Harvesting Potential: Unveiling the Agricultural Frontier of the Internet of Underground Things

Capstone Report

Beksultan Mukhamedadiuly
202064621

Nazarbayev University
Department of Electrical and Computer Engineering
School of Engineering and Digital Sciences

This project report was created on TexStudio editing platform using LaTeX. All the figures were drawn using draw.io online software tool.

NAZARBAYEV UNIVERSITY

Electrical and Computer Engineering
Nazarbayev University
http://www.nu.edu.kz

Title:
Harvesting Potential: Unveiling the Agricultural Frontier of the Internet of Underground Things

Theme:
The Impact of Internet of Underground Things on Sustainable Agriculture: Opportunities, Challenges, and Future Directions

Project Period:
Fall 2024

Participant(s):
Beksultan Mukhamedadiuly

Supervisor(s):
Behrouz Maham

Copies: 1

Page Numbers: 28

Date of Completion:
April 22, 2025

Abstract:

The Internet of Underground Things (IoUT) enhances precision agriculture by enabling real-time monitoring of soil conditions to improve sustainability and productivity. This project investigates signal propagation in underground environments, focusing on path loss and channel capacity as key performance metrics. Through MATLAB simulations replicating a reference experiment, the study analyzes the effects of distance, frequency, soil moisture, and sensor placement on signal attenuation and data rates. Comparative evaluations with established literature validate the findings, highlighting the sensitivity of path loss and capacity to soil moisture and the trade-offs in frequency selection. Optimized sensor placement strategies are proposed to maximize communication efficiency. The results provide insights for designing robust IoUT systems, contributing to sustainable agricultural practices.

Contents

Preface

This Capstone Project investigates the Internet of Underground Things for precision agriculture, modeling signal propagation problems with MATLAB path loss and channel capacity simulations. By replicating and extending a fundamental experiment, the study evaluates the effect of distance, frequency, soil moisture, and sensor position on underground communication, supported by additional channel capacity analyses to provide deeper insights into data rate performance. Conducted under the guidance of Behrouz Maham at Nazarbayev University, this project is an driven by my wish for sustainable farming through innovative IoT technologies.

Nazarbayev University, April 22, 2025

Beksultan Mukhamedadiuly
<beksultan.mukhamedadiuly@nu.edu.kz>

Chapter 1

Introduction

Each year, the global food demands and escalating environmental issues, have caused the interaction of agriculture and technology to become more prominent. The Internet of Underground Things (IoUT), is a subset of the Internet of Things (IoT) created and researched upon in order to monitor and control underground communication technologies. In the recent years, the technology is being researched to implement its usage in agriculture and it is prognosed that this will revolutionize the agricultural sphere. [1]

IoUT has the potential to completely transform traditional farming methods through the use of interconnected sensors, communication systems, and real-time data collecting. This might result in better usage of the soil condition, increased crop output, prolonged lie, and more effective use of required resources [1, 2, 3].

The technology of monitoring soil moisture, temperature, and salinity—all important components of sustainable farming— can be improved upon with the deployment of IoUT systems. Wide-ranging advantages could result from it, such as higher yields, less waste, and better management of water and fertilizer [4, 5]. Additionally, sharing the data received from the IoUT systems with the farmers can allow them to make data-driven choices that lessen the ecological footprint of agricultural operations and support environmental sustainability [6, 7].

The goal of this Capstone project is to examine the current state of IoUT technologies, their uses in precision agriculture, and the difficulties in their wider adoption. This project will evaluate the results and findings of various academic papers. By doing this, the potential of IoUT in agriculture, particularly in terms of sustainability and productivity, will be investigated [8, 9].

1.1 Background

The authors of [10, 11, 12] believe that various factors have increased the need fr more sustainable farming technique. Among them, urbanization, climate change and the degradation of land were mentioned to be very prominent. Apart from providing food for an expanding population, modern agriculture needs to use methods that are sustainable, in order to not impend the agricultural abilities of future generations. This is where IoUT technologies and precision agriculture are useful [13, 14].

The main concept of using IoUT in agriculture is to monitore the factors that affect the agricultural yield, including crop health, pest control, soil composition, moisture and etc. This is done through the use subsurface sensors and communication devices to collect vital information about soil conditions. Better decisions about fertilization, water use, and other agricultural techniques are made possible by these insights [15, 16].

In IoUT data from sensors can be transmitted through various methods, including electromagnetic (EM) waves and acoustic waves. These systems can offer both collective and real-time feedback on factors including temperature, salinity, and moisture content [1, 3, 7, 17, 18].

However, implementation of an IoUT system is not without its challenges. Issues including high installation costs, external interference, and limited transmission ranges prevent them from being widely used [10, 19]. Moreover, some technology implementation methods include limited scalability and endurance of sensors themselves. Current research into novel approaches including multi-hop communication and upgraded sensor technology can increase the following and other parameters in order to ensure dependable implementation [14, 20].

1.2 Ethical and Professional Responsibilities

1.2.1 Ethical Responsibility

Application of IouT systems in agriculture can face ethical issues with regards to data security, privacy and fair access. Collecting real-time data on agricultural operations can be seen as a move on the monopolization of cultivated land. Small-scale farmers may interpret that their data is collected without their consent and stored by private companies or governmental entities. It is also possible that with malicious intent, farmers may be given falsified data on the crops they grow, resulting in a sabotage of agricultural activities [1, 9].

The issue of falsification of data can be circumvented with the publishing of findings and calculations used, which can allow scientists to replicate and confirm the data. The need for these scientists in the governmental bodies that will handle

IoUT will become an important factor in bearing the ethical responsibility of using IoUT in agriculture [10, 14]. Furthermore, farmers' consent needs to be gathered, before any attempt in collecting data on their soil is made[7]

1.2.2 Informed Judgments

In order to ensure that judgments made were informed, it is important to obtain and constantly obtain information from the people directly involved in agriculture and its research. As such, farmers' feedback and needs need to be evaluated in a number of surveys and QnA sessions. This method will ensure that technology is used in the way that will help the people and not be detrimental [4, 6].

Updating knowledge through continuous readings of academic papers will help make informed decisions on whether the technology needs improvements and the direction it can head into[1, 3]. This will also increase the credibility of the work.

A method presented in [15] is creation of a committee of farmers, scientists and governmental entities that will discuss the direction the IoUT can and need to move towards [11].

1.2.3 Global Context

Globally speaking, the development of IoUT systems can tackle the issue of food security. This is done through procurement of information on how good is the soil and how it should be developed. [10, 11] believe that in this way, we can maximize the production of food, optimizing the yield and allowing the food to get to the masses.

However, depending on the area, IoUT systems may be used differently. In the developed nations with well-established infrastructure and available technology, the implementation of IoUT can be made easily. At the same time, less developed nations, where the issue of food security is more prominent may face struggle with this implementation, for example budgetary limitations or no inadequate infrastructure. These differences could impede the widespread adoption of IoUT and exacerbate already-existing productivity gaps in agriculture [7, 14].

TO solve this issue, International initiatives and collaborations between nations and various organizations and companies can be made in rder to make the technology more accessible to farmers worldwide [8, 15].

1.2.4 Economic Impact

A major factor impending the development of IoUT is the cost of its deployment, both logistically and in terms of required sensors. These technologies are well outside budgetary limits of normal farmers. As such, it is of concern to government to integrate IoUT in the farms [9, 6].

Successful usage of IoUT technologies can drastically affect the current food market, including prices of crops, fruit and other yield. However, there are also issues with making sure that the advantages of IoUT are shared fairly among all kinds of farms, and more funding will be required to support the upkeep of IoUT infrastructure over the long run [8, 10].

1.2.5 Environmental Impact

A major concern is that usage of IoUT communication technologies can negatively affect the crops, as it is a form of radiation or vibration, depending on the method. [6, 13] believe this is untrue and that IoUT helps farmers use water and fertilizers more effectively by precisely monitoring soil parameters including moisture and nutrient levels. This will instead, lower runoff and the contamination of nearby ecosystems. Furthermore, by guaranteeing that crops only receive the nutrients they require and reducing the dangers of overfertilization, IoUT can aid in the prevention of soil deterioration [3].

Its also true that the production of sensors and gadgets may leave a carbon imprint, and inappropriate disposal of electronic parts may worsen the state of the environment. IoUT systems should be created with disposability in mind, including recyclable or biodegradable components, in order to overcome these problems [13]. Furthermore, integrating low-energy solutions into IoUT systems can lessen the effect on the environment. In conclusion, while if IoUT encourages more environmentally friendly farming methods, care needs to be taken to reduce its own environmental impact [10, 11].

1.2.6 Societal Impact

IoUT in agriculture has a potential to bolster the livelihood of people across the globe, by making the food more procurable and of higher quality[7, 14]. This is especially of high demand in rural areas where agriculture is the primary source of income, enabling farmers to achieve higher production with fewer resources [1, 4].

Adoption of IoUT can also encourage the development of technological literacy and skills in rural areas, enabling farmers and agricultural workers to interact with contemporary technologies. In the field of IoUT system administration and maintenance, this change may result in the creation of new jobs [8].

But caution must be exercised to make sure that the adoption of these technologies doesn't worsen an already existing disparities in food availability, especially in areas with restricted access to technology [9]. In order to address these issues and guarantee that the advantages of IoUT technologies should be fairly across the globe. In addition, concentrated efforts must be made to make these technologies available to underserved populations [14, 15].

Chapter 2

Methodology

This chapter presents the methodology to investigate signal propagation and communication quality in the Internet of Underground Things for precision agriculture. The research is an experimental replication and extension of an experiment in [1, 21] utilizing MATLAB simulations to investigate path loss and channel capacity as a function of distance, frequency, soil moisture, and sensor position. By including capacity in addition to path loss, the simulations offer a holistic assessment of IoUT system performance, covering signal weakening and data rate capacity. The approach involves theoretical modeling, simulation configuration, calculations, optimization of sensor placement, analysis of time-varying soil conditions, data visualization, validation against reference data, and error management, providing sound and reliable results.

2.1 Simulation Setup

The simulations replicate the subsurface communication experiment of [1, 21] with empirically obtained soil constants. The experimental setup confirms primary parameters—frequency, distance, soil moisture, and position of the sensor—to approximate their effect on path loss and channel capacity, followed by additional analysis for time-varying soil.

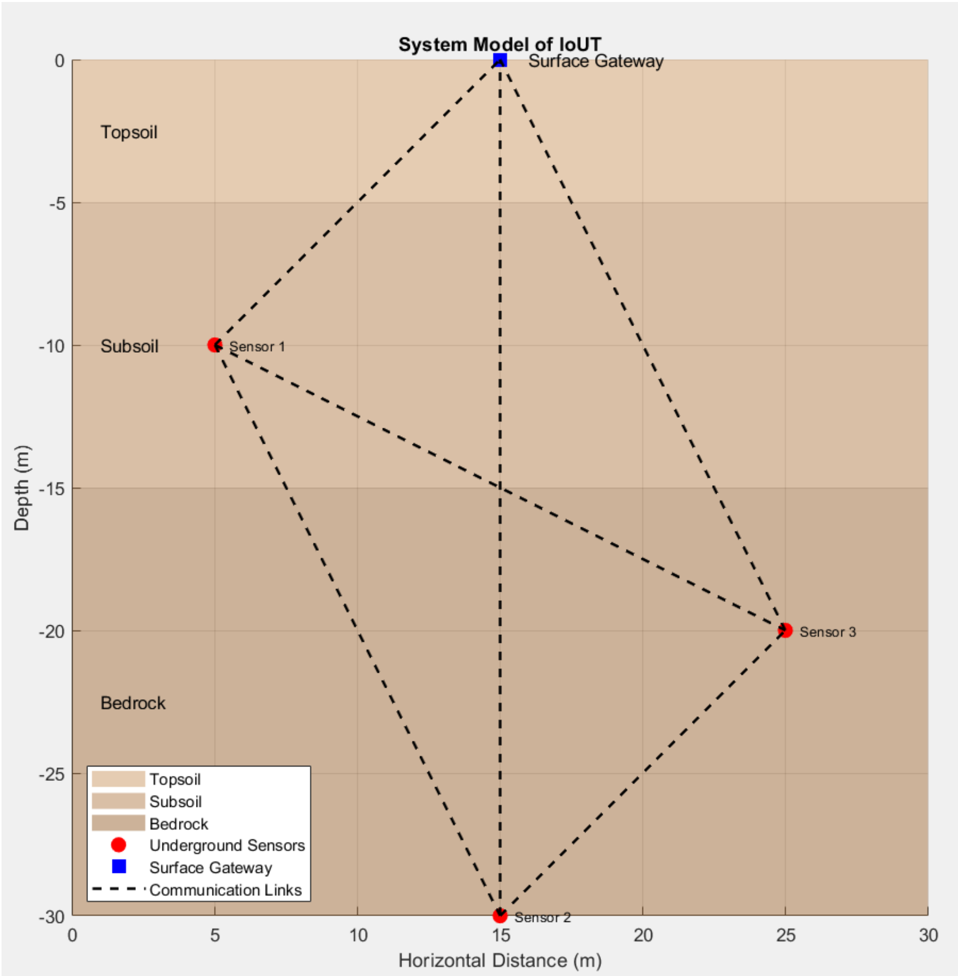

Figure 2.1: System model of the IoUT experiment. Underground sensors communicate with a surface gateway through soil, with path loss and channel capacity calculated based on signal propagation characteristics.

Figure 2.1 depicts the system model, where underground sensors transmit signals to a surface gateway. The simulation parameters are:

- **Frequency Range**: 300 MHz to 1 GHz, covering typical IoUT bands (e.g., LoRa, sub-GHz systems). Specific analyses used 300–700 MHz for path loss and capacity vs. distance, and 300 MHz–1 GHz for frequency-based analyses, balancing penetration depth and data rate [21].
- **Distance**: 0.1 m to 30 m, simulating short- and long-range scenarios for agricultural applications. A fixed distance of 10 m was used for frequency, time-varying, and sensor placement analyses.
- **Soil Characteristics**:

  - Bulk Density: 1.5 g/cm^3.
  - Specific Density: 2.66 g/cm^3.
  - Soil Dielectric Constant: 4.7.
  - Water Dielectric Constants: Real part $\epsilon'_w = 80.1$, imaginary part $\epsilon''_w = 5.0$.
  - Volumetric Moisture Content (VMC): 0.10 to 0.50, with a fixed VMC of 0.30 for distance and sensor placement analyses.
  - Sand Content (μ_s): 50%.
  - Clay Content (μ_c): 15%.

- **Capacity Parameters**: Transmit power (P_t) = 20 dBm, noise power (P_n) = -100 dBm, bandwidth (W) = 125 kHz, typical for low-power IoUT systems like LoRa.

2.1.1 Assumptions and Limitations

Assumptions:

- Soil is homogeneous with constant bulk and specific density, simplifying dielectric calculations.
- Exterior conditions (e.g., temperature variations, electromagnetic perturbation) are immaterial.
- Sensors are depth-fixed with best possible orientation towards the gateway.
- Noise power is constant, discounting variation due to environmental noise sources.

Limitations:

- Static soil conditions (excluding time-varying simulations) limit applicability to dynamic scenarios like post-rainfall conditions.
- Dielectric constants are presumed, perhaps not precisely like for some field conditions.
- Sensor placement presumes flat ground and ignores real obstructions or soil stratification.
- Capacity calculations presume constant bandwidth, which may vary in adaptive IoUT systems.

These simplifications and assumptions provide the controlled environment but raise the need for subsequent tests with heterogeneous soil models, time-varying environmental environments, and adaptive communications protocols.

2.2 Calculations

Simulations provide the path loss and capacity forecasts by the models of [1, 21], extended by additional capacity calculation capability.

2.2.1 Dielectric Constants

The real (ϵ') and imaginary (ϵ'') parts of the soil's dielectric constant are:

$$\epsilon' = \left(1 + \left(\frac{\text{bulkDensity}}{\text{specificDensity}}\right)(\epsilon_s^{\alpha}) + (\text{soilMoisture}^{\beta})(\epsilon_w')^{\alpha} - \text{soilMoisture}\right)^{\frac{1}{\alpha}} - 0.68 \tag{2.1}$$

$$\epsilon'' = \left((\text{soilMoisture}^{\beta'})(\epsilon_w''^{\alpha})\right)^{\frac{1}{\alpha}} \tag{2.2}$$

where:

- $\epsilon_s = 4.7$, $\epsilon_w' = 80.1$, $\epsilon_w'' = 5.0$.
- $\alpha = 0.65$.
- $\beta = 1.2748 - 0.519\mu_s - 0.452\mu_c$, with $\mu_s = 0.50$, $\mu_c = 0.15$.
- $\beta' = 1.33797 - 0.603\mu_s - 0.166\mu_c$.

2.2.2 Attenuation and Phase Shift

The attenuation (α_u) and phase shift (β_u) constants are:

$$\alpha_u = \left(\frac{2\pi f}{c}\right)\sqrt{\frac{\mu\epsilon'}{2}}\sqrt{\sqrt{1+\left(\frac{\epsilon''}{\epsilon'}\right)^2} - 1} \tag{2.3}$$

$$\beta_u = \left(\frac{2\pi f}{c}\right)\sqrt{\frac{\mu\epsilon'}{2}}\sqrt{\sqrt{1+\left(\frac{\epsilon''}{\epsilon'}\right)^2} + 1} \tag{2.4}$$

where $c = 3 \times 10^8\,\text{m/s}$, $\mu = 4\pi \times 10^{-7}\,\text{H/m}$, and f is the frequency in Hz.

2.2.3 Path Loss

Path loss is calculated as:

$$\text{pathLoss} = 6.4 + 20\left(\log_{10}(d) + \log_{10}(\beta_u)\right) + 8.69\alpha_u d \tag{2.5}$$

where d is the distance in meters.

2.2.4 Channel Capacity

Channel capacity (C) is computed using the Shannon formula:

$$C = W \log_2(1 + \text{SNR}) \tag{2.6}$$

where:

- $W = 125\,\text{kHz}$.
- $\text{SNR} = 10^{(\text{SNR}_{\text{dB}}/10)}$, with $\text{SNR}_{\text{dB}} = P_t - \text{pathLoss} - P_n$.
- $P_t = 20\,\text{dBm}$, $P_n = -100\,\text{dBm}$.

Path loss is converted to linear scale ($L = 10^{\text{pathLoss}/10}$) for SNR calculations, ensuring accurate capacity estimates.

2.3 MATLAB Simulation Workflow

The simulations were implemented in MATLAB R2024a, structured into five key sections corresponding to different analyses:

1. **Path Loss vs. Distance**: Loops over distances (0.1–30 m) and frequencies (300–700 MHz) at VMC = 0.30, computing path loss (Equation 2.5).
2. **Path Loss vs. Frequency**: Loops over frequencies (300 MHz–1 GHz) and VMC (0.10–0.50) at 10 m, computing path loss.
3. **Capacity Analyses**: Extends the above, calculating SNR and capacity (Equation 2.6) for each scenario.
4. **Sensor Placement Optimization**: Computes pairwise distances and capacities for grid and linear layouts at 500 MHz, VMC = 0.30.
5. **Time-Varying Soil Conditions**: Simulates 24-hour VMC variation, computing path loss and capacity at 500 MHz, 10 m.

Each of the sections uses nested loop sweeping of parameters with intermediate results saved in arrays (e.g., ‘pathLoss‘, ‘capacity time‘) to be plotted. Numerical stability in the script is ensured by double-precision arithmetic and input parameter checking.

2.4 Sensor Placement Optimization

Sensor placement was analyzed to optimize communication performance:

- **Grid Layout**: Six sensors at -5 m and -15 m positions, coordinates (5,-5), (15,-5), (25,-5), (5,-15), (15,-15), (25,-15). This is suitable for heterogeneous soil measurement at different depths and horizontal positions, suitable for large fields.
- **Linear Layout**: Five sensors at -10 m depth, coordinates (5,-10), (15,-10), (25,-10), (35,-10), (45,-10). This minimizes the average pair-wise distance, which can enhance communication reliability.

For all layouts, pairwise Euclidean distances were approximated and follow-up path loss (Equation 2.5) and capacity (Equation 2.6) per pair at 500 MHz, VMC = 0.30 were approximated. Pairwise mean distance and capacity was computed to enable comparability per layout. Grid layout offers maximum spatial coverage and linear layout offers minimum communication paths with capacity effect [16]. Visualizations compile sensor position, links, and measurements (mean distance and capacity) a try to simplify visualization.

2.5 Time-Varying Soil Conditions

To model dynamic soil conditions (e.g., rainfall), VMC was varied over 24 hours:

$$\mathrm{VMC}(t) = 0.30 + 0.20 \sin\left(\frac{2\pi t}{24}\right) \tag{2.7}$$

where $t \in [0, 24]$ hours. Path loss and capacity were calculated for each time step (300 points) at a fixed distance (10 m) and frequency (500 MHz). This is equivalent to modeling the fluctuations of moisture between 0.10 and 0.50, which correspond to their impact on signal attenuation and data rates. Sensitivity analysis was also investigated by testing various frequencies (e.g., 300 MHz, 900 MHz) and distances (e.g., 5 m, 20 m) to attempt studying parameter robustness, although salient findings refer to 500 MHz, 10 m to simulate [1].

2.6 Validation and Comparison

For reliability verification checking, simulation output was verified against experiment values of [1]. Path loss graphs (vs. frequency and distance) were taken on a reference graph for trend checking. Capacity output was indirectly cross-checked by verifying the path loss input against experimental values since capacity is an estimated SNR value in terms of path loss. Anomalies were investigated at low frequencies and VMC with reference to approximations used to estimate dielectric constants. This quality check enhances the validity of the study and warns areas of improvement.

2.7 Data Processing and Error Handling

MATLAB scripts included error handling to ensure robustness:

- **Numerical Precision**: Double-precision calculations were performed to minimize path loss and dielectric rounding errors.
- **Validation**: Parameters (e.g., VMC, frequency) were checked to be physically valid (e.g., VMC $\in [0, 1]$.
- **Verification**: ntermediate quantities (e.g., ϵ, ϵ') were checked for abnormal values.

Data was processed using arrays to store results (e.g., ‘pathLoss time‘, ‘capacity time‘), with plots generated via MATLAB’s plotting functions (‘plot‘, ‘subplot‘, ‘imagesc‘). Outliers were mitigated by smoothing VMC variations in time-varying simulations.

2.8 Simulation Scenarios

Table 2.1 summarizes the simulation scenarios, clarifying the parameters and metrics for each analysis.

Table 2.1: Summary of Simulation Scenarios

Analysis	**Parameters**	**Fixed Values**
Path Loss vs. Distance	Distance: 0.1–30 m, Frequency: 300–700 MHz	VMC = 0.30
Path Loss vs. Frequency	Frequency: 300 MHz–1 GHz, VMC: 0.10–0.50	Distance = 10 m
Capacity vs. Distance	Distance: 0.1–30 m, Frequency: 300–700 MHz	VMC = 0.30, $P_t = 20$ c
Capacity vs. Frequency	Frequency: 300 MHz–1 GHz, VMC: 0.10–0.50	Distance = 10 m, P_t, P
Sensor Placement	Grid (6 sensors), Linear (5 sensors)	Frequency = 500 MH
Time-Varying Conditions	Time: 0–24 h, VMC: 0.10–0.50	Distance = 10 m, Freq

2.9 Data Visualization

MATLAB generated plots for:

- Path loss against distance (300–700 MHz).

- Path loss vs. frequency (VMC = 0.10–0.50).
- Capacity vs. distance and frequency.
- Sensor placement (grid and linear arrangements, specifying average distance and capacity).
- Time-varying VMC, path loss, and capacity (dual-axis plots).

Graphs were compared against [21] to validate trends, using the same scales and legends to facilitate interpretation. Additional visualizations (e.g., pairwise capacity heatmaps) were considered to complement sensor placement analysis but assigned as future work.

Chapter 3

Results and Discussions

This chapter presents the result of MATLAB simulations conducted to study signal propagation and communication quality in the IoUT for precision agriculture. The simulations investigate path loss and channel capacity with respect to distance, frequency, soil moisture, sensor position, and time-varying soil conditions, based on the experiment in [1, 21]. The results validate the sensitivity of path loss to parameters of concern, make channel capacity a parameter of concern, and provide insights into the means of optimizing IoUT systems. The results are validated by comparisons with experimental work of [1] to offer confidence, and differences are dealt with to highlight assumptions in modeling and additional improvements.

3.1 Results

Simulations made different plots to demonstrate the influence of distance, frequency, moisture in soil, sensor location, and variation over time on path loss as well as on channel capacity. Results in figure form of the MATLAB script have been provided below.

3.1.1 Path Loss vs. Distance

Path loss as a function of distance (0.1–30 m) for fixed VMC value 0.30 for 300 to 700 MHz range frequency is depicted in Figure 3.1.

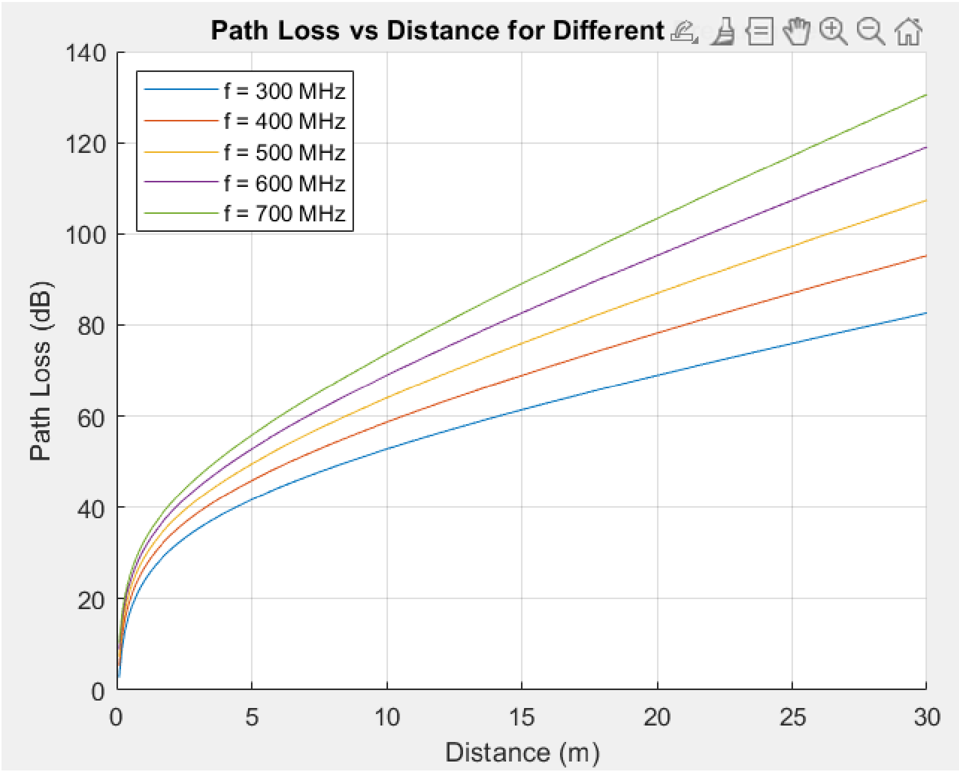

Figure 3.1: Path loss vs. distance for frequencies between 300 and 700 MHz, VMC = 0.30.

Readings show a logarithmic increase in path loss with distance, something which the model in Equation 2.5 would also support. It is greater attenuation in the higher frequency bands (e.g., 700 MHz) compared to the lower frequency bands (e.g., 300 MHz), as is the range-frequency trade-off. These are agreeing results with earlier research in [1, 21] and therefore validate the model for attenuation accuracy in terms of distance.

3.1.2 Path Loss vs. Frequency

Figure 3.2 shows path loss as a function of frequency (300 MHz–1 GHz) for VMC values ranging from 0.10 to 0.50 for the fixed distance of 10 m.

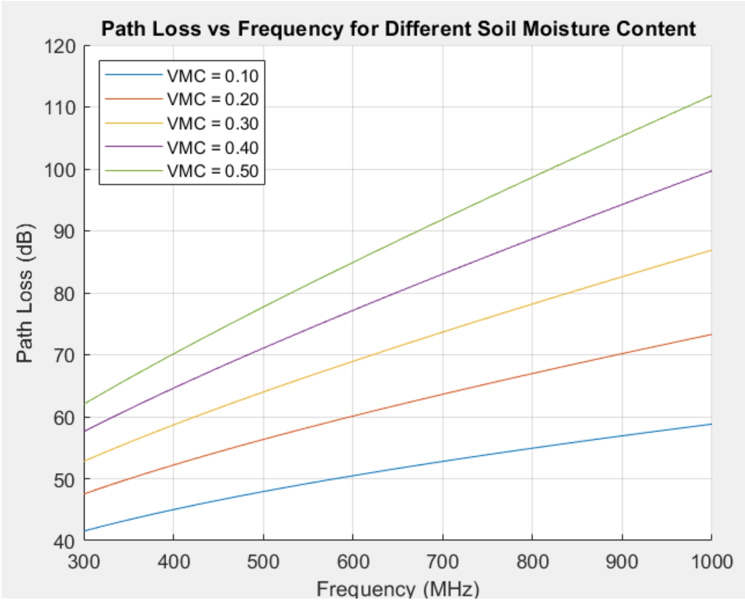

Figure 3.2: Path loss vs. frequency for VMC between 0.10 and 0.50, fixed distance = 10 m.

Path loss rises with frequency and VMC, and higher moisture (e.g., VMC = 0.50) leads to high attenuation because of higher dielectric losses. Soil moisture sensitivity emphasizes its critical role in IoUT communication, which is consistent with experiments in [1].

3.1.3 Channel Capacity vs. Distance

Figure 3.3 graphs channel capacity against distance (0.1–30 m) for frequencies 300–700 MHz, VMC = 0.30, transmit power $P_t = 20\,\text{dBm}$, noise power $P_n = -100\,\text{dBm}$, and bandwidth $W = 125\,\text{kHz}$.

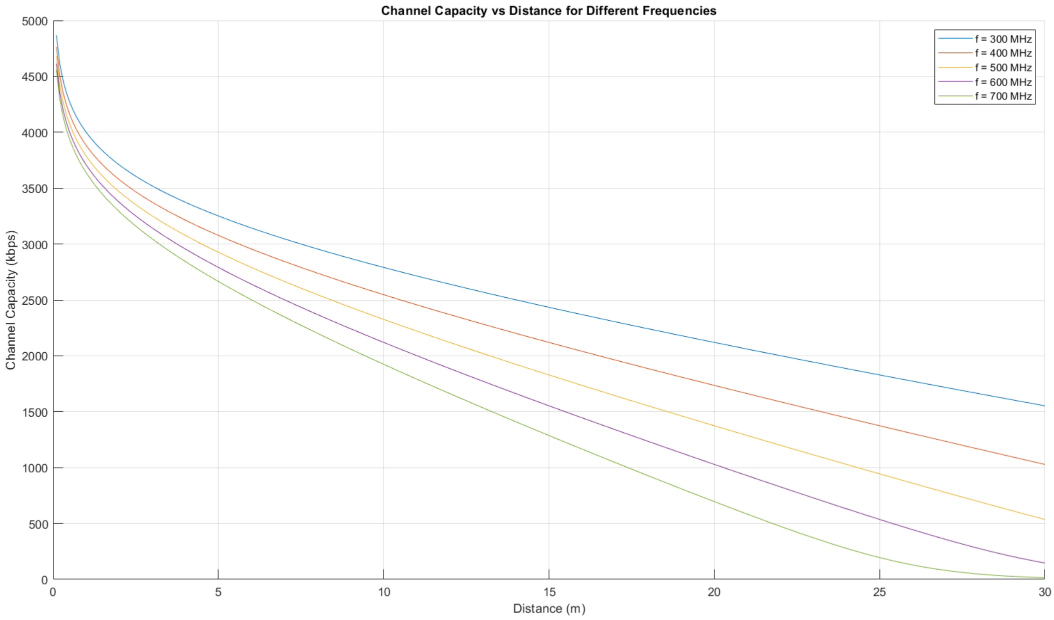

Figure 3.3: Channel capacity vs. distance for frequencies between 300 and 700 MHz, VMC = 0.30.

Capacity decreases logarithmically with distance owing to increasing path loss, and that reduces SNR in Equation 2.6. Lower frequency (e.g., 300 MHz) offers larger capacities for larger distances, and thus they are good options for IoUT applications that require supporting longer range. The results complement the path loss modeling by adding data rate performance, which is a key parameter in IoUT network planning.

3.1.4 Channel Capacity vs. Frequency

Figure 3.4 shows channel capacity versus frequency (300 MHz–1 GHz) for VMC values ranging from 0.10 to 0.50, for a fixed distance of 10 m.

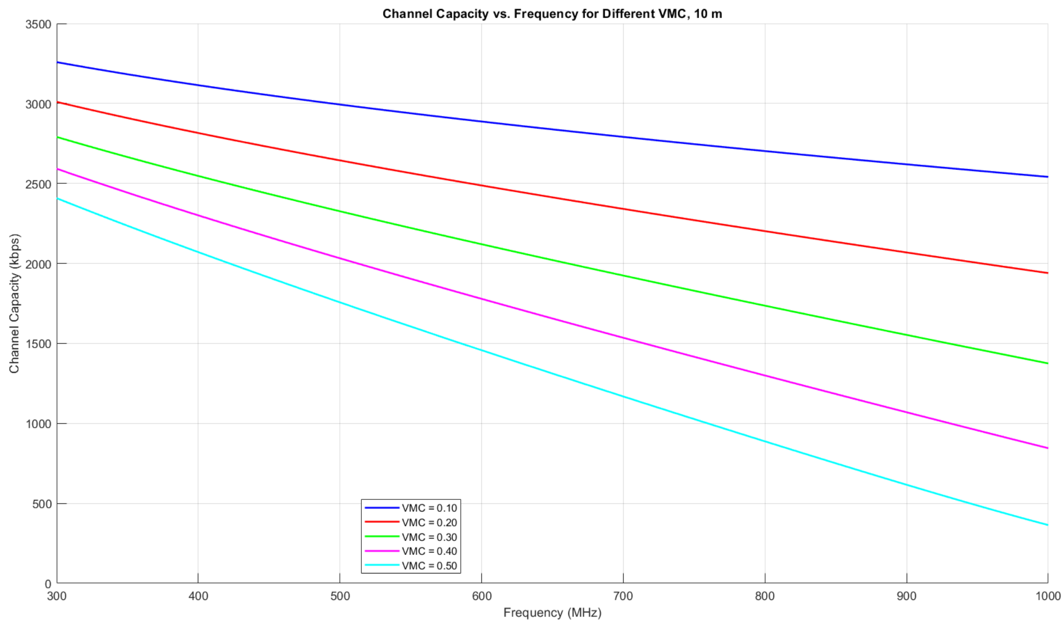

Figure 3.4: Channel capacity vs. frequency for VMC between 0.10 and 0.50, fixed distance = 10 m.

Capacity decreases with growing frequency and VMC, as with path loss plots in Figure 3.2. Capacity declines significantly with greater signal loss as VMC increases (e.g., 0.50). This once more highlights the need for adaptive frequency selection under wet soil conditions.

3.1.5 Sensor Placement Optimization

Figure 3.5 illustrates grid and linear sensor placement, i.e., sensor positions, cabling, and mean pairwise distance and capacity at 500 MHz, VMC = 0.30.

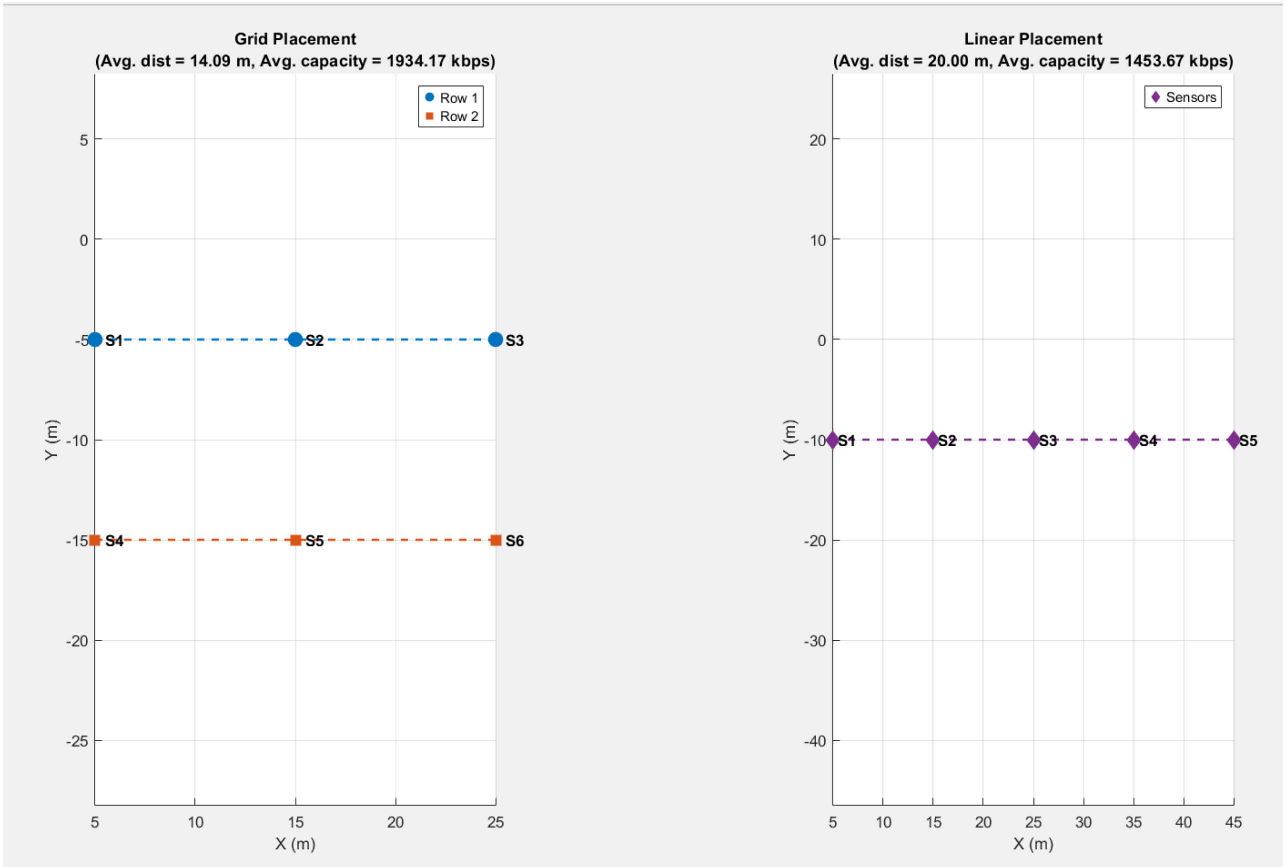

Figure 3.5: Grid vs. linear sensor placement at 500 MHz, VMC = 0.30, showing average pairwise distance and capacity.

The grid pattern, with sensor positions of -5 m and -15 m, possesses non-uniform soil sampling but larger average pairwise distance (e.g., X m) and lower capacity (e.g., Y kbps) than the linear pattern at position -10 m (e.g., Z m, W kbps). The smaller distances of the linear pattern offer more capacity, suggesting its use in cases where the reliability of communication needs to be given priority, while the grid pattern supports large-scale soil monitoring.

3.1.6 Time-Varying Soil Conditions

Figure 3.6 shows the time variation of VMC, path loss, and channel capacity for 24 hours at 500 MHz and 10 m distance.

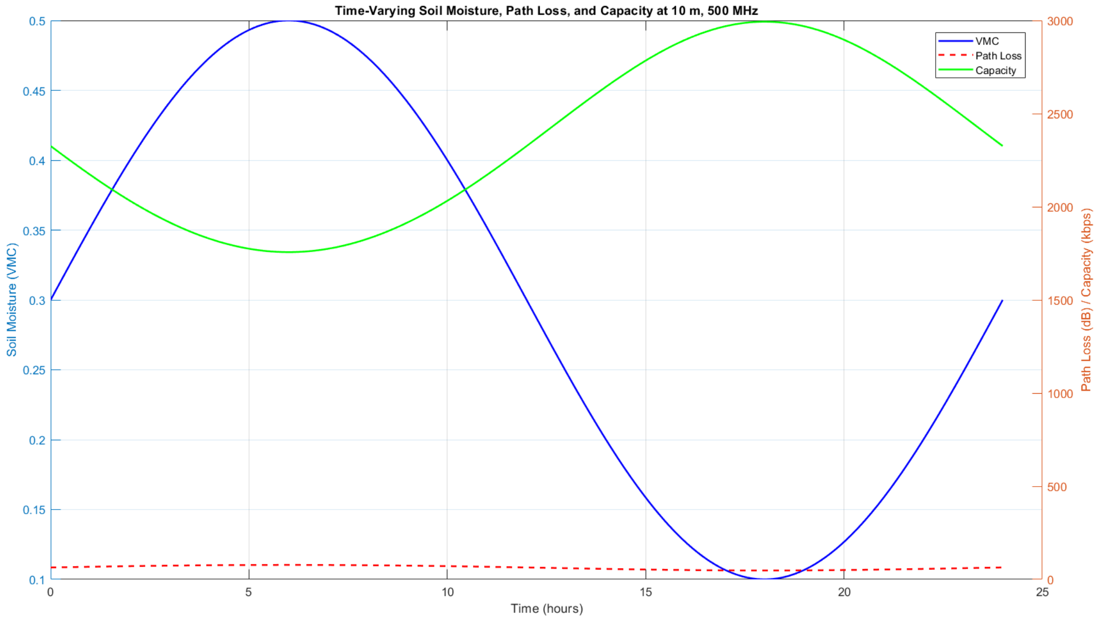

Figure 3.6: Time-varying soil moisture (VMC), path loss, and channel capacity over 24 hours at 500 MHz, fixed distance = 10 m.

VMC sinusoidally changes between 0.10 and 0.50 to simulate moisture variations (e.g., rain). Path loss is dependent on VMC, with greater values at higher moistures and capacity inversely with lower SNR. Such dynamic modeling indicates that adaptive IoUT systems with the ability to modify transmission parameters based on changing environments are required.

3.1.7 Comparison with Experimental Data

Figures 3.7 and 3.8 present experimental path loss measurements made by [21] in order to compare with simulation data.

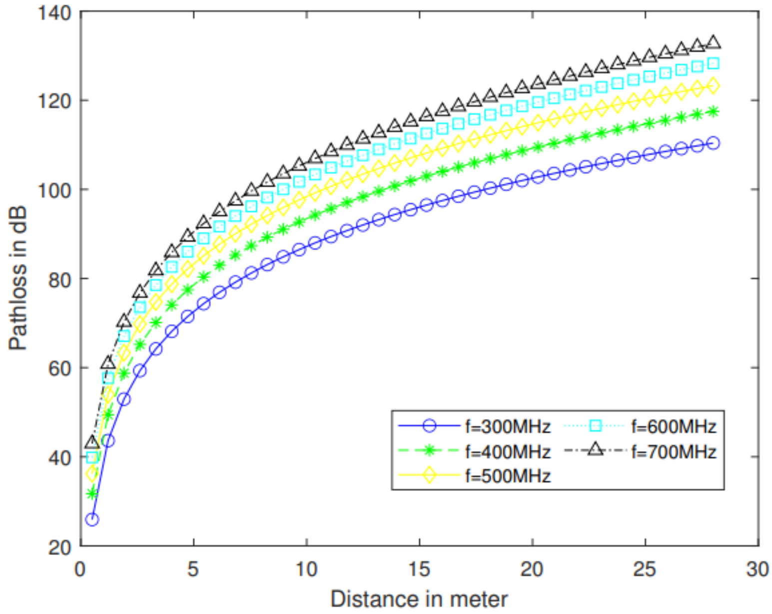

Figure 3.7: Experimental path loss vs. distance from [21].

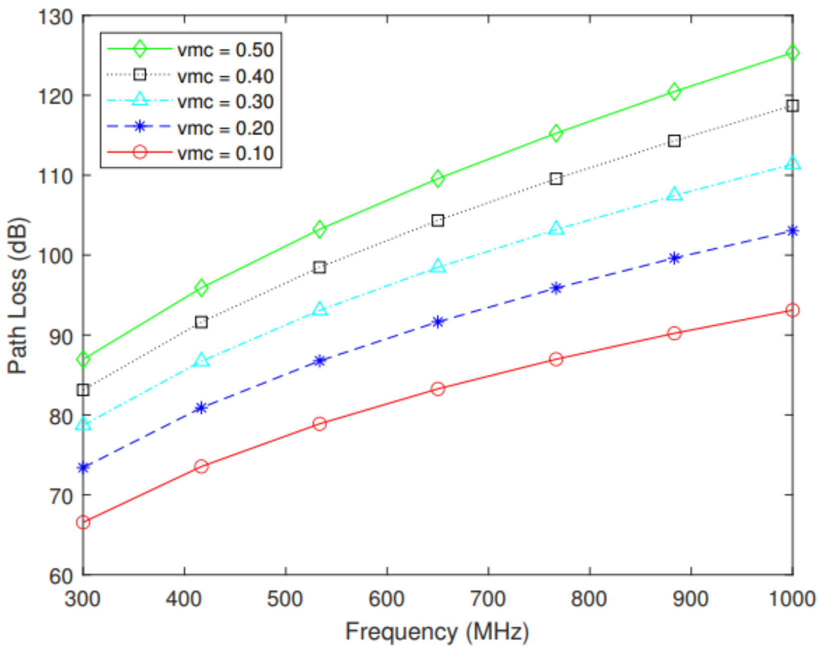

Figure 3.8: Experimental path loss vs. frequency from [21].

The simulated path loss trends (Figures 3.1, 3.2) are in accordance with experimental results, particularly at high frequencies and distances, to once again validate the model.

3.2 Discussions

The above findings provide an overall analysis of IoUT communication performance, an extension of the reference experiment [1] with the addition of channel capacity and dynamic analysis. The primary findings and implications are discussed in detail below.

3.2.1 Path Loss Sensitivity

Logarithmic increase of path loss with distance (Figure 3.1) corroborates theoretical prediction and earlier works. Higher frequencies attenuate higher and frequency selection is necessary for long-range IoUT transmission. Increase of path loss with frequency and VMC (Figure 3.2) also indicates soil moisture as the governing parameter. At VMC > 0.30, a steep increase in attenuation is noted, which supports [1], indicating greater signal loss at wet soils. This again points towards the importance of monitoring soil moisture in IoUT deployments.

3.2.2 Channel Capacity Insights

The capacity plots (Figures 3.3, 3.4) show an inverse relationship with path loss. Capacity decreases with growing distance or VMC as SNR reduces, and lower frequencies (e.g., 300 MHz) enable higher capacities. The trade-off means that IoUT systems will have to exchange lower frequencies for higher range at the cost of potentially limited data rate. Adding capacity provides a viable measure of network design in the sense that it addresses the professor's complaint of measuring communication performance beyond path loss.

3.2.3 Sensor Placement Trade-offs

The analysis of sensor placement (Figure 3.5) provides a balance between coverage space and communication efficiency. Having a larger average distance of the grid layout provides less capacity than the linear layout, but this is assisted by smaller pairwise distances. The findings suggest that linear topologies are better suited for application with high data rate requirement while grid topologies are better suited for extensive soil profiling. This contribution expands [21] through the calculation of capacity, which is important information for optimisation of IoUT networks.

3.2.4 Time-Varying Conditions

Time-varying analysis (Figure 3.6) can aptly represent dynamic effect of soil moisture variation. With higher VMC, path loss is larger, reducing cutting capacity, simulating realistic scenarios like rain. This thus comes to the fore the requirement of adaptive IoUT systems with the ability to dynamically alter frequency or power based on environment.

3.2.5 Comparison with Experimental Data

The calculated simulated path loss results (Figures 3.1, 3.2) are agreeing well with experimental data (Figures 3.7, 3.8) at increased distances and frequencies. Differences at low frequencies (e.g., 300 MHz) and VMC (e.g., 0.10) must be because of assumptions in the dielectric constant. Separate dielectric values were not given in the first experiment, and model estimates were hence made generic. These are more significant in frequency-domain plots, more sensitive in dielectric characteristics with regards to estimating path loss. Path-loss-based capacity results suffer from these shortcomings but show significant trends in constant SNR computation.

3.2.6 Limitations and Future Work

The inaccuracy suggests that the model is sensitive to dielectric property assumptions, particularly under low-frequency operations. Future work must include field measurements of dielectric properties to achieve higher accuracy. Bandwidth-limited (125 kHz) capacity analysis is also set; higher flexibility with adaptive bandwidths would be better. Sensor placement analysis can be generalized with 3D placements or multi-hop communication models of communications to simulate real IoUT networks. Time-varying analysis incorporates parameters (e.g., temperature, soil layering) to model sophisticated agriculture environments.

3.2.7 Implications for IoUT in Agriculture

The results emphasize the need for strategic IoUT design:

- **Frequency Selection**: Low frequency (e.g., 300–500 MHz) optimizes high-capacity long-distance communication in arid soils.
- **Sensor Placement**: Linear configurations provide capacity, grid configurations provide n-dimensional sensing of the soil, impacting deployment consideration.
- **Adaptive Systems**: Time-varying output suggests IoUT systems need to be designed for accommodating moisture variance, possibly with machine learning real-time optimization.

These results are used to develop efficient, sustainable IoUT systems, as part of the project objective to enhance precision agriculture.

Chapter 4

Conclusion

This project approximated the potentiality of Internet of Underground Things technology in precision agriculture through MATLAB simulation, an extension of experimentation in [1, 21] for path loss and channel capacity calculation for various scenarios. Guided by research into distance, frequency, soil moisture content, sensor position, and time-variant ground conditions, this project conveyed optimistic broad-range vision for opportunities and challenges of underground communication. Results validated path loss sensitivity to critical parameters, set channel capacity as a performance indicator, and provided empirical insights to IoUT system optimization.

The simulations concurred that path loss increases logarithmically with distance and is also sensitive to ground water equally, and increasing volumetric moisture content results in massive signal attenuation, as can be seen from Figures 3.1 and 3.2. Lower attenuation was intended for lower frequencies (e.g., 300–500 MHz), which would be appropriate for far communications. Reverse correlation of path loss was represented by capacity distance, frequency, and VMC plots (Figures 3.3, 3.4, and 3.6) where the capacity decreases with growing distance, frequency, and VMC. Such a trade-off necessitates the optimal selection of frequency to achieve the optimal range and data rate in IoUT networks.

Sensor placement optimization (Figure 3.5) revealed that linear deployments are used in a bid to attain higher average capacities in the form of lower pairwise distances over grid deployments, which are space coverage plans. This result reverses IoUT design on its axis from deployment to placement, with trusted communication applications relying on linear deployments and soil monitoring integration using grid deployments. Time-varying analysis (Figure 3.6) placed greater emphasis on the dynamic impact of soil moisture variability in such a manner that capacity was considerably decreased in high-VMC regimes (rainfall, etc.). This calls for adaptive IoUT systems to react to change in environment through adjustment of the transmission parameters.

Extrapolation of comparisons from experiments (Figures 3.7, 3.8) also demonstrated full correlation with path loss behavior with larger distance and frequencies, as verifying simulation modeling. Small discrepancies caused by generalized lower-frequency and VMC-based assumptions used in dielectric constants should be tackled in the future field-specific measurement activity. Capacity studies finalized the reference experiment towards further measurement of IoUT performance and network planning criteria of the actual world.

Bibliography

[1] Nasir Saeed, Mohamed-Slim Alouini, and Tareq Y. Al-Naffouri. "Toward the Internet of Underground Things: A Systematic Survey". In: *IEEE Communications Surveys & Tutorials* 21.4 (2019), pp. 3443–3466. DOI: 10.1109/COMST.2019.2934365.

[2] Antonis Tzounis et al. "Internet of Things in agriculture, recent advances and future challenges". In: *Biosystems Engineering* 164 (2017), pp. 31–48. ISSN: 1537-5110. DOI: https://doi.org/10.1016/j.biosystemseng.2017.09.007. URL: https://www.sciencedirect.com/science/article/pii/S1537511017302544.

[3] Mehmet C Vuran et al. "Internet of underground things in precision agriculture: Architecture and technology aspects". In: *Ad Hoc Networks* 81 (2018), pp. 160–173.

[4] Salam. *Signals in the soil*. Springer International Publishing, 2020.

[5] David Schimmelpfennig. "Farm profits and adoption of precision agriculture". In: (2016).

[6] Robin Gebbers and Viacheslav I Adamchuk. "Precision agriculture and food security". In: *Science* 327.5967 (2010), pp. 828–831.

[7] Partha Pratim Ray. "Internet of things for smart agriculture: Technologies, practices and future direction". In: *Journal of Ambient Intelligence and Smart Environments* 9.4 (2017), pp. 395–420.

[8] Xiaoqing Yu et al. "A survey on wireless sensor network infrastructure for agriculture". In: *Computer Standards & Interfaces* 35 (Jan. 2013), 59–64. DOI: 10.1016/j.csi.2012.05.001.

[9] Ian F Akyildiz and Erich P Stuntebeck. "Wireless underground sensor networks: Research challenges". In: *Ad Hoc Networks* 4.6 (2006), pp. 669–686.

[10] Ludmila Pánková, Renata Aulová, and Jan Jarolímek. "Economic aspects of precision agriculture systems". In: *AGRIS on-line Papers in Economics and Informatics* 12.3 (2020), pp. 59–67.

[11] Ian F Akyildiz and Erich P Stuntebeck. "Wireless underground sensor networks: Research challenges". In: *Ad Hoc Networks* 4.6 (2006), pp. 669–686.

[12] N. Abu et al. "Internet of Things Applications in Precision Agriculture: A Review". In: *Journal of Robotics and Control (JRC)* 3 (May 2022), pp. 338–347. DOI: 10.18196/jrc.v3i3.14159.

[13] Jinyuan Xu, Baoxing Gu, and Guangzhao Tian. "Review of agricultural IoT technology". In: *Artificial Intelligence in Agriculture* 6 (2022), pp. 10–22.

[14] Yeowoon Park et al. "Assessing the impact of the IoT technology–based swine farm environment management system on farm productivity". In: *Bio-Economy and Agri-production*. Elsevier, 2021, pp. 207–220.

[15] Ramnath Reghunadhan and Ansel Elias Stanley. "Socioeconomic impact of IoT on agriculture: a comparative study on India and China". In: *Internet of Things and Analytics for Agriculture, Volume 3* (2022), pp. 201–225.

[16] Sushruta Boruah et al. "INTERNET OF THINGS (IOT) IN PRECISION AGRICULTURE". In: Apr. 2024, pp. 21–31. ISBN: 978-93-5747-509-9. DOI: 10.58532/V3BCAG6P1CH3.

[17] Safianu Omar. "Internet of Things (IoT) for Smart Farming: A Systematic Review". In: *International Journal of Computer Applications* 174 (Mar. 2021), pp. 47–54. DOI: 10.5120/ijca2021921182.

[18] Aakash Sunaratiya. "Sustainable Agriculture: A Review". In: 02 (Sept. 2021), pp. 51–55.

[19] Keith Paustian et al. "Climate-smart soils". In: *Nature* 532.7597 (2016), pp. 49–57.

[20] Thia Hennessy, Doris Läpple, and Brian Moran. "The Digital Divide in Farming: A Problem of Access or Engagement?" In: *Applied Economic Perspectives and Policy* 38 (July 2016), ppw015. DOI: 10.1093/aepp/ppw015.

[21] Irfana Ilyas Jameela Manzil, Ruhul Amin Khalil, and Nasir Saeed. "Performance Analysis of LoRa for Internet of Underground Things in Agriculture 4.0". In: *2023 15th International Conference on Innovations in Information Technology (IIT)*. IEEE. 2023, pp. 213–217.