CORNELL ENGINEERING. ELECTRICAL AND COMPUTER ENGINEERING
ESCUELA TÉCNICA SUPERIOR DE INGENIEROS INDUSTRIALES Y DE TELECOMUNICACIÓN

CORNELL UNIVERSITY
UNIVERSIDAD DE CANTABRIA

Final Degree Project

FOREIGN OBJECT DETECTION FOR A CAPACITIVE WIRELESS CHARGER
(Detección de objetos extraños para un cargador inalámbrico capacitivo)

To access the Title of

GRADUATED IN INDUSTRIAL TECHNOLOGIES ENGINEERING

Author: Raquel Sarabia Soto

June-2022

ACKNOWLEDGMENT

To my family that has always helped me and supported me to achieve my dreams.

To Khurram, who welcomed me in his research group and offered me the opportunity to do this project. To Sounak and Dheeraj who guided me through the process.

To my Redbuddies, who helped me concentrate in the dining room (or the complete opposite thing) specially Nat and Vaish who thought me ML, and Rachel, who supported me through the entire process of writing this thesis and was the best roomate I could have had.

To the Cornell Triathlon Club that was like a family for me and brought wonderful people to my life.

To Juan, for everything.

To Cornell University that exceeded all my expectations and gave me an experience I will never forget.

Finally, to the University of Cantabria that gave me this exchange opportunity, to the people that have made me achieve it and to all the professors who made all this possible.

Thank you all.

ABSTRACT

One area that is currently attracting a lot of interest is the development of electric vehicles and the associated charging infrastructure. An approach for charging being considered is wireless charging. Wireless charging, inductive or capacitive, presents many advantages, but certain problems still need to be addressed, such as the creation of potentially hazardous conditions in the presence of foreign objects including living objects.

This thesis focuses on foreign and living object detection for a capacitive wireless charger. The object detection is based on the measurement of the wireless charging transmitter’s output impedance and the temperature of the surrounding objects before the charger is turned on. The objects are classified into different categories using a logistic regression algorithm which is able to correctly classify objects with an 89% accuracy. Furthermore, the classification has 100% accuracy for the case when there are no objects in the neighborhood of the charger or when a living object is present.

RESUMEN

Una de las áreas que más interés está suscitando en la actualidad es el desarrollo de vehículos eléctricos y su infraestructura. Una de las opciones para su carga que se está considerando es la carga inalámbrica. La carga inalámbrica, ya sea inductiva o capacitiva, presenta muchas ventajas, pero hay problemas que aún necesitan ser resueltos como la creación de condiciones potencialmente peligrosas en presencia de objetos extraños incluyendo seres vivos.

Ésta tésis se centra en la detección de objetos extraños y vivos para un cargador inalámbrico capacitivo. La detección de objetos se basa en la medida de la impedancia de salida del transmisor del cargador inalámbrico y de la temperatura de los objetos antes de que el cargador sea encendido. Los objetos se clasifican en cuatro categoría diferentes usando un algoritmo de regresión logística, que es capaz de clasificar correctamente los objetos con una precisión del 89%. Además, la clasificación tiene un 100% de precisión en el caso de que no haya objetos alrededor del cargador o cuando el objeto presente es un ser vivo.

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1 INTRODUCTION

1.1 WIRELESS CHARGING

Wireless charging is a technology whose usage is expanding. It is already commonly used to charge small devices such as smartphones and smartwatches. However, new applications and use cases are demanding higher performance from it. One of the most prominent examples of a new application that is driving the further development of wireless charging is electrical vehicles (EV). Although they are nor dominant in the vehicle market, sales of EVs are increasing at a high rate every year. In 2021 there was an increase in EV sales of 8.3% compared to 2020 [1]. This increase is not only observed in passenger vehicles, but also in public transportation such as buses in cities.

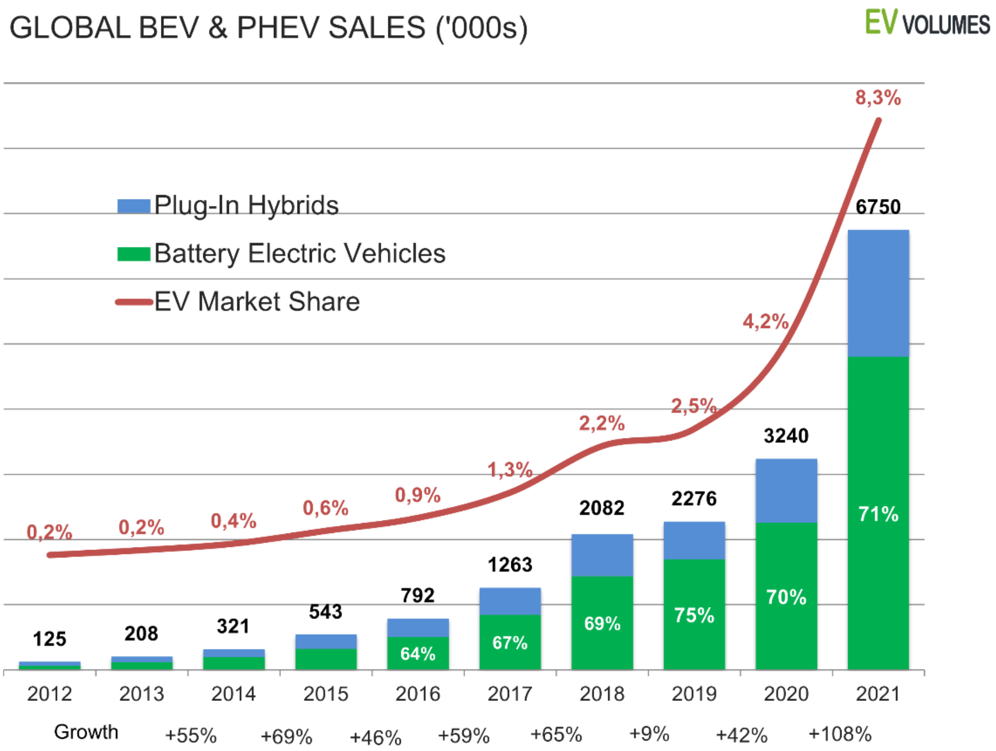

Figure 1. Evolution of EV sales (2012-2021) [1]

As this number increases, it becomes necessary to develop new ways of charging EVs. Wireless charging for EVs offers lots of advantages. For example, it eliminates the expense of wires, cables and connectors, and it allows vehicles to charge without human intervention in convenient locations such as parking lots and traffic lights.

Wireless charging of EVS can even take place while they are being driven on roads. The two types of wireless charging techniques, stationary wireless charging and dynamic wireless charging, can be differentiated based on how the charging takes place.

The two types of wireless charging techniques, stationary wireless charging and dynamic wireless charging, can be differentiated based on how the charging takes place.

Stationary wireless chargers require the EVs to be stopped. The stationary charging could take place in a parking lot, in front of a traffic light, or even in garages. In contrast to stationary wireless chargers, dynamic wireless chargers would work when the EV is moving along the road by placing a network of chargers under the road. Even if dynamic chargers present more challenges and room for error such as misalignment between plates or big air gaps between the plates, they could offer benefits such as decreasing the size of the batteries needed in EVs and hence reduce their cost [2].

Near-field wireless power transfer (WPT) systems can be classified into two categories: capacitive WPT and inductive WPT. Inductive WPT systems are the most common type of wireless chargers and have been extensively researched and developed. However, they use ferrite cores that are heavy, fragile and expensive. The ferrite cores also limit the operating frequencies of the charger due to core losses. This makes inductive WPT systems large and expensive. On the other hand, capacitive WPT systems do not require the use of ferrite cores making them less expensive [2]. Since they do not utilize ferrite cores, capacitive WPT systems can operate at higher frequencies than the inductive systems, providing an opportunity for size reduction [3].

1.2 INDUCTIVE WIRELESS CHARGING

Inductive Wireless Charging is the first WPT method that was used and was developed by Nikola Tesla over 100 years ago. It is also the most widely researched and used type of wireless charger in literature and in real life applications. Due to its extensive use, a lot of research has also been done on foreign object detection (FOD) for inductive wireless chargers.

The main characteristic of this type of charger is that the power is transmitted through coupled inductors by a magnetic field. The advantages of these type of chargers are that they have relatively good efficiency and they have been developed to the level that they can already be used and there is a lot of research in this area.

1.3 CAPACITIVE WIRELESS CHARGING

Capacitive Wireless Chargers use capacitively coupled plates instead of inductively coupled coils, so the power is transmitted through an electrical field. While they present many advantages compared to inductive ones, they are still in early stage of development. They are being researched as there are some challenges that still need to be solved before they can get introduced into the market. Unlike inductive wireless chargers, capacitive systems are not readily available in the market and most such systems are found in research labs. For this reason, there is not a lot of research that has been done on certain aspects of capacitive wireless charger, including on FOD.

1.4 FOREIGN OBJECT DETECTION

In WPT systems (both inductive and capacitive), the electric power is transmitted from the transmitter to the receiver through an air gap. Different foreign objects can get into this gap, which could affect the performance of the charger, harm the foreign object, or damage the wireless charger. The case in which the foreign object is a living object is especially critical, as the living object could get seriously harmed when it entered the gap while the WPT was activated and delivering appreciable power.

Because of this, it is crucial to be able to detect foreign objects in order to further develop capacitive wireless charging technology. Object detection can help determine whether the system should or should not be activated if an object is present in the gap depending on the type of object identified.

Several methods of detecting foreign objects have been studied for inductive WPT systems [4]. These methods are mainly focused on metal object detection (MOD) because if metal goes into time varying magnetic fields, it gets heated by eddy currents and its temperature increases rapidly, which can start a fire and damage the charger [5]. Living object detection has also been studied, with several different approaches. The majority of these studies utilize GHz radar sensors and are only focused on living object detection (also known as living object protection) but there have also been some methods that propose a combined object detection and living object protection. [6]

Capacitive WPT systems are less common, so there is not much literature about foreign object detection. Some of the object detection strategies that have been used in inductive systems could also work for capacitive systems. However, most of the strategies that have been used will most likely not work due to the magnetic properties of the foreign objects that inductive systems focus on.

1.5 MACHINE LEARNING

In order to determine whether the charger should be turned on in the presence of an object, a Machine Learning (ML) approach can be beneficial to help classify the detected object. ML is a type of artificial intelligence that can analyze and process data and learn from it in a manner similar to how humans learn. Its algorithm has three main steps. First, a decision process is executed where, given some input data, the process will make an estimate based on a pattern found in the data. Secondly, the process will compare this result with an error function which will determine the accuracy of the result. Lastly, the model will optimize itself until a sufficient level of accuracy is reached.

Given that the ML used in this project is aimed to identify objects by classifying them into different categories, supervised ML will be used. Supervised learning is a type of ML that uses labeled data in the training process and adjusts the weights given to each category to increase the accuracy of the model. Several supervised ML methods will be considered to try to solve the problem such as logistic regression, k-nearest neighbors and decision trees [7].

1.6 OBJECTIVES

The main objective of the present work is to determine if it is possible to classify objects placed on top of the transmitter of a capacitive wireless charger. To do this, several experiments are run in the lab. Each object is placed on top of the charger's transmitting plates and two types of information is gathered. First, using an impedance analyzer, the effective output impedance of the transmitter and other associated electrical parameters are measured. Secondly, the temperature of the object placed on top of the charger is measured.

Once all the data is collected, it is fed into a ML algorithm. For doing this, part of the collected data is used as training data, which is used by the ML algorithm to determine a pattern in the data and create the classifier. The remaining data is used as testing data to determine the accuracy of the classifier. The classifier classifies the objects in the training data into different categories. If the results of doing this testing are good, that is, the ML model has a high accuracy, then it will be possible to use this classifier to detect and classify objects present on top of the charger.

2 FOREIGN OBJECT DETECTION

While WPT systems have their advantages, there can be some safety issues given the fact that there exists a physical gap between the transmitter and the receiver which a foreign object could enter and cause a hazardous situation. Depending on the type of object that enters the gap, there may be a resultant loss in efficiency, a malfunction of the transmitter or harm caused to the foreign object. Not only can this create a problem for the wireless charger itself, but it can also cause harm to living objects.

While some objects can negatively impact the wireless charger or themselves get harmed or damaged, there are some objects that would not be affected by the electric fields of the capacitive wireless charger and would also not damage the charger. With such objects in the air gap the charger will be able to transfer power without any concern for harm or loss of efficiency. For this reason, it is important to be able to identify the objects that can cause an issue versus those that will not cause a problem. This will allow the charger to be shut down only when needed.

2.1 METAL OBJECT DETECTION

Metal objects are affected by electromagnetic fields and can therefore impact the functioning of wireless charging systems that transmit electric and/or magnetic fields. For example, nearby metal objects could change the output impedance of a wireless charger's transmitter which could cause large currents to flow and lead to a malfunction of the wireless charger. In addition, the metal object could get affected by the electromagnetic field in such a way so as to get heated very fast [5], which could result in a fire in case it is in contact with a flammable object such as a piece of paper. In inductive WPT systems, several studies have shown that when a metal object gets between the inductive coils, it gets heated by the eddy currents induced by the time varying magnetic fields through induction. This makes Metal Object Detection (MOD) very important for inductive wireless charging systems. The impact of metal objects on capacitive wireless charging system has not been studied extensively. In theory, the heating of metal objects should not happen in capacitive WPT systems, as time varying electric fields impinging on metal objects do not produce eddy currents.

However, there can always be unanticipated second order effects due to non-idealities in a practical system. Therefore, there is a need to study how metal objects interact with capacitive WPT systems and determine if foreign metal objects cause any problems. Furthermore, metal object detection (MOD) will also be studied.

2.2 LIVING OBJECT DETECTION

Living objects can be harmed if they enter the gap between the transmitter and receiver of a wireless charging system. They may even be harmed if they are in close proximity of the charger if the electric fields are high. Putting aside how the device can get affected, it is imperative that the device shuts down to avoid harming any living object. Regarding living objects, there is a need of being able to both detect the object and differentiate it from others. With the method that will be used the way of detecting them will be first by observing the electrical variations that the object causes in the device and also by measuring its temperature. We can expect that at least for warm-blooded living objects, the temperature will help a lot to differentiate them from other objects as their temperature is usually higher.

Some limitations that are present is that it is really difficult to collect data from living objects as we will need to take them to the lab. Because of this, the model developed will include as data the experiments done by placing hands over the device with power turned off instead of doing the experiments with different living objects such as animals.

2.3 OTHER OBJECTS

A wireless charger for electric vehicles could be used in the future anywhere, both in closed spaces and in open spaces such as the street. Because of this, they are susceptible to being surrounded by multiple objects. Studying how different objects affect the system will help us to determine which ones we will have to check, and which ones are harmless and do not affect the device or its efficiency. Objects such as dust, wet surfaces, tree leaves, sticks, mud, or any other object that can be in the ground may have different effects, and even if they might not be harmful, they could decrease the efficiency of the device. Against these objects, we might not need to do anything in some cases, but maybe in others the surface of the charger should be cleaned to avoid power losses. In addition to this, if some of these objects could cause harm, the device should be turned off as well. Thus, the model should be able to differentiate between when there is an object or there is not and it should be able to detect how much the parameters of the device are changing as well. By doing this the objects can be classified as objects that will decrease the performance of the charger and objects that will not.

3 SENSING AND DETECTION

As mentioned in the introduction, detecting certain objects and being able to turn off the device to avoid any harm will be crucial. All the methods presented in this section are limited to sensing and collecting information. In order to be able to classify and identify the objects, the sensing information will have to be analyzed with classification or detecting algorithms.

There are many ways that we can use for detecting foreign objects. Some of them will be limited to a certain number of objects and will be useless for others, while other methods will be useful to deal with many different objects. Depending on how each method measures, we can differentiate between two different ways of detecting foreign objects: electromagnetic detection methods and sensor-based detection methods.

3.1 ELECTROMAGNETIC DETECTION METHODS

Foreign objects may cause a variation in the electric fields of a capacitive WPT system. For this reason, if we can measure different parameters of our system, we will be able to determine if there is an object in the air gap of our system or in its vicinity. Depending on if we have an external circuit to measure these changes or if we are directly measuring the system's parameters, we can make two categories:

3.1.1 Detection methods without an additional circuit

A variation in the system is used to determine the existence of an object. As well, the different variations compared between them might help us to determine what type of object is being observed.

- Detection method based on an impedance deviation

  By measuring and computing the ratio of the voltage and the current at a port of the wireless charging system we can track variations in the value of the port's output impedance, and if this impedance varies from the value without any foreign object, we can determine the presence of an object.

- Detection method based on a voltage and current deviation

As seen in the previous method, a change in the system's impedance will affect the current and the voltage. By measuring the drain waveform deviation of the power switches objects can be detected.

- Detection method based on a phase shift
  If the phase shift between the current and the voltage exceeds a threshold, we could state that there is an object affecting the system.

- Detection method based on a resonance frequency deviation
  A change in the impedance of the system will cause a variation on the resonance frequency of the system, thus by comparing the frequency with no foreign object present, the presence of an object could be determined.

- Detection method based on a Q factor deterioration
  The loaded quality factor changes when there is a change in the output impedance and the resonance frequency, so again, if we compare the actual value with the value of Q without any foreign object, we can detect an object.

- Detection method based on power loss
  An external object can cause the efficiency to decrease, forcing the transmitted power to change, as a result, comparing the power loss with measured input and output powers, an object can be detected.

3.1.2 Detection methods with an additional circuit

Methods that utilize additional circuits and/or coils have been developed for inductive wireless charging systems. These use the coupling properties of the coils. Some of the methods that have been proposed are the following:

- Detection method based on an active impedance deviation
- Detection method based on an active power deviation
- Detection method based on a passive induced voltage deviation [4]

In this study, detection using additional circuits for capacitive WPT systems will not be developed as this is beyond the scope of this work.

3.2 SENSOR-BASED DETECTION METHODS

Sensor-based methods are an external way of detecting objects. As these methods do not depend on electrical properties of the wireless charging system, they do not have to change between inductive and capacitive WPT. Because of this, existing literature will guide us towards existing methods that have been already tested on inductive systems and that we can use in a capacitive system. They also have some advantages compared to the electromagnetic methods, as not being limited by the WPT's power or operating frequency, it allows misalignments between the plates and some of them can detect any kind of object including small objects.

The different methods we can use are the following:

- Temperature sensor, thermal camera, or thermistor
- Pressure sensor
- Radar sensor and ultrasonic sensor
- Camera
- Infrared sensor [8]

4 CAPACITIVE WIRELESS CHARGING MODEL

4.1 CAPACITIVE WPT ARCHITECTURE

The wireless charging system that is being used in this work is the capacitive wireless charger developed by the power electronics group at Cornell University led by Professor Khurram K. Afridi. The wireless charging system is the following:

The system transmits power across the air gap utilizing two pairs of capacitively coupled plates, two plates located underneath the EV and the other two in the roadway or wherever the charger is located.

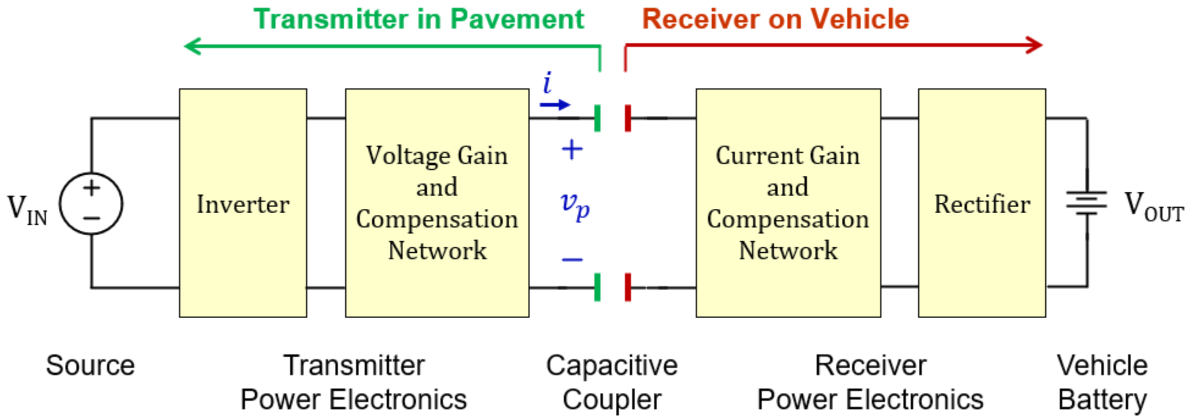

Figure 2. Schematics of a capacitive wireless charger [9]

The electrical power is supplied by a dc input voltage source. In order to be able to transmit the power across the capacitively coupled plates, the voltage needs to be ac. For this a series of power electronics devices are used. First, the input dc voltage is converted into a high-frequency ac voltage by the inverter, and then it gets transformed by a gain and compensation network. Once the voltage gets to the coupled plates, it is transmitted across them and gets to the receiver side. There, the voltage is again converted in a compensation network and the ac voltage is now converted into dc by the rectifier to be delivered to the EV battery to be charged.

4.2 MECHANISM OF A CAPACITIVE WPT SYSTEM

A simplified equivalent circuit can be used to explain how the power is being transmitted (Figure 3).

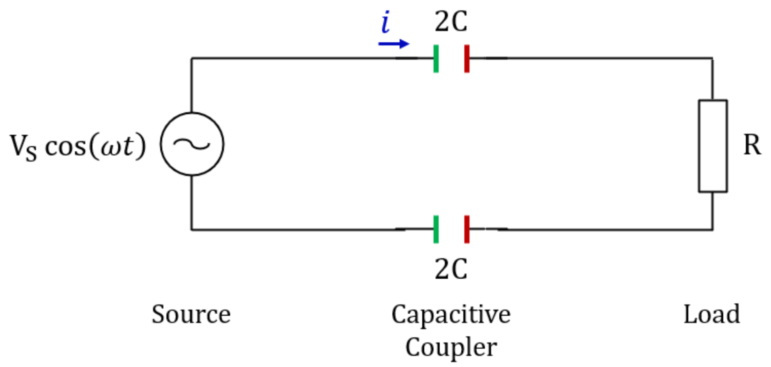

Figure 3. Equivalent circuit [9]

With a sinusoidal source and approximating that each pair of capacitive plates can act as parallel capacitors, and that the value of each capacitance is 2C; using the equation (4.1) we can know the value of the capacitance, where ϵ_0 is the vacuum permittivity, A is the area of the plates and d is the distance between the plates.

$$2C \approx \frac{\epsilon_0 A}{d} \tag{4.1}$$

Capacitance is a property that describes how well the current is able to get transmitted in a capacitor. With big values of capacitance, it is easier to transmit ac current than with a low capacitance. If it is DC current, the capacitor will act as an open circuit and no current will ever get transmitted.

Following this, the capacitance would need to carry a large value. Analyzing the equation (4.1) it can be seen that the value is directly proportional to the vacuum permittivity which has a small value ($\varepsilon_0 \approx 8.85x10^{-12}F/m$). This is a constant that could be improved by using a dielectric between the plates, but the system is limited because there will be air between the plates that separate the vehicle and the charger. As the dielectric constant of the air is approximately 1.00059 this is not a way of increasing the capacitance. Another parameter is the distance between the plates, which is inversely proportional to the capacitance, which means that a small distance is desirable. However, the distance between the plates is always going to be limited by the distance between the ground and the bottom of the car, which is always going to be considerably large (around 12 cm to 20 cm). Lastly, the other parameter is the area of each plate. Even if this parameter could be changed more easily than the other ones, we are limited by the area in the bottom of the car. Furthermore, since we have two plates, we could only use half of the available area for each plate.

Since the capacitance cannot be increased as much as it was desirable, we can look at another parameter that can be analyzed: the power transmitted to the load. For the circuit shown in Figure 3, the power seen by the load is the following:

$$P_{out} = \frac{\omega^2 R C^2 V_S^2}{2(1+\omega^2 R^2 C^2)} \approx \begin{cases} \frac{(\omega C V_S)^2 R}{2} & if\ \omega \ll \frac{1}{RC} \\ \frac{V_S^2}{2R} & if\ \omega \gg \frac{1}{RC} \end{cases} \tag{4.2}$$

This approximation depending on the value of the frequency leads to a system that acts as shown in the following graph:

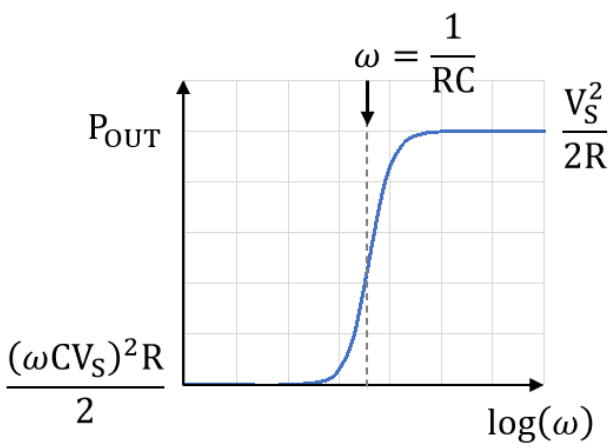

Figure 4. Output power vs frequency for the simplified model [9]

Analyzing Figure 4, two main regions can be identified that are separated by a value of the angular frequency of $\omega = \frac{1}{RC}$. When the charger works at a frequency smaller than this, the power transmitted is practically zero, but when the frequency is higher the power transmitted to the load takes high values. The solution then is to work at high frequencies. The problem with working with high frequencies is that they are hard to achieve (it is still hard to produce waveforms with frequencies near the Gigahertz) and once they are used a high number of parasitic effects that were not observed at low frequencies start to appear, causing losses and decreasing the efficiency of the device.

If we assume then that we are working with low frequencies, the voltage needed to achieve a desired output power is going to be very high (around hundreds of kiloVolts).

On the other hand, using very high frequencies is not possible. Yet, there are no high power transistors that can create frequencies in the order of Gigahertz available in the market.

The next approach is then to create a resonant circuit in order to achieve these high voltages without needing an extremely high voltage input from the source. To achieve resonance electrical storage elements are needed. Capacitors are already storage elements, as they store energy as electrical fields. On the other hand, inductors are another electrical element that storage electricity in electromagnetic fields. By combining these two elements a resonant network can be achieved as shown in Figure 5.

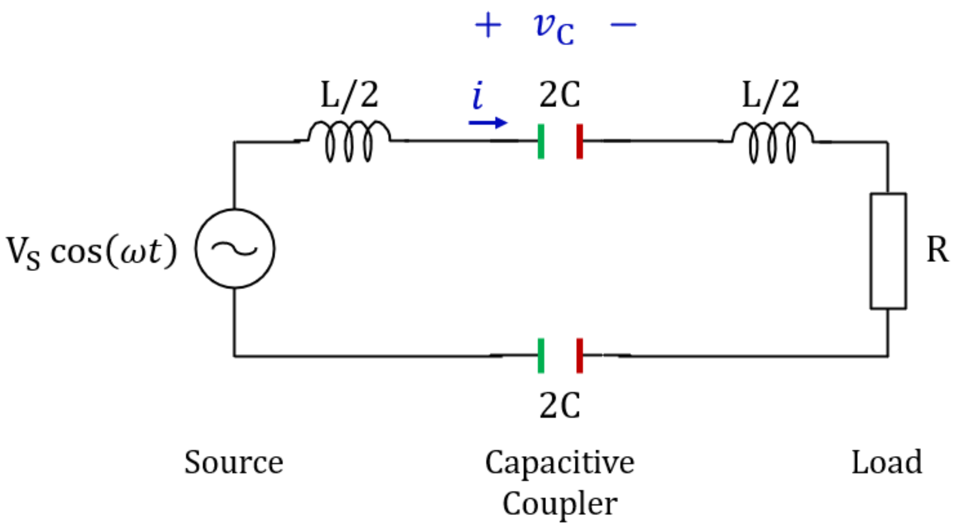

Figure 5. Resonant network [9]

When inductors and capacitors are combined working with an ac current, when the current is high, high magnetic energy is stored in the inductors, and when the current is low, high electric energy is stored between the capacitor plates. However, the only frequency at which the system will transmit energy is at the resonant frequency that has the value shown in the equation (4.3).

$$\omega = \frac{1}{\sqrt{LC}} \tag{4.3}$$

In resonance, the LC circuit will be a short circuit, giving the load a power of $\frac{V_S^2}{2R}$ as it was desired in equation (4.2) but without using an unreasonable value of both ω and

V_S by just choosing the correct values of L and C. However, this approach is not that simple as the value of L will be:

$$L = \frac{1}{\omega^2 C} \tag{4.4}$$

Given that the value of C is going to be a small number and that the value of ω is limited to a certain value, the value of L will be too large in order to be able to physically achieve it.

Because of this, matching networks are introduced as seen in Figure 6.

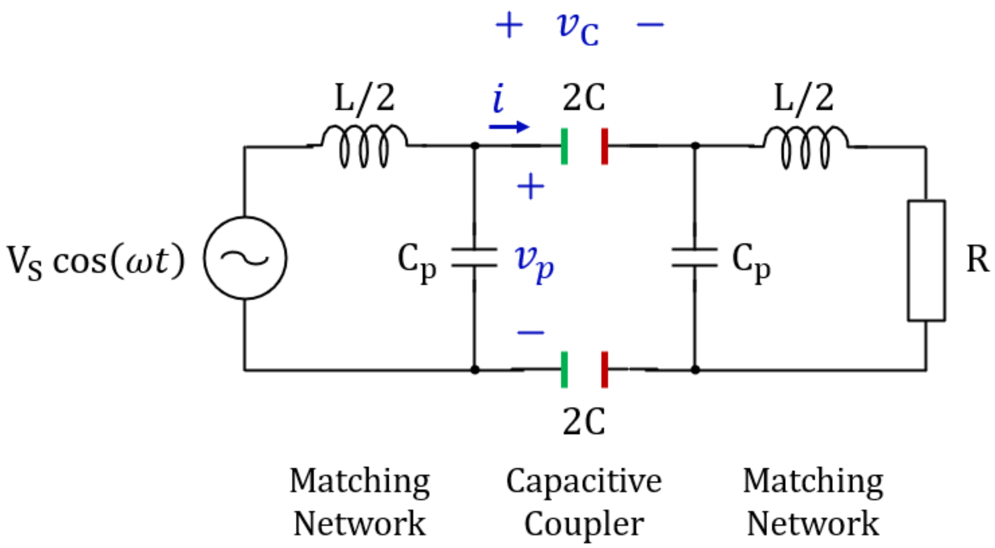

Figure 6. Capacitive WPT System with Resonant Matching Network [9]

By introducing the shunt capacitors (C_p), the current that gets to the Capacitive Coupler is smaller, as part of the current goes through C_p. This also decreases the voltage across the capacitive coupler. The new value of L needed becomes smaller as the equivalent capacitance becomes bigger.

Once the basic capacitive WPT System is designed, there is a need of being able to first from a dc voltage obtain an ac voltage and then from an ac voltage obtain a dc voltage to apply in the load. This is achieved as shown in Figure 7.

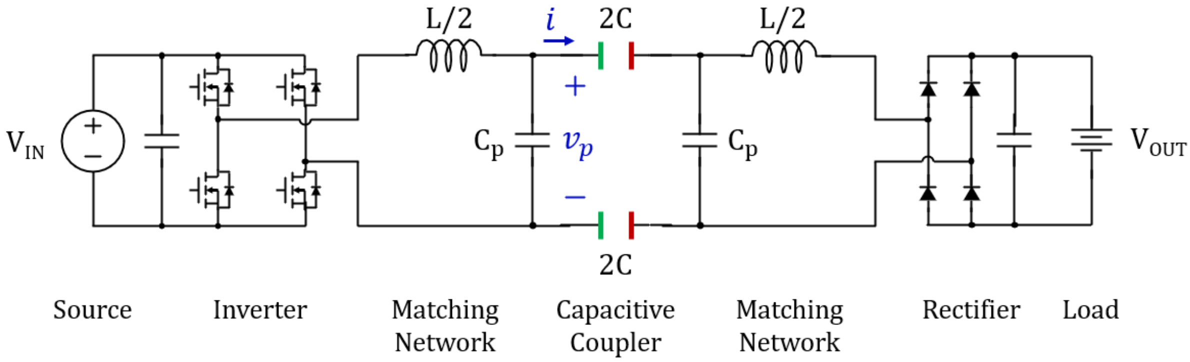

Figure 7. Capacitive WPT System with and Inverter and a Rectifier [9]

First the inverter is used to generate a square wave voltage by turning on and off alternatively the switches, which then gets transformed into sinusoidal ac in the matching network. Afterwards in the rectifier the opposite process takes place and the ac voltage that has been transmitted through the WPT system goes back to dc voltage to charge the battery. After all this analysis we obtain the architecture shown in Figure 2. [9]

5 OBJECT DETECTION BY MEASURING ELECTRICAL PARAMETERS

Every foreign object that gets close to or in contact with the coupling plates is going to influence the circuit. This influence will change the equivalent circuit. The change will depend on the object.

In our approach, the object detection in the capacitive WPT system is going to be made before the charger is turned on to charge. For this initial study we also only consider the case when there is no vehicle in top of the charger.

The equivalent circuit in this case will be the following:

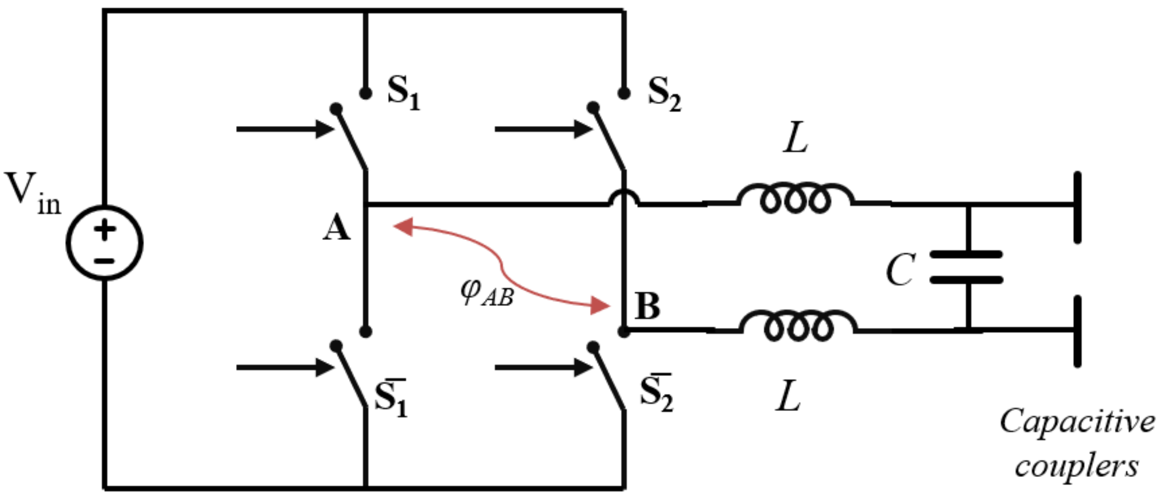

Figure 8. Equivalent circuit of the charger when there is not a vehicle.

When an object gets close to the capacitive couplers, the output impedance seen from the points A and B looking towards the gain and compensation network and the charger side coupling plates in Figure 8 will change. By measuring the output impedance when different objects affect the charger different values will be obtained for each different object that gets tested. Then, by analyzing these different results ML can be applied to differentiate between objects.

When trying to identify the different objects, it will be more important to be focused on differentiating between different categories of objects than being able to perfectly know what object is being detected. This categorization can be done in several ways:

- Groups of objects with similar electrical properties
- Groups of objects that have common characteristics

- Groups of objects depending on how much the charger gets affected
- Groups of objects depending on how much the charger affects them

All these categories can always be mixed. For example, a living object, that would obviously fall under the category ‘living objects’, can potentially fall under the category of ‘high impedance’. These decisions will be made by analyzing the different results obtained both in the lab and when the ML algorithm is applied.

The way the impedance is going to be measured is by utilizing an impedance analyzer, and the circuit used will be one that was already assembled for another experiment.

6 FOD WITH A THERMAL CAMERA

Along with the electrical parameters of each object, other methods can be used to differentiate between objects or groups of objects. For this project, the temperature of each object will be used to gather more information about the object that is being observed. This decision was made because it will make living object detection much simpler. Most of the living objects that we will want to detect have warm blood, as it is mainly focused on animals that can be easily found on or near roads such as cats, squirrels, dogs or even humans. In this approach we will not consider cold-blooded animals such as reptiles as it will not be possible to test them. It is also difficult to use animals to test, as we would need to take them to the lab. As all the experiments that are going to be done will be run at low power, the way of simulating living objects will be by placing the hand on the device.

For measuring the temperature of each object, a FLIR camera will be used. As a low power is applied, the charger will not have a big effect on the object that is being tested, so the temperature measurements will be more information to use in order to classify the different objects.

7 MACHINE LEARNING ALGORITHMS

As mentioned in the introduction, several ML methods will be used in order to determine which one yields the best results for the experiments. In the following sections the different ML methods will be explained, as well as tools that will be used.

7.1 LOGISTIC REGRESSION

Logistic regression is a classification algorithm. It is a statistical technique for predicting a binary outcome based on prior observations of data formed by independent variables, being the output a probability by using a binomial probability distribution [10]. In this work, as the desired outcome will have four different possible outcomes, multiclass logistic regression will be used. In order to do a multiclass classification, the binomial logistic regression method is modified by using a multinomial probability distribution. [11]

7.2 K-NEAREST NEIGHBORS

The k-nearest neighbors algorithm is a supervised learning classifier that uses proximity to make classifications of each data point, under the assumption that similar points can be found near another. Depending on the value of the ‘K’, a different number of neighbors will be considered, and its value will vary depending on each application. [12]

7.3 DECISION TREE CLASSIFIER

Decision Tree is a supervised learning technique that takes its name from being a tree-structured classifier. In it, nodes within a data set represent characteristics, branches represent decision rules, and the leaves represent the outcomes. It is a process that tries to imitate the human thinking ability for decision-making, so within the ML algorithms it is easier to understand. [13]

7.4 CROSS-VALIDATION

For every ML method that will be tested, cross-validation will be applied. The main objective of cross-validation is to ensure that the training and the testing data are independent from each other. The way it works is by repeating each algorithm several times so that every experiment is used as testing data while the remaining experiment are used as training data. Afterwards, the mean of the different results is calculated, in order to get a result that represents the whole set of data.

8 EXPERIMENTS

8.1 First steps

The first thing that needed to be done before running the experiment was to determine what objects we wanted to test and what results we could expect from their measurements. Later it had to be determined what approach was going to be taken for measuring data by choosing the instruments that we needed to run the experiments. Last, it had to be determined how to interpret the data and how to get conclusions from it.

In the process of looking for good results, several different experiments were needed where the way of taking data changed between experiments. In the following parts the different experiments that were run will be explained along with pros and cons of those approaches.

8.2 Test setup

In most of the experiments there were three main components that were used to run the experiments. First, in order to simulate the charger, a prototype that was build for another project was utilized. To make it easier to do the measurements with objects placed over the plates, the mobile part of the prototype was used as the circuit of the mobile part (i.e., the vehicle side) was the same as that on the charger side.

Figure 9. Prototype of the charger used for running the experiments.

In Figure 9 it can be seen how the prototype was. In this prototype, instead of having the transmitter fixed on the bottom, the transmitter was on top and the receiver on the bottom.

Since the objective is to analyze the changes in impedance and not the values of the parameters themselves, the bottom part can be used for the experiments, which is the element shown in Figure 10.

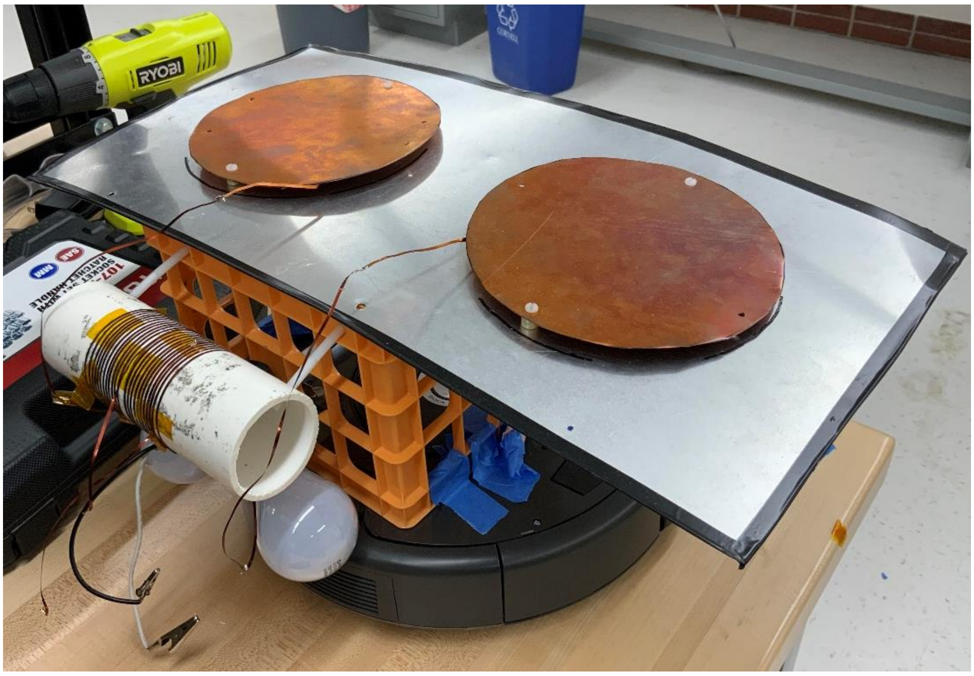

Figure 10. Bottom part of the prototype that was used for the experiments.

For analyzing the impedance a HP–Hewlett Packard 4194A Impedance/Gain Phase Analyzer was used. Among the lots of things that we can measure with this device, we can measure the impedance at different frequencies. For the experiment, a certain resonance frequency was chosen, around the one the data was collected, which will be explained in the following sections.

Last, for collecting the temperature data, a FLIR infrared camera was used.

8.3 Experiment 1.

For the first experiments the following objects were analyzed:

- None
- Wood between the plates
- Metal between the plates

- Living object between the plates
- Plastic object
- Paper
- Water

The way the objects were analyzed was by placing the objects directly over the plates. The first thing that was done was measuring the impedance of the device without any object in it as shown in Figure 11 to get an impedance and a resonance frequency to use as a reference.

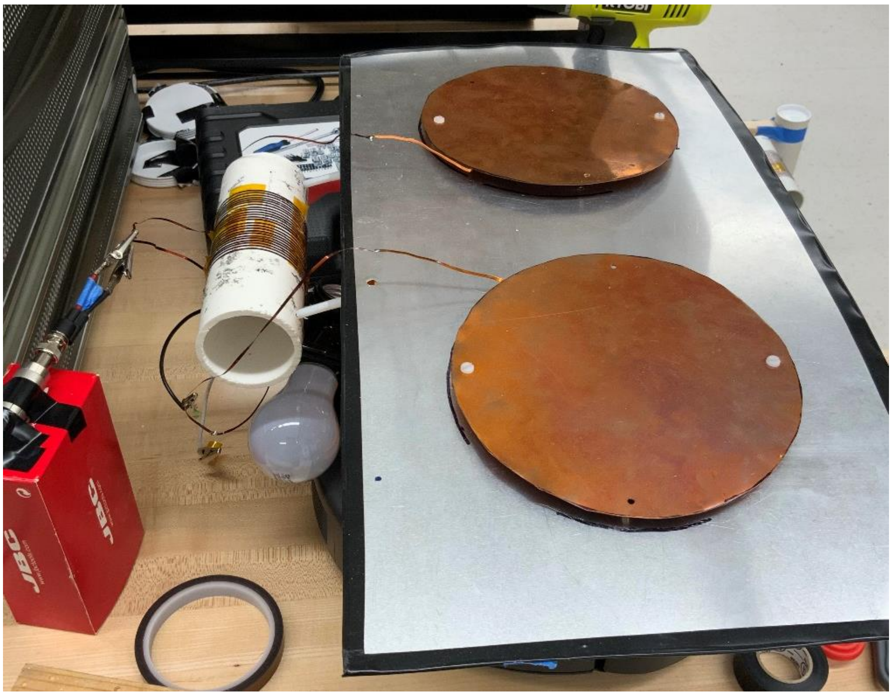

Figure 11. Measuring the parameters of the device without any object on it.

For this first experiment the data collected was the value of the cartesian form of the impedance shown in (8.1).

$$Z = R \pm jX \tag{8.1}$$

The value of the resistance (R) was recorded directly from the data given by the impedance analyzer. Meanwhile, the value of the reactance (X) is the one shown in (8.2):

$$X = \omega L \ or \ X = \frac{1}{\omega C} \tag{8.2}$$

Instead of recording the value of the reactance, the value of the inductance (L) was recorded.

For this first experiment for each different object the R and L were measured for their own resonance frequency, a data that was collected as well. The problem with this first approach is that as every object was measured at different frequencies there was not a good reference object with the it could be compared with.

8.4 Experiment 2.

For this experiment, more objects were tested, and more data was collected from each object. The experiment had two parts. For the first one, every object that was big enough was placed touching both plates as it can be seen in Figure 12. For the second one, every experiment was done placing the objects touching only one of the plates.

The objects that were tested were the following:

- None (the device itself)
- Wood
- Metal
- Living object (hand)
- Plastic
- Plastic container (the one used next for holding the water)
- Tap water in a plastic container
- Distilled water in a plastic container
- Recycled paper
- Metal coins
- Sand

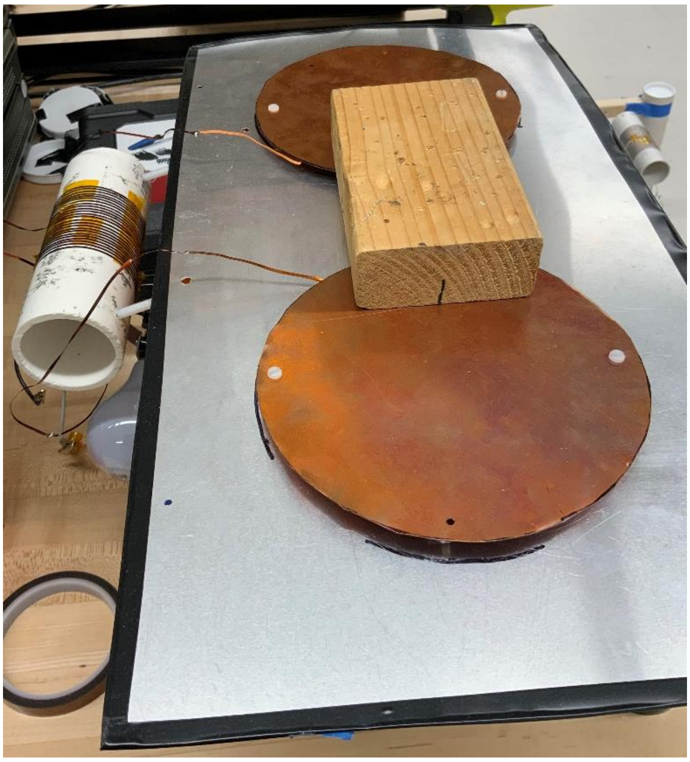

Figure 12. Metal object placed touching both plates.

For each object, the data that was collected was the impedance in its polar form at the resonance frequency of the device. This is the impedance module and its phase. Later, the resonance frequency of the resultant electric circuit originated by the object was found and the impedance was measured.

In this approach, even if the data that was collected was much better than in the previous experiment a problem was found with this way of measuring the data.

First, for most of the objects a simplified equivalent circuit could be the one showed in Figure 13.

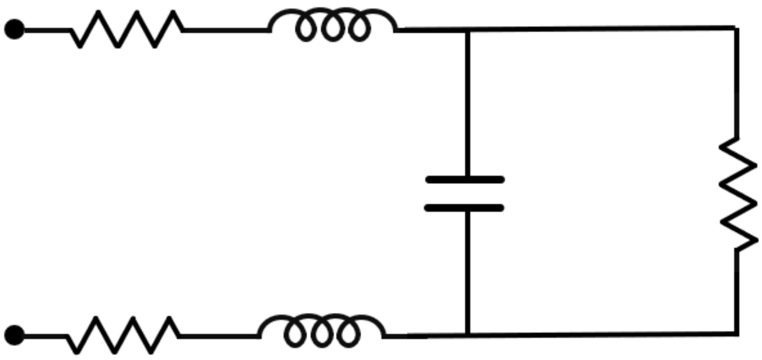

Figure 13. Equivalent circuit when there is an object.

However, for some objects as metal, the object acts as a connector between plates and the capacitor gets shorth circuited. The circuit gets modified into the equivalent circuit shown in Figure 14. Also, as there is not a capacitor anymore, there is not a resonance frequency.

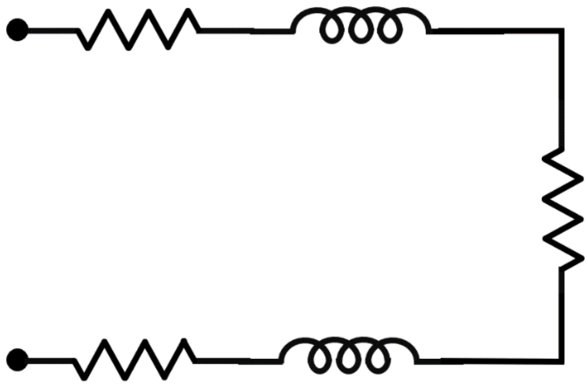

Figure 14. Equivalent circuit when the object short circuits the capacitor.

The main problem with this approach is that it was not considered that in the real world the plates will be isolated, so cases as the one that occurred with metal objects would not happen and the objects will not modify that much the impedance of the equivalent electric circuit.

8.5 Experiment 3.

For this third experiment, the problem of isolation was addressed by placing every object inside of a big plastic box as shown in Figure 15. In addition, more objects that could be easily found on the road were added for analyzing. These new objects were the following:

- Snow
- Tree leaves
- Glass
- Cloth
- Pieces of asphalt

Another thing that was done differently in this experiment was collecting more information about each object. In terms of electric parameters, the impedance (module and phase) was measured for different frequencies: the resonance frequency of the device without any object, at 1.1 times and at 0.9 times the original frequency and lastly the resonance frequency of the new circuit with the object placed. This new resonance frequency was recorded as data as well. In addition to the electrical parameters in this experiment the temperature of each object was also measured. The temperature information is helpful to classify objects as it gives independent information, while the electrical parameters might be dependent from each other and would not give new information.

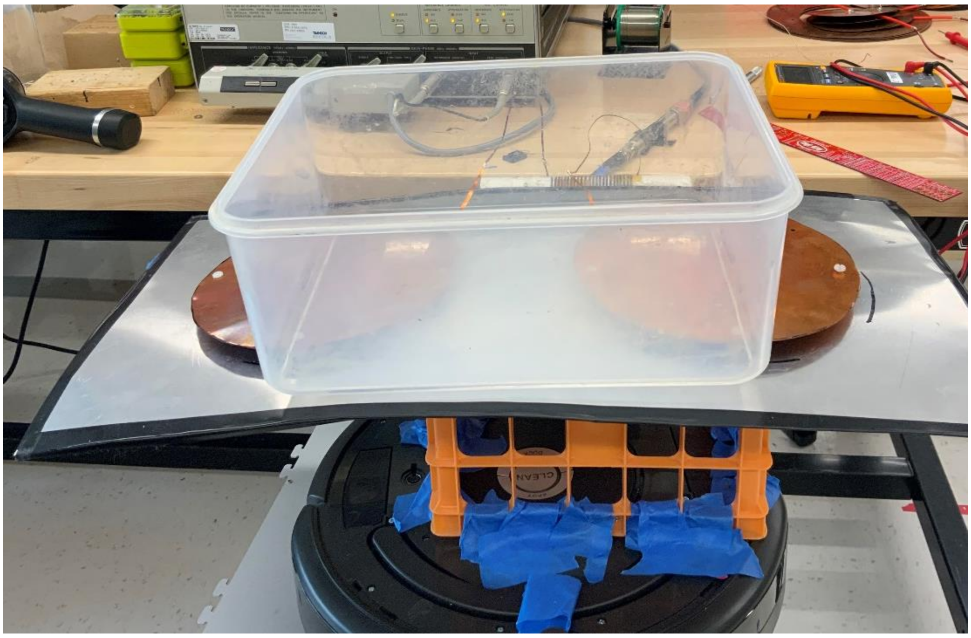

Figure 15. Device with the box where objects were placed.

This approach was thought to be the final one and it is where ML was applied for the first time. In order to apply ML, a set of data is needed to train the model and another set of different data is needed to test the model. The data collected in the lab corresponded to 14 different objects. This means that out of those 14 objects, 11 of them had to be used for training the algorithm and 3 for testing it. The ML method that was applied for this first attempt was k-nearest neighbors (KNN) for a number of neighbors equal to 1. Since most of the data that was collected for each object was dependent on the other data, not all of it was used for the ML program. Out of every data that was collected, the parameters that were used were the impedance of each object (module and phase) at the resonance frequency of the device without any object, the new resonance frequency of the equivalent electric circuit when the object is over the device and the temperature of the object.

Before applying the ML method, the objects were classified in different groups of objects:

None	**Plant products**	**Metal objects**	**Living objects**	**Water**	**Things found in the road**
-No objects	-Wood -Paper -Cloth -Tree leaves	-Metal	-Hand	-Tap water -Distilled water -Snow	-Plastic -Sand -Asphalt -Glass

Table 1. Groups of objects that were analyzed.

The 11 objects that were used to train the model were the following:

- None
- Wood
- Metal
- Living object
- Paper
- Distilled water
- Sand
- Tree leaves
- Road
- Glass
- Snow

The 3 objects that were used for testing the model were the following:

- Plastic
- Tap water
- Cloth

According to the classification that was made the results given by the model should have been ‘Things found in the road’ for plastic, ‘Water’ for tap water and ‘Plant product' for cloth. Instead, the results that were observed were 'Plant product' for plastic, 'Metal' for tap water and 'Plant product' for cloth. This means that only one out of three results were correct. To improve the accuracy of the model, several things were tried as decreasing the weight of some of the data were or changing the objects that were used for training and testing. However, it was determined that with the amount of data that was collected, there was not enough information to create an accurate model that was able to predict the type of object that was being detected.

8.6 Experiment 4.

As explained in the previous section, more data was needed to be able to apply an accurate ML model. Because of this, another experiment was run in the lab. This time, instead of only measuring once each object, six experiments were run each time for each object. On each experiment, a few things changed about how each object was being measured, such as the position of the objects, the quantity, the size… In this experiment, instead of measuring a lot of data from each object as we did in the previous experiment, only 4 data was collected for each run of each experiment. First, the impedance (module and phase) of the circuit at the resonance frequency of the original circuit was measured. Later the new resonance frequency was recorded, as well as the temperature of the object. This time, the objects that were measured change slightly from the ones used in experiment number 3. As an example, due to meteorological issues ice was used instead of snow. The objects used were the following:

- None
- Wood
- Sheet of metal
- Metal coins
- Living object (hand)
- Plastic
- Paper
- Tap water

- Distilled water
- Sand
- Cloth
- Asphalt
- Glass
- Ice
- Rubber

In this case there were also groups made for the classification of objects. The groups made were the following:

None	Others	Conductive	Living objects
-No object	-Wood -Plastic -Paper -Sand -Cloth -Asphalt -Glass -Rubber	-Sheet of metal -Metal coins -Tap water -Distilled water -Ice	-Hand

Table 2. Classification of objects in experiment 4.

For solving the classification problem, several ML methods were tried, and the results provided by each of them were compared. This comparison is shown in the following section: RESULTS.

9 RESULTS

9.1 Comparison between different ML algorithms

The data collected in the lab was used in three different ML methods: logistic regression, k-nearest neighbors, and decision trees.

To compare the different methods, something similar to K Fold cross validation was applied. Since there are 6 experiments, the first step would be using 5 of them for training and 1 of them for testing. However, to create a model that best represents reality, we ran the algorithm six different times for each ML method. Of these tests, the first five were used for training and the sixth was used for testing. By doing this it was possible to compare the different methods for a larger set of data. The results for each different method were the following:

Method	Score	Results
Logistic Regression	0.9	89%
Decision Trees	1	87%
k-nn (k=1)	0.986667	84%
k-nn (k=2)	0.886667	73%
k-nn (k=3)	0.875556	80%
k-nn (k=4)	0.877778	79%

Table 3. Accuracy of the different ML methods.

Analyzing the results, one can conclude that even if some methods had a model with a better score, the one that had a best result is Logistic Regression. This method will be used to find the specific time at which a prediction failed, so that it can be determined if there is a logical explanation to this result to fail.

9.2 Results using Logistic Regression with 5 experiments for training and 1 experiment for testing

With the results obtained from running logistic regression six times, changing the data set every time, a confusion matrix was created to show the overall results. This matrix is shown in Figure 16:

Actual \ Predicted	None	Conductive	Others	Living Objects
None	6	0	0	0
Conductive	0	23	7	0
Others	0	3	45	0
Living Objects	0	0	0	6

Figure 16. Confusion matrix of the experiment results.

It can be seen from the confusion matrix that for both Living objects and None, the accuracy of the ML program was of a 100%. This shows good results, as it means that the system can differentiate first, if there is or there is not an object in the device, and second, if the object is a living object. On the other hand, when predicting Conductive objects or other objects the system sometimes failed. The case that failed the most was when the system predicted Others while the actual object was one classified as Conductive. It will be later analyzed more in detail the reason of this failing, but the most probable explanation is that the object was set as conductive because it was made out of metal (mainly the coins) but the effect that the object has in the device is so small that it gets detected as 'Others' which means that the equivalent input impedance barely changes. On the other hand, there were some cases where the system predicted Conductive, when in reality the object should have been classified as Others. In this case the reason is the opposite as before. Even if it is an object that is supposed to have a small effect in the device, the equivalent impedance shown is relatively high, which makes the system think that it is a 'Conductive' object.

Analyzing separately each run in the logistic regression model, it can be seen which objects failed and try to find an explanation more in detail.

In the first case that was studied, experiments one through five were used for training and the sixth was used for testing. For this last case, there are two objects that are incorrectly predicted, and they are both metals (a sheet of metal and some coins). Instead of metal they are predicted as ‘Others’, which means that the effect these objects have on the device is small. This makes sense, as in that experiment the metal sheet was placed folded over one side and there were only a few coins and placed over only one of the pads. Next, experiment number one was used as testing data. In this case, the objects that failed were the sand and the rubber. For both, instead of classifying them as ‘Others’ they were classified as ‘Conductive’. In experiment number one, every object was placed touching both plates, so these objects being classified as ‘Conductive’ show that they create a high impedance. That means that they might affect the performance of the charger and that they should be retired. In the next case, with experiment number two as the testing data, there was only one object that was incorrectly assigned. Metal coins were classified as ‘Others’ instead of ‘Conductive’. Again, the reason for this is probably that the impedance shown by the coins was small. Analyzing the Table 4, we can see that again in the rest of experiments, the objects that were incorrectly classified were the metal coins and sand. The most probable explanation is that for the coins the equivalent impedance is low, so the system thinks it’s a ‘Conductive’ object, while for the sand is the opposite when it fails. The impedance is larger than expected and it gets classified as ‘Conductive’ instead of ‘Others’.

Testing set	**Elements incorrectly classified**	**How they were classified**	**What is their group**
1	-Sand -Rubber	-Conductive	-Others
2	-Metal coins	-Others	-Conductive
3	-Metal coins -Sand	-Others -Conductive	-Conductive -Others
4	-Metal coins	-Others	-Conductive
5	-Metal sheet -Metal coins	-Others	-Conductive

6	-Metal sheet -Metal coins	-Others	-Conductive

Table 4. Elements incorrectly classified.

Having observed these results, it can be determined that with the data collected the system was able to achieve its main objective. The objective was to differentiate between when there are or aren't objects in the charger, and in the case that there is an object, to identify whether or not it is a Living Object or an object that will affect the performance of the charger. Based on the effect that the object has on the charger; it will be determined whether the object should be removed or neglected. Another outtake that can be extracted from this experiment is that there are objects that can look as if they will affect the performance of the device such as metal coins, though their effect is small enough to create a noticeable disparity. Furthermore, based on this experiment, the device could still work with coins or small pieces of metal present. In addition to these experiments, other ways of classifying the data from the experiments were executed to observe different results that could be obtained. First, a larger amount of data was used for testing (two out of the six experiments) and a smaller one for training (four out if the six experiments).

9.3 Results using Logistic Regression with 4 experiments for training and 2 experiment for testing

The logistic regression algorithm was applied again with a different distribution of the data. For doing it, two of the experiments were used in this case for testing and the other four for training. Using cross validation with every possible combination, the accuracy of this method was 87%, compared to the accuracy of 89% obtained in the previous case. Considering that in this case less data is being used to train the models, the result is good. In Figure 17 the new confusion matrix can be observed, which was done with this method:

Actual

None	30	0	0	0
Conductive	0	109	41	0
Others	3	15	222	0
Living Objects	0	1	0	29
	None	Conductive	Others	Living Objects

Predicted

Figure 17. Confusion matrix for training with 4 experiment and testing with 2 experiments.

In this case the results were worse as there were three times where some objects were classified as if there was no object and a time where a living object was classified as a conductive object. In theory this should not be that bad as they are a few objects and ‘Other’ objects being classified as no objects could just show that the change in impedance with the presence of that object is negligible. Also, for the living object being classified as conductive, even if this is not desirable, the object will be likely to be retired before starting the device as a ‘Conductive’ object will decrease the performance of the charger. In respect to ‘Other’ objects being classified as ‘Conductive’ and vice versa, there should not be a problem as it is again a result of metal objects causing a small variation in the impedance or objects as sand that show a high impedance when present.

9.4 Results of testing the data collected in experiment 3 and training with the data from experiment 4

Of the 14 objects that were analyzed in experiment three, only one of them was classified incorrectly. This object was tree leaves, that had such a small impedance that it got detected as ‘None’. Also, as the impedance of this object was so small, it was not analyzed in experiment number four, which is probably a reason for why the classification failed. However, there is another object that has been correctly classified that was not present in experiment four due to meteorological reasons: snow. The snow that was collected for experiment three was correctly classified in the category ‘Conductive’, which is the one that corresponds to metal, water and ice.

9.5 Results of testing objects that were not part of the training set

Last, another experiment that was studied was aimed to try to classify an object that the model was not trained with and see if it was classified correctly. For doing this, the training data was formed by every object in the six experiments with the exception of rubber, and the test data were the six data sets from rubber from the six experiments. The results of doing this were that five times out of six, it was classified as ‘Others’, which was the correct category. Only one of them was classified as ‘Conductive’, which makes sense as in the first experiment the object was touching both plates and the impedance was relatively high compared to the other measurements.

As seen in the previous part, the data collected from the snow in experiment three was used as testing data with experiment four as training data. The system was able to correctly classify snow as a ‘Conductive’ object, which means that it will affect the performance of the device if present.

10 BUDGET

For running the experiments two main instruments that were available in the power electronics research lab in Cornell University were used.

-The vector network analyzer that was used was the HP–Hewlett Packard 4194A Impedance/Gain Phase Analyzer.

Figure 18. IMPEDANCE/GAIN PHASE ANALYZER (HP – HEWLETT PACKARD)

-The thermal camera that was used was the FLIR-E6390.

Figure 19. Thermal Camera FLIR-E6390

As software, the two main programs that were used were Microsof Excel for managing all the data collected in the experiments and Jupyter Notebook for coding in Python the ML algorithms.

Finally, as objects that were studied, they were all objects that were found in the lab, in the street or that were personal objects. The objects that were used are shown in the following pictures.

- None

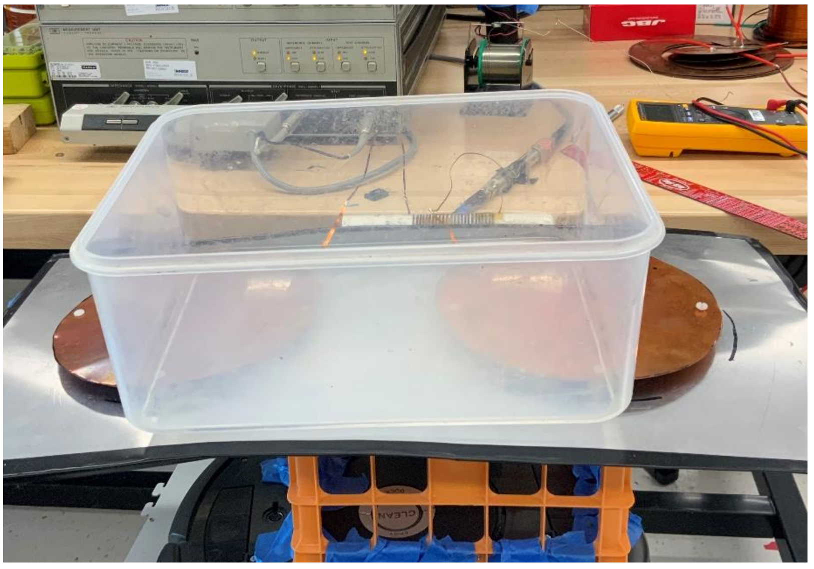

Figure 20. Empty plastic box on the device ('None')

- Wood

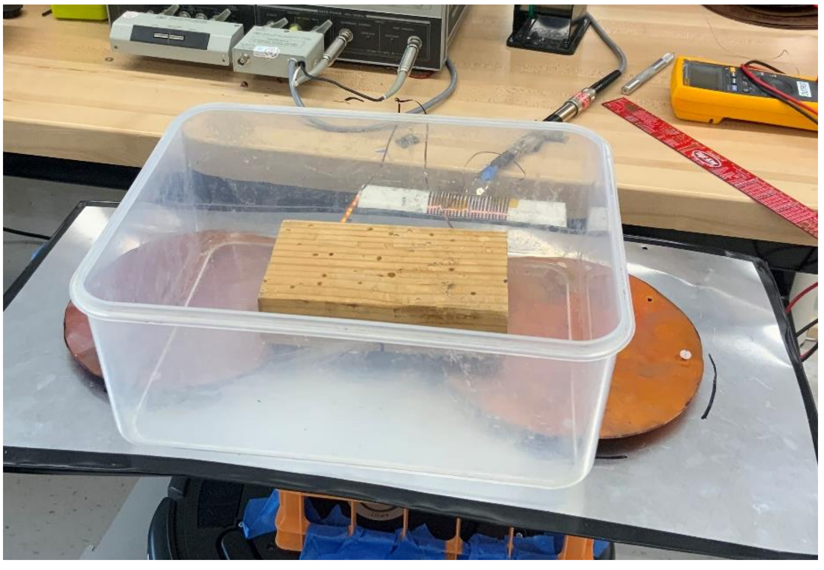

Figure 21. Wood in the plastic box ('Wood')

- Sheet of metal

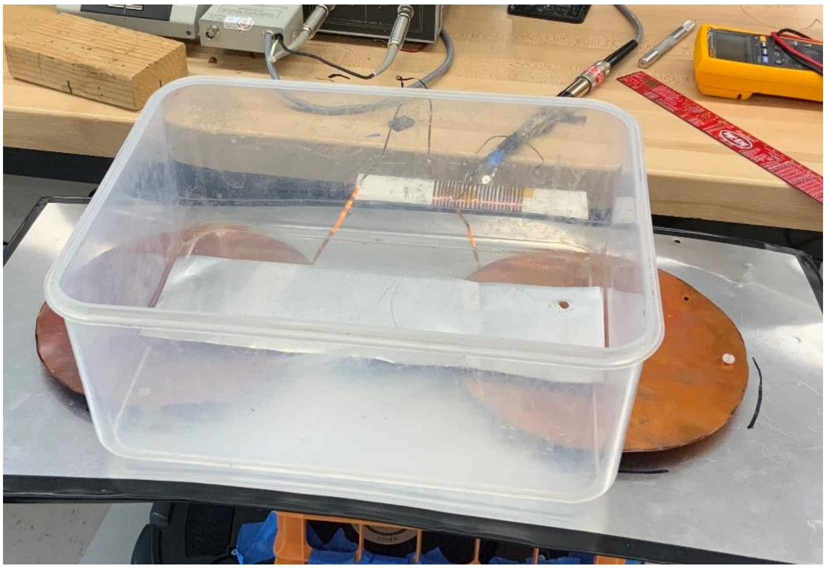

Figure 22. Metal sheet in a plastic box ('Metal (sheet)')

- Metal coins

Figure 23. Metal coins in a plastic box ('Metal (coins)')

- Living Object

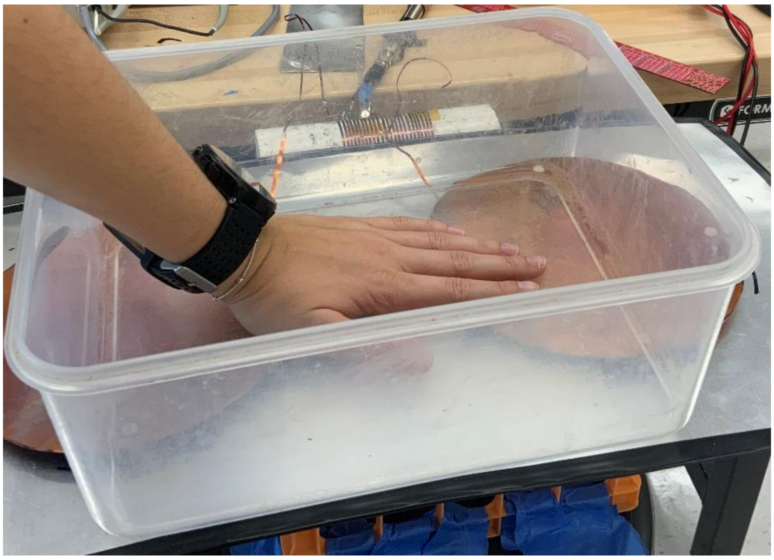

Figure 24. Hand in a plastic box ('Living Object')

- Plastic

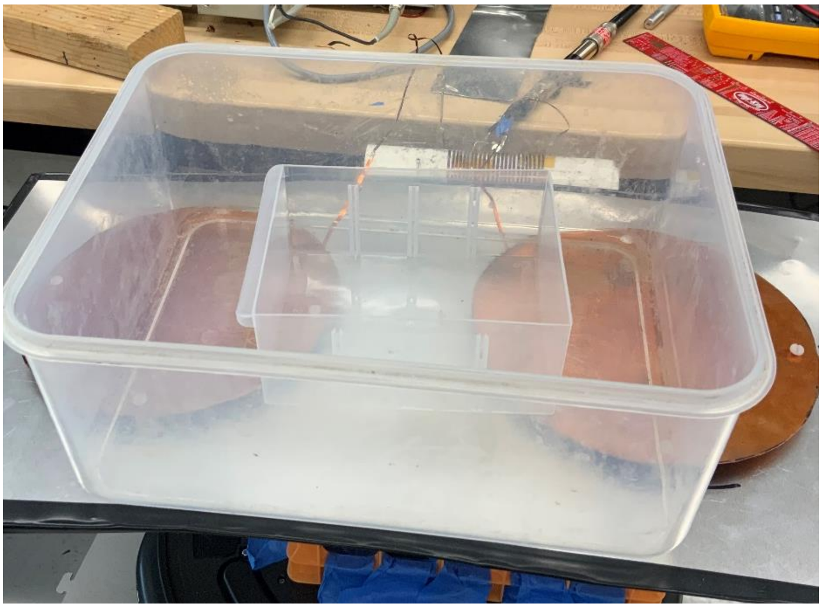

Figure 25. Plastic container within a plastic container ('Plastic')

- Paper

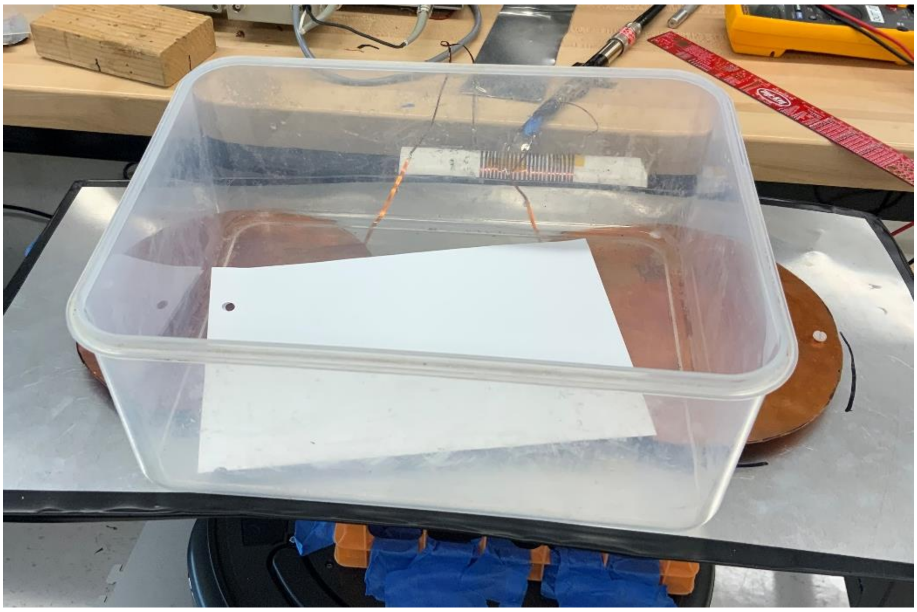

Figure 26. Sheet of paper in a plastic container ('Paper')

- Tap water

Figure 27. Tap water in a plastic container ('Tap water')

- Distilled water

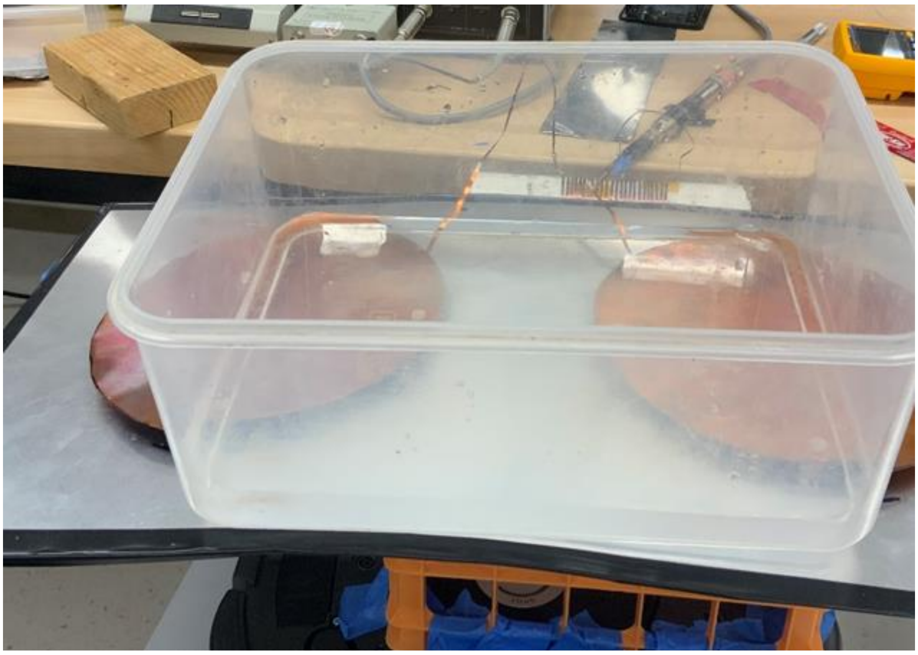

Figure 28. Distilled water in a plastic container ('Distilled water')

- Sand

Figure 29. Sand in a plastic container ('Sand')

- Cloth

Figure 30. Cloth in a plastic container ('Cloth')

- Road

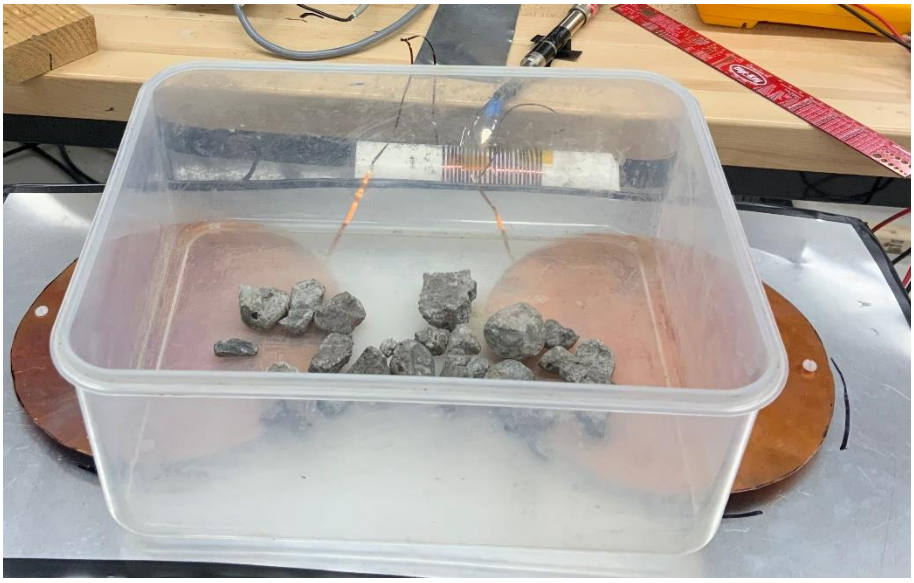

Figure 31. Pieces of asphalt in a plastic container ('Road')

- Glass

Figure 32. Glass bottle in a plastic container ('Glass')

- Ice

Figure 33. Ice bag in a plastic container ('Ice')

- Rubber

Figure 34. Bike inner tube in a plastic box ('Rubber')

- Tree leaves

Figure 35. Tree leaves in a plastic box ('Tree leaves')

- Snow

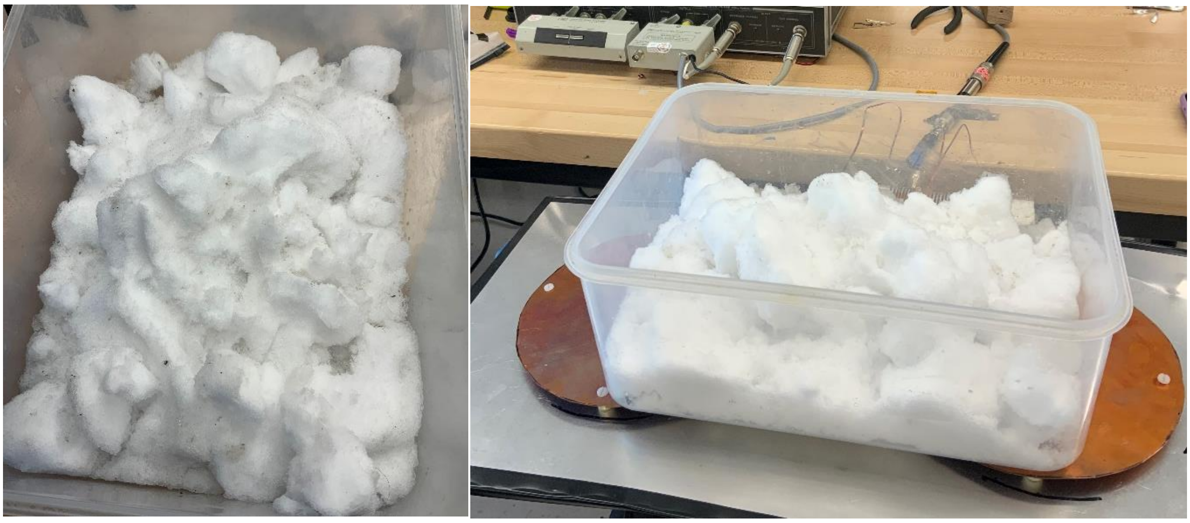

Figure 36. Snow in a plastic box ('Snow')

11 CONCLUSIONS

Capacitive Wireless Power Transfer is an area that is still being studied but starting to take care of security issues is something important. Foreign Object Detection is a field that has been already studied for Inductive WPT. However, by the time this work was done (May 2022) there were no published works about Foreign Object Detection for Capacitive Wireless Transfer Systems. Because of this, several existing methods already existing for Inductive Systems were analyzed to determine if it was possible to use them in Capacitive Systems. Combining existing methods and the devices that were available in the lab a solution was found to be able to start the experiments.

In the present work it has been shown that by using an impedance analyzer, a thermal camera and a ML algorithm such as logistic regression it is possible to determine first, if there are no objects over the charger or if there is an object over it. Secondly if there is an object, it has been possible to determine if it was a living object or if it was not. If they were not a living object, the program was able to differentiate between objects that caused a big variation in the output impedance.

By doing this classification, it will be possible to communicate these results to another part of the program and determine whether if the device can work normally (if there are no objects or if there are objects that will not affect the performance of the charger), if there is an object that should be removed to allow the device to work correctly or if the charger cannot be turned on at all if there is a living object that has been detected over the device.

Last, it was also shown that at least in the cases that were studied the program was also able to classify an object that was not part of the training and classify it in its respective category as it was the case of rubber and snow.

12 FUTURE WORK

In this work, the way each object was analyzed was by using a really small power (the one given by the impedance analyzer), so the results obtained, and the work done is the first step of the work that needs to be done in order to make Capacitive WPT systems safe for living objects and avoid performance errors due to the presence of foreign objects.

The next experiments that should be done would be first, repeating the same experiments but with both the charger and the object that wants to be charged present but again with low power (charger off and the only power used being the one from the impedance analyzer). By doing this, it will be possible to know if objects can be detected when the charger is about to start working.

Next, it will be useful to do some experiments with higher power. With this several things will be studied. In the one hand, it will be possible to determine if any of the objects could be dangerous for the device as it happened with metal in the inductive systems. From the experiments done, any of the objects that have been analyzed have shown a behavior that could lead to problems like this, but that could change with high powers. Lastly it would be useful as well to do experiments for foreign object detection while the device is working at the operating frequencies (which are high). The problem of doing this is that there will be limitations about what objects to test. Living objects will not be able to get tested as they could get harmed and if any other object is found to react badly with high frequencies it might not be able to get tested either.

13 ANNEXES

13.1 Data from experiment 3

EXPERIMENT 3					
	Object	Z(w_0) Ω	phase(w_0)(º)	w_0' (MHz)	Temperature
1	None	0.38	0	7.606	29.2
2	Wood	9.87	79.19	7.572	28.6
3	Metal	247	85.4	6.785	30.4
4	Living object	134	86.4	7.13	38.1
5	Plastic	4.57	-85.3	7.621	29
6	Paper	5.7	-84.54	7.625	28.3
7	Tap water	296.36	70.06	6.622	24.1
8	Distiled water	188.214	86.39	6.977	27.6
9	Sand	15.5	81.17	7.555	27.7
10	Cloth	6.38	-70	7.626	28.6
11	Tree leaves	2.54	19.4	7.602	28.2
12	Road	8.5	64.017	7.58	28
13	Glass	8.44	71.4	7.577	28.4
14	Snow	27.17	74.14	7.509	-1

13.2 Data from experiment 4

EXPERIMENT 4					
	Object	Impedance	Phase	Frequency	Temperature
1	None	0.35	0	7.606	27.3
2	Wood	16.4	84.7	7.547	25.1
3	Metal (sheet)	256.22	87.3	6.756	27.1
4	Metal (coins)	21.1	90.17	7.533	27.8
5	Living object	140.73	87.8	7.138	36.4
6	Plastic	2.95	88.15	7.595	26.8
7	Paper	1.42	82.24	7.6	27.5
8	Tap water	100.166	62.9	7.296	18.2
9	Distilled water	115.124	88.4	7.215	23.1
10	Sand	17.68	89.91	7.545	25.8
11	Cloth	4.51	84.85	7.59	28.6
12	Road	18.43	83.97	7.542	28.7
13	Glass	15.06	90.35	7.553	29.2
14	Ice/Snow	47.6	48.59	7.471	-6.2
15	Rubber	30.37	84.27	7.501	25.4
16	None	0.053	0	7.624	27.6
17	Wood	3.66	84.3	7.593	27.5
18	Metal (sheet)	24.38	91.43	7.521	27.3
19	Metal (coins)	11.65	91.11	7.566	26.2

20	Living object	101.78	77.6	7.269	36.1
21	Plastic	0.61	91.12	7.603	27.4
22	Paper	1.21	-85.75	7.61	26.4
23	Tap water	155.35	63.71	7.129	18.9
24	Distilled water	152.952	88.07	7.093	23
25	Sand	10.92	90.7	7.567	26.1
26	Cloth	0.816	-83.95	7.609	26.8
27	Road	1.87	-77.8	7.612	27.5
28	Glass	2.69	92.75	7.596	27.7
29	Ice/Snow	16.17	77.57	7.552	-5.3
30	Rubber	7.65	87.62	7.579	26.1
31	None	0.34	0	7.635	27.9
32	Wood	2.15	75.2	7.599	27.6
33	Metal (sheet)	36.91	88.52	7.482	27.4
34	Metal (coins)	7.47	89.08	7.578	27.7
35	Living object	92.12	60.4	7.278	35.9
36	Plastic	0.092	33.4	7.603	28.1
37	Paper	1.2	-85.93	7.61	26.3
38	Tap water	199.88	65.05	6.972	18.8
39	Distilled water	194.4	87.66	6.949	23.2
40	Sand	20.77	89.59	7.534	26.2
41	Cloth	0.509	-74.73	7.607	26
42	Road	3.74	-78.48	7.619	28
43	Glass	0.36	94.71	7.604	27.5
44	Ice/Snow	21.3	75.32	7.534	-6.8
45	Rubber	8.78	85.57	7.576	26
46	None	0.309	0	7.606	25.7
47	Wood	0.97	-66.7	7.609	27.4
48	Metal (sheet)	31.1	90.98	7.499	27.5
49	Metal (coins)	5.05	91.19	7.588	27.8
50	Living object	162.87	85.57	7.156	36.2
51	Plastic	0.042	26	7.605	27.8
52	Paper	1.3	-85.31	7.611	26.4
53	Tap water	238.41	66.31	6.846	18.4
54	Distilled water	221.1	87.34	6.859	23.4
55	Sand	4.4	88.65	7.552	26.3
56	Cloth	3.28	82.1	7.595	27.3
57	Road	0.838	30.35	7.604	28.5
58	Glass	4.89	91.3	7.588	27.7
59	Ice/Snow	51.75	61.79	7.449	-7.4
60	Rubber	19.34	84.46	7.538	28
61	None	0.543	0	7.621	25.9
62	Wood	2.73	-87.15	7.615	27.6
63	Metal (sheet)	16.33	91.48	7.551	27.5
64	Metal (coins)	2.47	-88.52	7.614	28.1
65	Living object	102.46	76.91	7.26	36.5
66	Plastic	0.771	-88.6	7.608	28

67	Paper	1.57	-87.7	7.612	26.3
68	Tap water	273.88	67.88	6.72	18.8
69	Distilled water	235.4	87.22	6.814	23.6
70	Sand	7.13	90.67	7.58	26.5
71	Cloth	1.15	-86.57	7.61	24.9
72	Road	1.38	74.73	7.601	28.9
73	Glass	1.75	93.73	7.599	27.5
74	Ice/Snow	16.25	72.41	7.552	-5.6
75	Rubber	9.84	86.19	7.572	27.8
76	None	0.427	0	7.619	25.5
77	Wood	3.47	-87.17	7.617	28.6
78	Metal (sheet)	17.62	89.48	7.545	27.5
79	Metal (coins)	1.153	89.63	7.601	28
80	Living object	87.87	62.04	7.354	36.9
81	Plastic	1.18	-88.38	7.61	28.2
82	Paper	1.52	-86.8	7.611	26.3
83	Tap water	304.01	68.95	6.589	19.1
84	Distilled water	248.49	87.08	6.774	23.6
85	Sand	10.76	89.3	7.569	26.2
86	Cloth	0.24	65.26	7.605	24.7
87	Road	3.74	-85.32	7.619	27.3
88	Glass	8.17	91.22	7.577	27.6
89	Ice/Snow	19.93	67.21	7.539	-4.3
90	Rubber	10.92	81.88	7.569	28.4

13.3 Logistic regression python code

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
import pandas as pd

df = pd.read_csv('TrainingData.csv')
df1 = pd.read_csv('TestingData.csv')

y = df['Object']
x = df.drop(['Object'],axis =1)
x = pd.concat([x,x**2],axis =1)

lm = LogisticRegression(multi_class='ovr', solver='liblinear')
lm.fit(x, y)

lm.score(x,y)

lm.predict(x1) == y1
lm.predict(x1)
y1
```

13.4 K-NN classifier python code

```
import pandas as pd
import numpy as np
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

df = pd.read_csv('TrainingData.csv')
df1 = pd.read_csv('TestingData.csv')

y = df['Object']
x = df.drop(['Object'],axis =1)
x = pd.concat([x,x**2],axis =1)

knn = KNeighborsClassifier(n_neighbors=1,metric='euclidean')
knn.fit(x,y)

knn.score(x,y)

y1 = df1['Object']
x1 = df1.drop(['Object'],axis =1)
x1 = pd.concat([x1,x1**2],axis =1)

knn.predict(x1) == y1
```

13.5 Decision Tree Classifier python code

```
import pandas as pd
import numpy as np
from sklearn.datasets import load_iris
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

df = pd.read_csv('TrainingData.csv')
df1 = pd.read_csv('TestingData.csv')

y = df['Object']
x = df.drop(['Object'],axis =1)
x = pd.concat([x,x**2],axis =1)

clf = DecisionTreeClassifier(random_state=0)
clf.fit(x,y)

clf.score(x,y)

y1 = df1['Object']
x1 = df1.drop(['Object'],axis =1)
x1 = pd.concat([x1,x1**2],axis =1)
```

```
clf.predict(x1) == y1
```

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