Receiver Threshold (dBm)	-250.0000
Transmission line loss (dB)	0.0000
VSWR	1.00

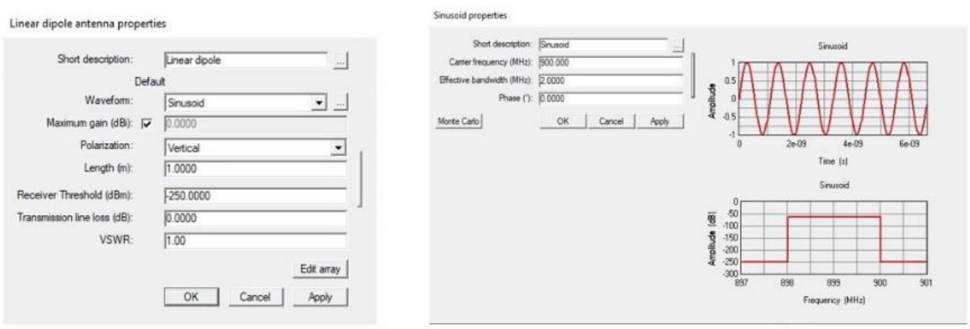


Figure 3. Linear dipole & Sinusoid properties

2.4. Material Selection and Properties Used

Wireless Insite provides varying materials and their respective properties that satisfy the recommendations of the International Telecommunication Union for 900MHz. The table below illustrates the values for the thickness, connectivity, and permittivity of the selected materials used in the simulation process and the simulated model illustrated in Figure 4.

Table 2. A table showing materials used and their corresponding properties.

Materials	Type	Thickness(m)	Conductivity(S/m)	Permittivity
Floor Concrete	One-layer dielectric	3.0e-01	1.5e-02	15
Wall Brick	3-layer dielectric	1.25e-01	1.0e-03	4.4
Plaster Board	One-layer dielectric	3.0e01	1.201e-02	1.99
Ceramics	Dielectric half-space	5.0e-01	1.5e-02	15
Glass	One-layer Dielectric	3.0e-03	0.0	2.4
Fresh Water (Model Human)	Dielectric half-space	1.10e-04	2.2e-01	81

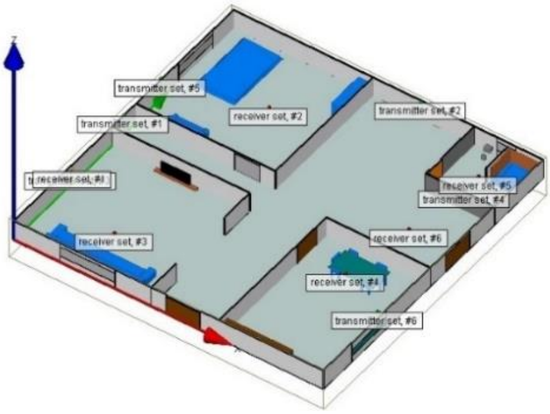


Figure 4. Simulated Environment

3. Results

3.1. Results Analysis from Data

After the experiment's results have successfully undergone all simulations and data computations. These data are acquired and examined from several propagation channels with various power values expressed in decibels (dBm). These colour differences depict the power variances with increasing and decreasing values as propagation patterns.

3.2. Standing & laid down positions

Data sets from a smart home with the model human in various places of the show propagation pathways. These channels change when people are present, showing energy absorption. This affects transmission compared to an empty room. Figures 5 and 6 depict human poses. This impacts the clarity of received and conveyed data and how long it takes transmitted power to reach each receiver. This information and understanding make it easy to discover loss paths, time delays, and power losses used to evaluate the findings.

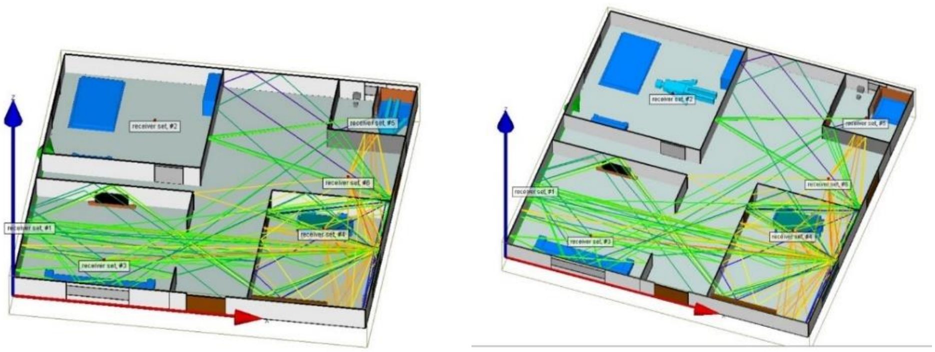


Figure 5. Patient lying down positions in different locations.

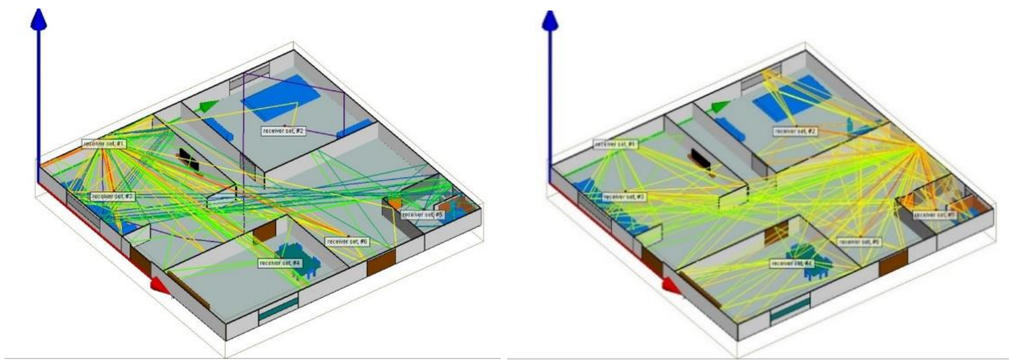


Figure 6. Patient standing in different locations.

3.3. Graphical Representation of Data

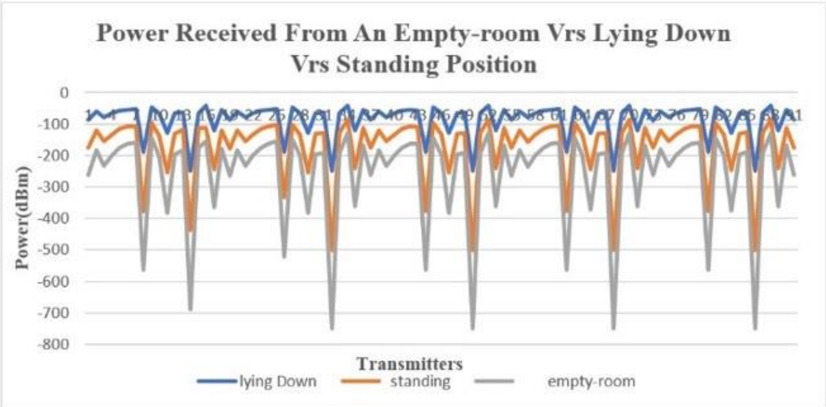


Figure 7. A graphical representation of the scenarios of power transmission

The diagram depicted in Figure 7 illustrates the variations in power reception across three distinct scenarios: an unoccupied room, standing, and lying down. The vacant room demonstrates the potential maximum power reception, as the simulated receivers in the room were not subject to significant interference. The remaining scenarios demonstrate diminished capabilities in relation to the orientation of the human model and external disturbance.

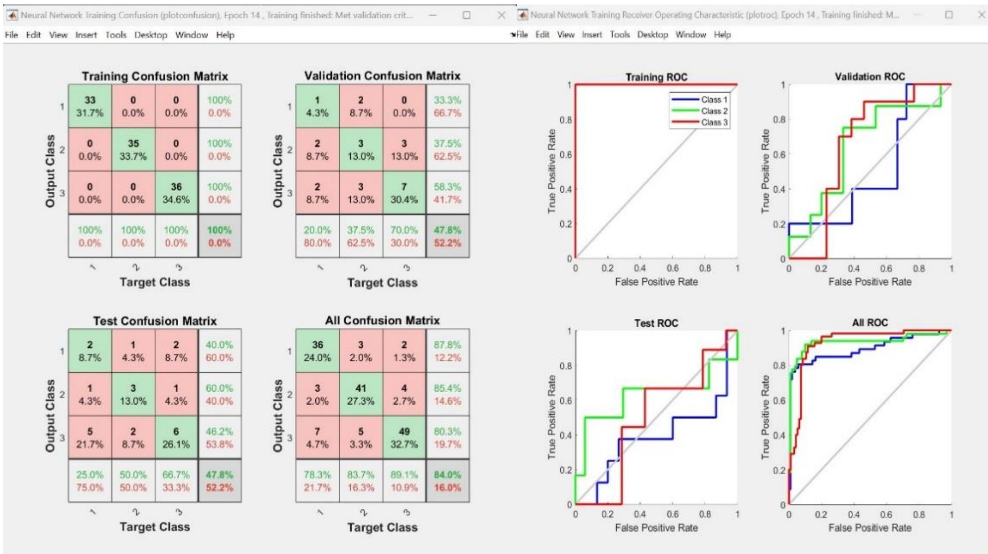


Figure 8 (left) Confusion Matrix of a simulated Object Standing and 9 (right). Receiver Operating Characteristics (ROC).

4. Results Of Neural Network

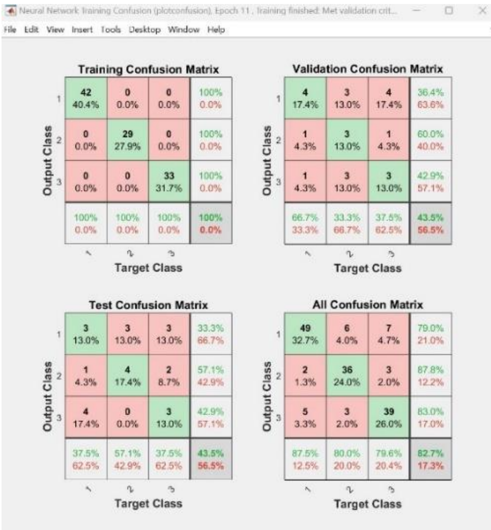
The sensitivity, also known as the true positive rate, for Class 1, which denotes an unoccupied room, is 88%, while the specificity, sometimes referred to as the false positive rate, is 78%.

Class 2 denotes a vacant chamber, exhibiting a sensitivity of 85% and specificity of 84% with genuine positive occurrences.

Class 3 is indicative of vacant space, with a sensitivity of 80% and a specificity of 89% in accurately identifying true positive instances.

The input data was properly entered with a total error of 25 out of 150 predicted results, as shown in Figs 8 and 9. The Neural Network quickly interprets input data. The Neural Network detected the model human's standing posture 84% accurately and 16% perplexity.
36 of 36 results reveal that the room is acknowledged as empty with 10 faults predicted to show 3 errors of the likelihood of an item standing, which is the model person standing, and 7 errors showing the model human lying down. 41 out of 41 shows that the room is acknowledged as displaying the model human standing, with 8 expected wrong values, 3 of which show an empty room and 5 showing the model human lying down. 49 of 49 values show the model human lying down, with 6 errors of 2 for an empty room and 4 for standing. Figure 9. shows that the Receiver

Operating Characteristics (ROC) have a high true positive rate (sensitivity) for the three classes. Training predictions also have few false positives. A true positive rate (TPR) of 1 and a false positive rate (FPR) of 0 show that the classifier identifies cases by passing through the top left corner.



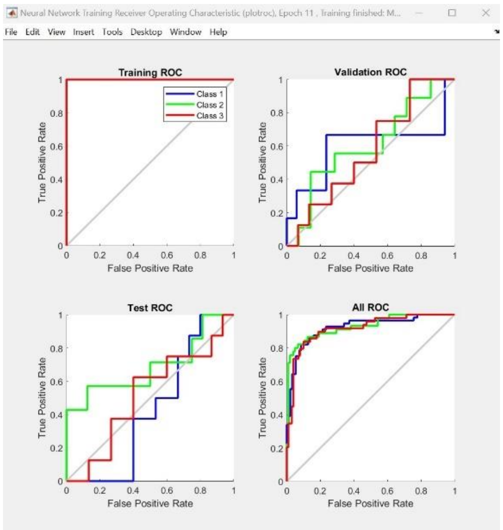


Figure 10 (left) Confusion Matrix of a simulated Object Lying down and 12 (right). Receiver Operating Characteristics (ROC).

In Figs 10 and 11, a perfect classifier can be shown in the Receiver Operating Characteristics (ROC) graph, which shows great sensitivity and perfect prediction for three recorded classes. A neural network's confusion matrix displays only 25 errors out of 150 expected results, with an accuracy rate of 84% and 16% bewilderment. The model recognises a standing stance with accuracy. While 41 out of 41 correctly identify a standing model person with 8 errors, 36 out of 36 results for an empty room display 10 errors. Finally, 49 out of 49 results identify a model human who is lying and makes 6 mistakes.

Also, in Figure 11 the Receiver Operating Characteristics (ROC) for three recorded classes have excellent sensitivity and a low false positive rate, which points to a robust classifier, as seen in the figure. With 82.7% accuracy and 17.3% confusion, the neural network correctly identified human direction. Additionally, it consistently recognised an empty room. It detected 3 errors in persons lying down and 7 errors in standing humans, 6 of which indicated an empty room.

5. Importance of Findings

The study examined power reception in various scenarios, including a vacant room, lying down, and standing. It found that power reception was affected by human presence, with lower reception when a human was lying down compared to standing. This aligns with previous research by A-Saman (2021) [13]. Additionally, the study noted that the movement or stillness of objects can impact data accuracy and sensitivity due to changes in their centre of gravity and gait.

6. Conclusion and Future Work

Remote patient monitoring using RFID technology may improve outcomes and treatment. However, ethical use of this technology is necessary to protect patient privacy and reduce social inequities. Telemedicine and RFID show healthcare promise. These technologies enable remote healthcare and patient data and equipment tracking. Electronic health systems have been innovated for decades, despite unsolved efficacy and safety issues. For accurate diagnosis and efficient treatment, varied monitoring measures customised to patient needs and symptoms are needed. This study also lays the groundwork for future data-driven patient localization studies. A virtual environment with different patient levels will also be used in this investigation.

Acknowledgement. This work is partially supported by the innovation programme under grant agreement H2020-MSCA-RISE-2022-2027 (ID: 101086492), Marie Skłodowska-Curie, Research, and Innovation Staff Exchange (RISE), and the financial support from the UK Engineering and Physical Sciences Research Council (EPSRC) under grant EP/X039366/1.

References

[1] MICHEL, J.-P., LEONARDI, M., MARTIN, M. & PRINA, M. 2021. WHO's report for the decade of healthy ageing 2021–30 sets the stage for globally comparable data on healthy ageing. The Lancet Healthy Longevity, 2, e121-e122.

[2] HAMBLIN, K. 2014. Care System Sustainability: what role for technology? Evidence review. Age, 2024, 2039.

[3] JO, O., KRUGER, E. & TENNANT, M. 2021. GIS mapping of healthcare practices: do older adults have equitable access to dental and medical care in the UK? British Dental Journal, 1-9.

[4] KRISTENSEN, S., MAINZ, J. & BARTELS, P. 2009. Selection of indicators for continuous monitoring of patient safety: recommendations of the project 'safety improvement for patients in Europe'. International Journal for Quality in Health Care, 21, 169-175.

[5] DENNISON, L., MORRISON, L., CONWAY, G. & YARDLEY, L. 2013. Opportunities and challenges for smartphone applications in supporting health behaviour change: qualitative study. Journal of medical Internet research, 15, e2583.

[6] UR REHMAN, M. F., FARIHA, C., ANWAR, A., SHAHZAD, N., AHMAD, M., MUKHTAR, S. & HAQUE, M. F. U. 2021. Novel coronavirus disease (COVID-19) pandemic: A recent mini-review. Computational and Structural Biotechnology Journal, 19, 612-623.

[7] FLYNN, D., MOLONEY, E., BHATTARAI, N., SCOTT, J., BRECKONS, M., AVERY, L. & MOY, N. 2020. COVID-19 pandemic in the United Kingdom. Health Policy and Technology, 9, 673-691.

[8] WATT, T., VARROW, M., ROBERTS, A. & CHARLESWORTH, A. 2018. Social care funding options. The Health Foundation (https://www.health.org.UK/publications/social-care-funding-options).

[9] CELLER, B., EARNSHAW, W., ILSAR, E., BETBEDER-MATIBET, L., HARRIS, M., CLARK, R., HESKETH, T. & LOVELL, N. 1995. Remote monitoring of health status of the elderly at home. A multidisciplinary project on aging at the University of New South Wales. International journal of bio-medical computing, 40, 147-155.

[10] WALLACE, M. & SHELKEY, M. 2007. Katz index of independence in activities of daily living (ADL). Urol Nurs, 27, 93-94.

[11] ORGANIZATION, W. H. 2021. Global status report on the public health response to dementia.
[12] EDEMEKONG, P. F., BOMGAARS, D. L., SUKUMARAN, S. & LEVY, S. B. 2021. Activities of daily living. StatPearls [Internet]. StatPearls Publishing.
[13] Al-Saman, H. (2021). Investigating the Effect of Human Shadowing on the Received Power of RFID Readers. IEEE Access, 9, 42038-42047.