Radio GOOGOO: Generation of Optimized Output Gain Over Oscillation

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Abstract— **Radiofrequency (RF) waves are oscillating electromagnetic fields generated by the movement of electric charges in an antenna. However, the utility of such waves is not limited to telecommunication applications in cellphones, TVs, and radios. Energy harvesting enables the extraction of electrical power from ambient radio-frequency signals, enabling the development of self-sufficient wireless technologies. Yet, the amount of RF energy harvested can vary due to environmental conditions and the presence of obstacles. Motivated by these challenges, we propose a system that estimates the effect of the operating environment on RF power harvesting. Data collected from humidity, temperature, and distance sensors will enable a comprehensive characterization of the weather impact associated with a specific location. An AI algorithm will process this information to predict the energy harvesting potential at future dates, along with the optimal frequency channels. All records will be available in the cloud, allowing other devices to automatically adjust to optimal settings when placed in the designated area, according to the particular time of the year.**

***Index Terms*— Radio-frequency (RF) energy harvesting, wireless power transfer, environmental sensing, self-powered sensors**

I. Introduction

Proposed by Nikola Tesla in the late 1800s, wireless power transfer aims to provide power without the need for conduits, or to be limited by the capacity of a battery [1]. Instead, the power is harnessed through induced currents from distant electromagnetic waves. Although high-power transmissions are impractical and dangerous, there are still thousands of sources of electromagnetic radiation passing through the air every second.

The objective of this design is to harness those waves, that would otherwise be reflected into space and use them in low-power circuits. This technology is already being researched today, with one of the key obstacles being the reliability of the power spectral density (PSD) [2].

Our design aims to gather data using the power, temperature and humidity, and distance sensors in different settings and at different times to analyze the availability of power in varying conditions. This analysis will be enhanced using machine learning, by feeding the data to an AI software and allowing it to create algorithms predicting the future availability of power.

II. Literature Review

As our description lays out, the design is oriented around the concepts of: RF power harvesting, IOT data acquisition, and machine learning algorithms. Based on these concepts we selected suitable articles to reference previous work in this field. The articles [3] and [4] provide information on the general design. We also chose works [5], [6] and [7] that involve the same RF power harvesting concept but lacked the machine learning aspect.

Designing a power harvesting device such as the one designed in [5] can involve several main aspects. The broader aspects include antenna selection, impedance matching, rectification, and voltage amplification, as is laid out in [5] and [6].

The antenna can be made simply as in [6], or we could implement a simple antenna such as a coiled wire or Bluetooth antenna. As is cited in [6], there are several different frequencies that can be harvested. The antenna developed in [6] is designed to capture 2.4 GHz, one of the commonly used wi-fi bands. Other antennas cited in 4 which may be simpler to design harvest the 520 MHz band and the 890 MHz ~ 960 MHz range.

Impedance matching is a well-studied topic and can be implemented using the methods in [5], [6] or [7]. The different networks all provide their own challenges and advantages. The methods displayed in [5] for creating an impedance matching circuit describes different techniques, such as a simple LC circuit using inductors and capacitors with fixed values, or tunable circuits using MOSFETs and BJTs. In [6] a simple impedance matching circuit is employed a simple T-Match impedance matching circuit which has a fixed value but is very simple to implement. In [7] the importance of an impedance matching circuit is stressed, with options for both single and multi-band networks.

The L-section circuit described in [5] provides passive voltage amplification using a simple capacitor and inductor. In [6] a more rigorous system is used, the Dickson voltage multiplier can double the output voltage with minimal power loss.

To analyze this system, integration of machine learning can pose several challenges. An interface between the Arduino and any machine-learning software could be very difficult to create. As a result, the simplest method would be to feed the machine learning software the information from the device stored in the cloud and create a system as is in [4]. Once this information is processed, a model of the expected power can be created based on sensor measurements. Just like the model created in [3], by recording the environment conditions, and applying this model, the received power can be predicted just as in.

Overall, an integration of the hardware found in [5] and [6] with machine learning described in [3] and [4], while following methodologies described in [7] should suit us best. It will present a suitable IOT design that will be able to receive, monitor, record, analyze and predict future RF power spectral densities.

III. Investigation Details

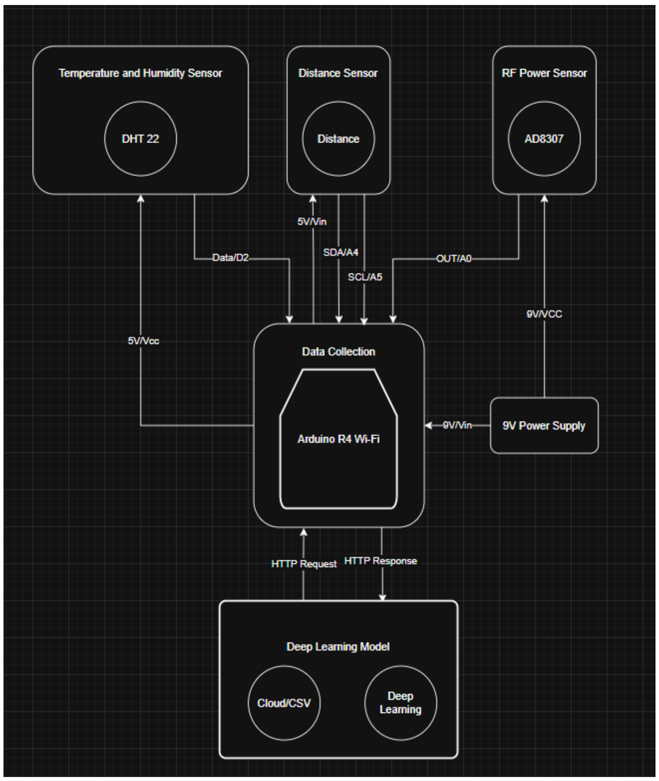

Fig. 1. Block diagram of the Radio GOOGOO channel characterization system, including sensors, an Arduino microcontroller and a Machine Learning (ML) unit.

Before developing our prototype, we needed to divide the design requirements into sections. This is how we arrived at the block diagram in Fig. 1, which outlines the different components of the system. We have environment sensors for temperature and humidity, a distance sensor, and an RF power sensor, all connected to an Arduino that serves as a data collection and management unit. The Arduino uploads unprocessed information to Thingspeak, an IoT platform, in CSV format, so that a Deep Learning Model can access it. To better understand the behaviour of each component individually and together, we constructed a Simulink model of Radio GOOGOO, including a harvesting system. This helped determine the output voltage of each component under trial weather conditions and how the Arduino would read it.

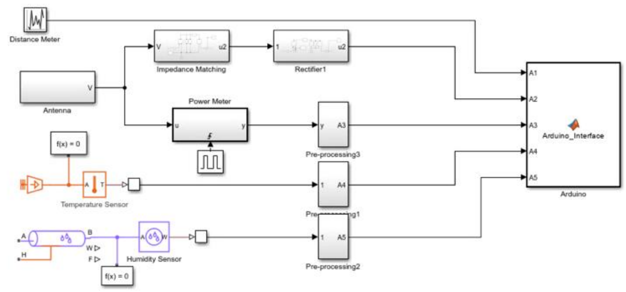

Fig. 2. Simulink model of the proposed system. The simulation includes all sensors connected to the Arduino framework.

After validating our design through simulation, we selected specific components for the device, as shown in Table I, with the corresponding sensor characteristics listed in Table II. The total cost was under 65 Canadian dollars (CAD), but some packages included multiple copies of the same component, so the actual cost to build one unit was lower, calculated at around 40 CAD.

Table I. Bill of Materials

Name	Description	Manufacturer	Cost (CAD)
DHT22	Environment sensor	SparkFun Electronics	13.9
VL5VL33L0X	Time-of-Flight distance sensor	Adafruit	21.78
LT5538 IDD#PBF	RF Power Sensor	Analog Devices Inc.	16.99
Arduino Uno	Microcontroller unit	Arduino	9.57

Table II. Sensor Characteristics

Sensor	Short Description	Main Parameters
Power	Monitors RF power received	- Bandwidth = 40 MHz to 3.8GHz - Dynamic range = 75dB - Sensitivity = -72dBm - Power supply range = 3V to 5.25V - RF Input power range = -75dBm to 10dBm
Temperature and humidity	Characterizes environmental conditions such as temperature and humidity	- Temperature range = -40°C ~ 80°C +-0.5°C - Humidity range = 0 ~ 100% RH ±2% RH - Power supply = 3.3-6V DC - Communication protocol = digital signal via MaxDetect 1-wire bus - Long term stability = +-0.5%RH/year
Distance	Calculates the distance from the closest obstacle	- Emitting wavelength = 940nm - Sensor Capabilities = 50mm – 1.2m - Operating voltage = 2.6-3.5V DC - Communication protocol = I2C - Operating temperature = -20 to 70°C

All components were integrated into a single PCB that acts as a shield on top of the Arduino. We first built the schematic in Altium (Fig. 3) and then designed the PCB with both top and bottom layers populated (Fig. 4 and Fig. 5, respectively). Since the RF Power sensor has a higher voltage rating than the Arduino can provide, we added a 9V battery to the prototype. Therefore, Pin 2 is not connected to anything on the board because it is connected to the positive terminal of the battery. The copper layers represented by the solid blue and red colours on the design are polygon pours associated with the ground (GND) net and are connected to the negative of the battery.

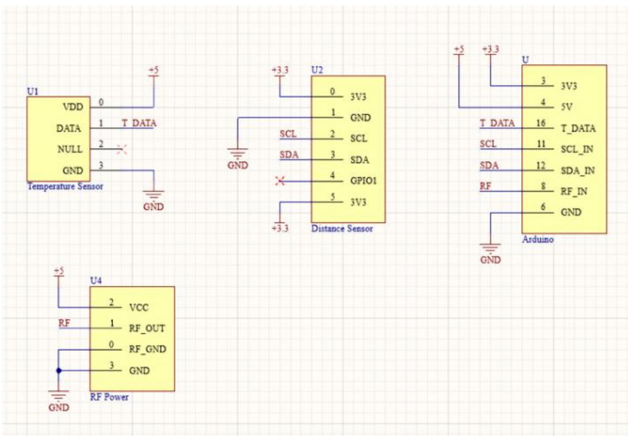

Fig. 3. Schematic of the circuit containing the sensors and Arduino.

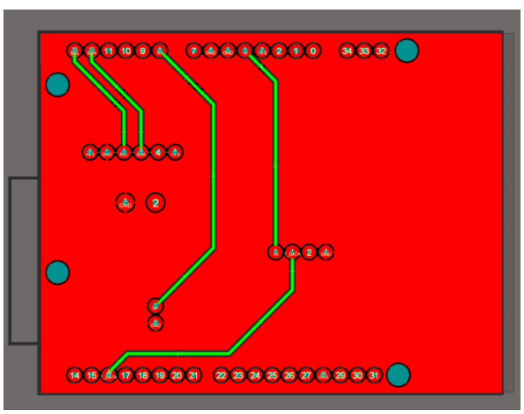

Fig. 4. Top layer of PCB. It includes data traces for all the sensors and power traces for the temperature sensor. Pin 2 is not connected to a power trace since it is externally attached to the 9V battery. The red plane is a shared ground between all GND pins.

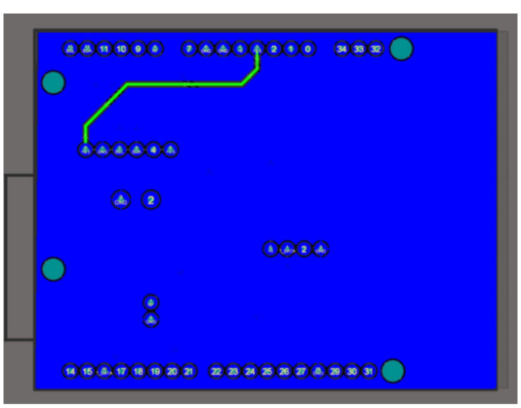

Fig. 5. Bottom layer of PCB. Includes a power trace for the distance sensor, along with a ground plane represented by the solid blue colour.

During the implementation process, we used the PCB milling machine at the University of Ottawa Maker Space because it enabled shorter iteration times. This approach was more demanding than ordering a PCB from a manufacturer, since the milling machine can only drill and carve the traces on the copper sheet, without additional processes. Soldering also presented a significant challenge. The drilled board does not have connections between the top and bottom layers in the pads. As a consequence, we have to solder the pins to both the top and the bottom to ensure the connection. Additionally, the lack of dielectric material on the PCB surfaces increases the chances of shorts. After four board iterations, we arrived at the functioning prototype in Fig. 6.

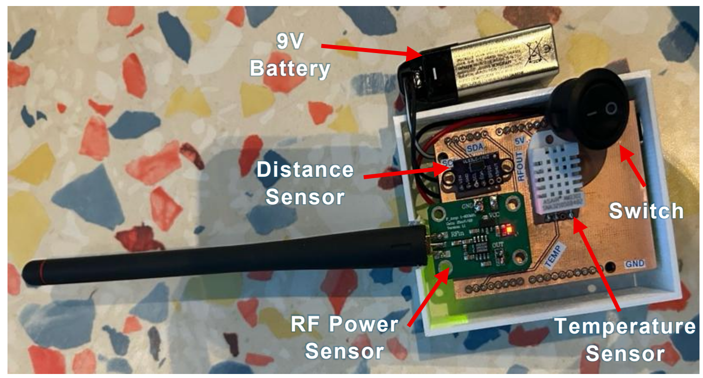

Fig. 6. Functional prototype inside the open enclosure. The PCB is placed as a shield on top of the Arduino in order to reduce space requirements.

Once we confirmed that the board could collect data, the next step was to transmit the information via Wi-Fi to ThingSpeak host platform in CSV format. This is done via HTTP using the Arduinos Wi-Fi capabilities. A sample of the data produced is presented in Fig. 7 and demonstrates a visualization of the data received. This readily available dataset can be appended and improved in future exploration and can be readily employed to any machine learning platform required.

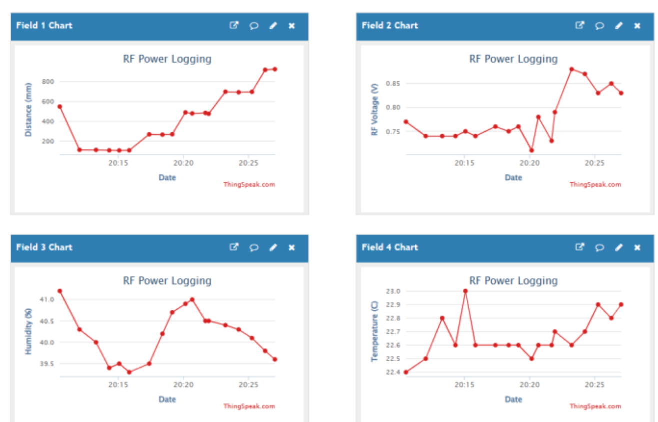

Fig. 7. Sample ThingSpeak channel monitoring the progress of the sensor data

With the improved accessibility of the data produced, a test was conducted to demonstrate the capabilities of the device's sensor data. Placing the device on the floor at the end of a hallway in front of an exterior door, the device produced data points as it was moved progressively backwards. This test does not fully demonstrate the effects of the temperature and humidity on the data but shows the predictive features of the dataset based on distance from a significant object. In real scenarios the device would collect data at different times of day or different times of year. This would allow the model to predict patterns in the RF power based on time and weather conditions.

The results of the test were exported via CSV to an accessible environment. Then, using two machine learning models from Scikit-Learn, the data was cleaned and processed as proof of concept. Training the model with so few data points required very few epochs to obtain the same results. Although our data did not provide much insight into the overall availability of RF power, it demonstrates the functionality of the device and the transfer of data to the deep learning model.

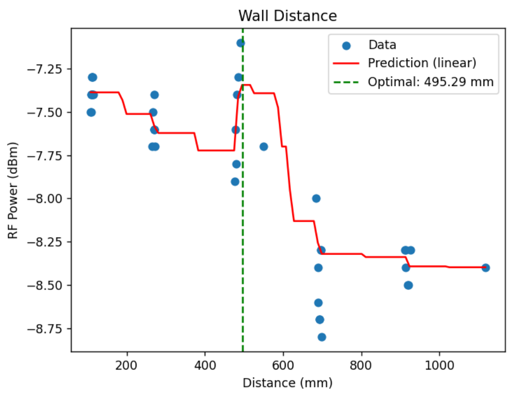

Fig. 8. Trained RandomForestRegressor machine learning model optimal distance from the wall to obtain the best power.

The plot in Fig. 8 demonstrates the output of the trained model based on a nonlinear training model, RandomForestRegressor. Which produces a trained model that closely follows the limited data provided. With improved data this model could understandably provide a very accurate description of the available RF power. In this implementation, because of the limited dataset, the regression is choppy and uncertain but can certainly improve.

Then Fig. 9 depicts a different model LinearRegression is implemented to attempt to characterize the channel with a linear fit. The fit is fairly accurate, capturing the decreasing availability of power as the device moves away from the door. Notably it defines the closest point to the door as having the most power. This is evident in the raw data which the Random-Forest-Regressor failed to predict.

Fig. 10 demonstrates a trained model, also using LinearRegression, with a second order polynomial fit. This can be more appropriate in scenarios where the received power drops off exponentially. Such as with free space loss as in the line-of-sight formula

$$P_R = G_T G_R P_T \left(\frac{\lambda}{4\pi r}\right)^2 \quad (1)$$

where the received power P_R decreases exponentially with r. Although this model does not fit our data very well, over larger distances it could be very useful.

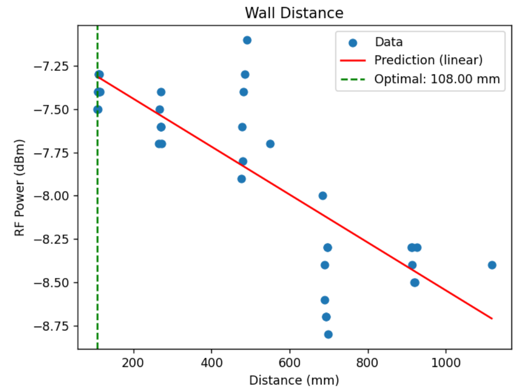

Fig. 9. Trained LinearRegression machine learning model optimal distance from the wall to obtain the best power.

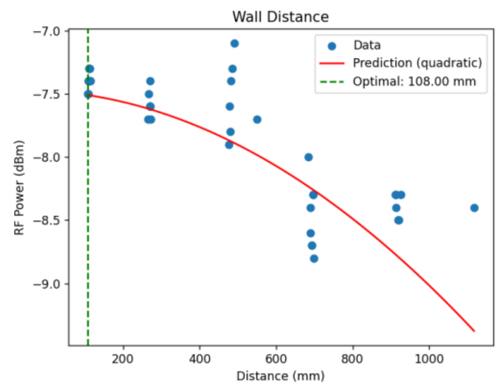

Fig. 10. Trained LinearRegression machine learning model with second order polynomial features optimal distance from the wall to obtain the best power.

The machine learning predictive plots produced demonstrate an impressive prediction of the available power channel even with very limited data, providing potential for future implementation.

IV. Discussion

This paper proposes an altercation to a recently popularized technique to characterize and parameterize RF channels for power harvesting purposes, implementing deep learning techniques in pursuit of accurate predictions of available power. The revolutionary concept has already been explored by several other groups [2] [3] [4] hoping to create new branches of channel modeling. To further parameterize the RF channels ability to provide power, we implement additional sensing capabilities in temperature, humidity and the distance to an appropriate object or surface.

The temperature is an important characteristic of RF channels and is the main contributor to added white gaussian noise in RF channels. If an RF power harvester expects a signal with a particular frequency, then for the rectification process to perform well, certain capacitance and resistance values must be tuned to optimal values. The introduction of random noise to the channel produces random fluctuations that have the potential to hinder the rectification process. The noise power is an important metric of the noise in a channel:

$$P_n = kTB. \quad (2)$$

Where T is the temperature, B is the bandwidth, and k is Boltzmann's constant. By increasing the temperature of the system, this metric increases and the noise received by the device is increased.

Additionally, the humidity of the channel can significantly decrease the received power as the ambient water molecules will absorb the transmitted power and reduce the available power. The equations that characterize the effects of humidity on wireless channels are often detailed and lengthy to solve.

A well-documented impact of shadowing, losses caused by the nearest large object to the device. Huygen's principle dictates the diffraction caused by large objects with complex formulas and notation. For the loss caused by multiple screens, the Epsein-Peterson method is used to determine the diffraction losses caused by a series of large objects.

Each of the listed constraints on power harvesting capability is incorporated into our measurement device. The device aims to gather data from these sources and produce a deep learning model. This model will circumvent the complex analysis typically required to assess the characteristics of an RF channel and improve the implementation of RF power harvesting devices.

The simulation of our device seen in Fig. 2 demonstrates its functionality, gathering data from the sensors and recording it in the Arduino interface. Once the project was fully assembled as seen in Fig. 6, the full functionality was demonstrable, and data could be recorded.

The next step to utilize the data gathered by the device was to effectively record the data within a database. To do this we utilized the Thingspeak IoT platform, as seen in Fig. 7, to record data and ensure that the information recorded by the device was accurate.

Then a simple experiment was performed to gather data for analysis to determine the availability of RF power in a hallway at various distances from the door. This data was recorded in Thingspeak and uploaded to CSV format.

Once the data was made fully accessible within a convenient format, it could be introduced to a deep learning model to create models of the behavior exhibited by the RF power under various conditions. The results of the two regression models are surprisingly insightful for the limited scope they perform. Despite the crude nature of the test, the results show a rough trend as the distance is varied, and this is well captured by the nonlinear and linear regression models.

V. Conclusion

To conclude, the results of this paper detail the procedure that produced a successful implementation of an RF power measurement tool and could prove incredibly useful top the field of RF power harvesting as well as other related fields.

Despite several setbacks throughout the process, including PCB printing issues, Wi-Fi and Bluetooth data transfer problems and a limited timeframe, the project was successful. The device is capable of gathering accurate data which can be easily transferred to an appropriate machine learning model to assess the characteristics of the local RF power.

Future investigation into this domain could certainly seek to improve on the size and scope of the research, however this paper outlines the framework needed to produce a replicable IoT system to measure and analyze ambient RF power in different environments.

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References

[1] Nikola Tesla, *"The Transmission of Electrical Energy Without Wires," Electrical World and Engineer*, vol. 39, pp. 23–24, 1902.

[2] *"Energy Harvesting Sensor Nodes: Survey and Implications,"* IEEE Communications Surveys & Tutorials**,** vol. 13, no. 3, pp. 443–461, 2011.

[3] R. H. B. A. F. M. B. K. L. K. H. Chen Huang, "Artificial Intelligence Enabled Radio Propagation for Communications—Part I: Channel Characterization and Antenna-Channel Optimization," IEEE Transactions on Antennas and Propagation, vol. 70, no. 6, pp. 3939-3954, 2022.

[4] A. S. M. A. Y. H. A. F. E. Shaimaa H. Mohammed, "A complete artificial intelligence pipeline for radio frequency energy prediction in cellular bands for energy harvesting systems," Engineering Applications of Artificial Intelligence, vol. 133, 2024.

[5] K. M. Zohaib Hameed, "Design of impedance matching circuits for RF energy harvesting systems," Microelectronics Journal, vol. 62, pp. 49-56, 2017.

[6] D. T. C. M. Shobha A.S., "Design and Development of RF Energy Harvesting Module for Low Power Device using Propulsion Concepts in Renewable Energy," Journal of Propulsion Technology, vol. 44, no. 3, pp. 891-898, 2023.

[7] M. J. S. S. S. A.-B. S. K. I. M. T. I. A. A. M. S. I. Husam Hamid Ibrahim, "Radio Frequency Energy Harvesting Technologies: A Comprehensive Review on Designing, Methodologies, and Potential Applications," Sensors, 2022.

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