

**Finding an Empirical Relationship Between Chloride Loading Density and Conductance
for the Prevention of Galvanic Corrosion in Real Environments**

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Empirical Model Relating Chloride Loading Density and Conductance for Prediction of Galvanic Corrosion

EXECUTIVE SUMMARY

The research presented investigates and develops a correlation model in which chloride loading density (LD) may be determined from relative humidity (RH) and conductance (G) data in the context of galvanic corrosion in outdoor environments. In real applications, the water layer created by the deliquescence of salt on a metal surface at high RH may have non-uniform distribution and thickness, causing significant variability in G for a given LD. In order to create a model that reflects realistic water layer geometries, laboratory data of conductance as a function of relative humidity at 30°C was examined for known LD values.

Hysteresis-like loops were observed in the graph of $G(RH)$ as RH increased and decreased periodically. The wetting (increasing RH) and drying (decreasing RH) halves of these loops were split. For low LD values, a logistic function was fit to each half and the coefficients corresponding to the best fit were noted. For high LD values, the linear region of the drying curves were fit to a line and the x-intercept was recorded. For each case, the parameters were then correlated to the known LD value. Finally, experiments were conducted in an outdoor environment by applying a known LD to the same sensors as those from the laboratory tests and measuring G, RH, and temperature. These experiments showed that temperature also plays a significant role in this system by changing the activity of salt in the water layer, resulting in different conductance values than those predicted by our model created from isothermal conditions.

The technical project concluded with a successful model predicting LD using the x-intercept from the linear-fit method. However, the isothermal conditions presented by the lab data proved insufficient for fully predicting LD from conductance and relative humidity data in a complex real environment. By using our procedure for the outdoor experiment to collect more data, the modeling approach used here could be used to more accurately quantify LD from temperature, conductance, and relative humidity data.

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Empirical Model Relating Chloride Loading Density and Conductance for Prediction of Galvanic Corrosion

INTRODUCTION

Modern engineered systems have optimized cost, efficiency, and mechanical properties through multi-material systems. In the aerospace industry, aluminum alloys and carbon fiber reinforced polymers are often used for structural components on an aircraft due to their strength-to-weight ratio. Aircraft components which are subject to higher stresses are often made from high strength materials such as steels and titanium alloys [1]. When these unlike materials are in electrical contact, galvanic corrosion can occur.

To better study galvanic corrosion, Luna Labs developed the Acuity LS Sensor. This device measures both environmental parameters and galvanic corrosion rates during laboratory and outdoor exposure tests. Corrosion measurements taken by the Acuity Sensor can be used to directly estimate the corrosion magnitude of a system, while environmental parameters can be used to further understand and predict corrosion distributions. Currently, there have been studies conducted which used thermodynamic models to determine an equilibrium molarity and conductivity of salt water as a function of the relative humidity [2]. However, not all correlations between the parameters that the Acuity measures exist.

The problem being explored in this project is the fact that only a preliminary analysis has been conducted to quantify the correlation between conductance and chloride loading density. The objective of this capstone project then became to analyze previously collected Acuity and chloride density data to find empirical and quantitative correlations. The benefits of finding this relation would be far reaching. The most obvious benefit would be the creation of a finite element method model which could be used to predict corrosion rates through deployments of the Acuity LS Sensor in a wide range of environments. Better material performance testing and material selection as well as condition monitoring would all be possible with this model. Marine infrastructure, offshore energy, automotive, aerospace and other industries would all benefit from such a development. The benefits do not extend just to industry; with this relation, it would be possible to better correlate laboratory accelerated corrosion tests and outdoor exposure tests.

There are a few key known concepts we used to aid our project. The first is known as a deliquescence point, where there is enough humidity for droplets to form on the surface of a material [3]. Humidity cycles were used in laboratory experiments to gain the most information from critical points such as these. This is also why conductance increases with relative humidity [4]. It is also important to know that conductance increases with temperature [5]. As a result, the laboratory environment was held to a constant temperature. Lastly, it is important to define our

two key terms: conductance and chloride loading density. Conductance is the degree of ease of electric flow [6]. Chloride loading density is the mass of salt per unit area [7].

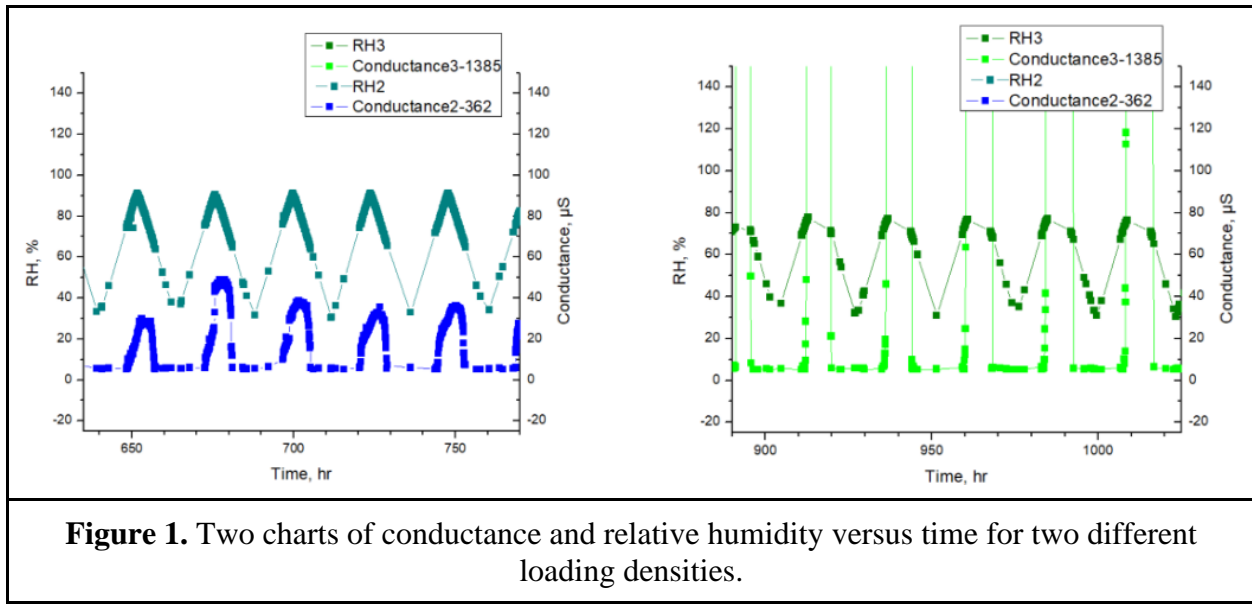
Problem Statement

The design challenge given by Luna Labs is to create an empirical model that can predict the instantaneous chloride loading density of a surface in an outdoor environment from the conductance of the solution on said surface. Conductance is similar to conductivity, but it is scaled by a geometric factor that is composed of the area of the solution surface divided by the characteristic depth of the water layer. By analyzing data collected by the sensor, we should be able to predict the chloride loading density independent of the wetting geometry of the corroding surface. The supplied data is in the form of Acuity sensor data in both laboratory and in situ tests. Following model creation, experiments of our own design were conducted in order to verify the accuracy of the model we have created, alongside attempting to identify a temperature dependence.

RESEARCH

Conductance and Relative Humidity vs. Time

The first model the group attempted to create was based on previous work conducted by Luna Labs. Luna Labs had looked into constructing a model which could relate conductance and relative humidity with time. Using this previous work, we looked at correlating conductance and relative humidity by analyzing the slope of the conductance data between 76% and 85% relative humidity. Figure 1 below shows the typical pattern for the laboratory data with the relative humidity alternating between 30 and 90% and the conductance increasing at 76% relative humidity, which is the deliquescence point of sodium chloride.



Our hope with this model was to determine if any differences in slope could be attributed to different chloride loading densities. For instance, we hypothesized that a higher chloride loading density might result in steeper conductance slope when compared to lower loading densities. From this, we hoped to find that unique slopes could be paired with the different loading densities. From the given laboratory data, we would be able to extrapolate slopes for loading densities which were not within the laboratory data set giving us slopes for all possible loading densities. A model could then be constructed to return a predicted chloride loading density based on the slope of the conductance data between certain relative humidity values.

Upon analyzing the laboratory data, it became clear that the slope of the conductance values between 76% and 85% relative humidity were similar regardless of the loading density. From this discovery, we were able to conclusively say that conductance and relative humidity have no time dependence and that there was no use developing this model any further.

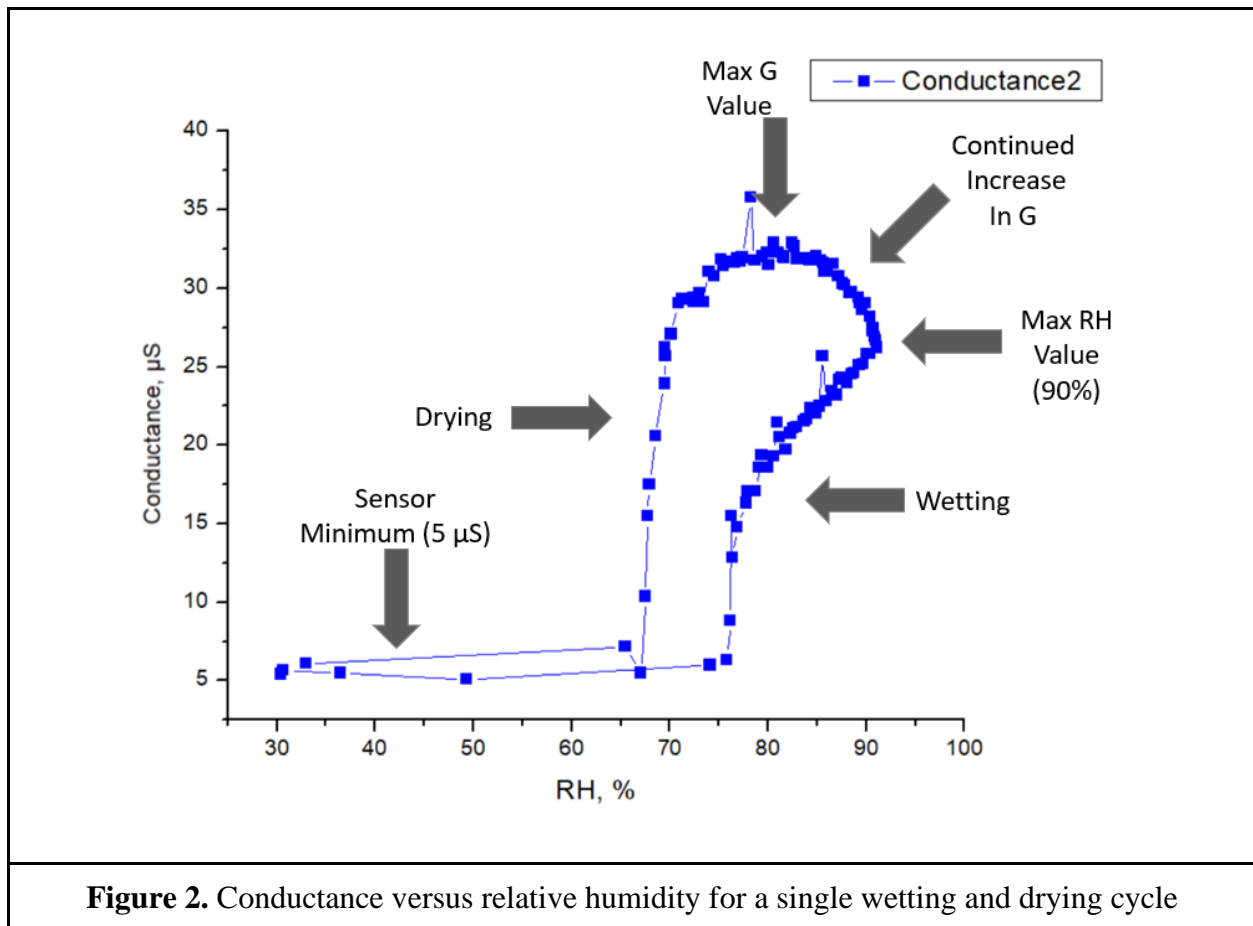
Conductance vs. Relative Humidity

Initial Graphical Investigation

The principal relationship within the data that we decided to use in our model was the relationship between the conductance (G) data and the relative humidity (RH) data. This choice had quasi-theoretical backing, and there were promising trends in the data that indicated a relationship to chloride loading density (LD). Since conductance values for a given area (the area of our sensor surface) changes with changing ion concentration in a solution, we hypothesized that the conductance would be related to the relative humidity, the source of liquid on the sensor

surface, and chloride loading density, the source of ions in the solution. Since the sensor outputs conductance data and relative humidity data, we hoped to use the change in relationship between these two variables to model a change in the loading density.

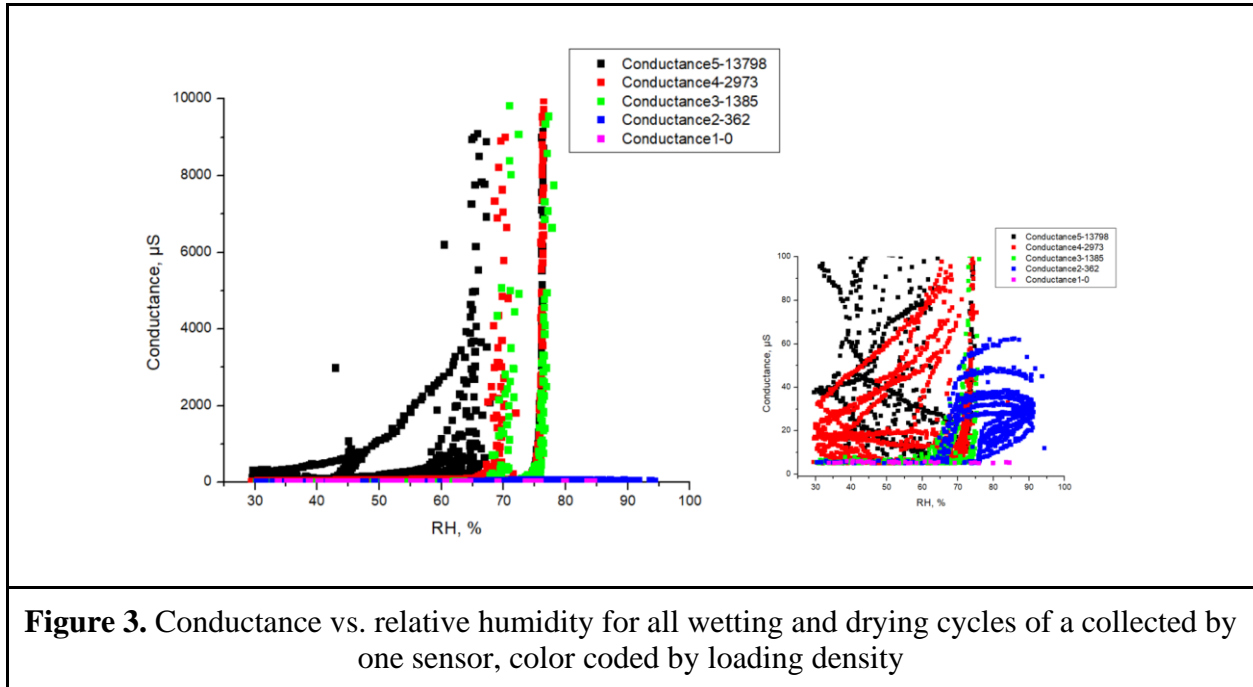
We began by graphing G vs. RH for a single cycle of relative humidity (30%-90%-30%) at a single loading density from sensor 588. We noticed that the curve resembled a hysteresis loop, and further discussion with Luna labs revealed the physical meaning of the graph in Figure 2:



The minimum values at low RH are explained by the minimum recordable conductance value of 5 μS . At the deliquescence point of NaCl, 76% RH, we saw conductance increase as the humidity became high enough to create a solution on the surface. G asymptotically increases to the maximum RH value, and continues to increase in the early stages of drying. This increase is due to the evaporation of the water while the amount of salt in solution stays the same, increasing the concentration of the solution and its conductance. Once RH decreases back to the deliquescence point, G begins to sharply decrease to below the sensor minimum. Seeing this

relationship was instrumental in choosing how we would go about modeling the data as accurately as possible within our design constraints.

Next, we graphed G versus RH for a single sensor, color-coding each separate LD:



Through visual analysis, we noticed a few things. Firstly, for the four loading densities tested on each of the six sensors, only the lowest LD showed the full hysteresis loop of data; the other LDs had a maximum G value above the sensor maximum of 10,000 μS . Based on the data collected by the sensor, it was reasonable to assume that the other loading densities followed the same hysteresis loop, but much of this shape was not recordable by the range of the sensor. This would eventually make it difficult to develop a comprehensive model that portrayed the full relationship. We also noticed that the decreasing portion of the graph seemed to happen at lower RH values for higher LDs. We hypothesized that this was a result of a larger maximum G value creating a wider hysteresis loop, but without the maximum values recorded, we could not confirm. Still, this relationship did reflect the change in loading density, as we had predicted, and we would be able to quantify the change for use in a predictive model. With this in mind, we decided to focus on the drying portion of the data.

Data Analysis Methods Investigation: Curve Fitting

Our next task was to investigate the best method for modeling the relationship we had identified; we began with the low LD data, since we had the full loop of values. After testing a few different mathematical functions, we found that using two logistic functions (one for the “wetting portion” of increasing RH, one for the “drying portion” of decreasing RH) modeled the data quite well and took into account the initial increase of the drying portion. Once we fit the data to a logistic curve, we would be able to use the coefficients of the fitted function to predict the loading density.

The higher LD data with incomplete loops, posed some issues with our methods. The inherent noisiness of the data and the lack of a full shape of the graph made it very difficult to automatically fit the data with a curve fit program; the noise seemed to confuse the fit and would result in clearly poor fits. We made several attempts to address this issue.

Our first attempt was to transform the data to be linear. Our reasoning was that if the data was linear, then there would be no missing features of the graph and our curve fit program would have less trouble recognizing the shape. There is no easy way to linearize a logistic curve, but there is a method called Hubbert linearization, which plots logistic data against the ratio of the data to its derivative to yield a linear graph whose intercepts are the coefficients of the logistic curve:

$$\frac{1}{G} \frac{dG}{dRH} = mG + B$$

While we did not have data corresponding to the derivative of instantaneous conductance, we developed a method to find the coefficients. First, we generated a column of data by inputting G and RH data into the derivative function of a logistic curve, dG/dRH of our logistic equation. Then, we adjusted the coefficients of the new function until our Hubbert graph exhibited maximum linearity. Plugging these coefficients into our original logistic function gave a very good fit for the data (Appendix A). Unfortunately, for some reason, the lack of a complete loop still interfered with this method, and we were not satisfied with the additional jump in complexity that our model’s input would need.

Our chosen method to model the high LD data is a simple linear fit to the middle of the logistic curve. Unlike the low LD curves, the high LD data exhibited a steep enough increase and decrease that a linear fit could be used to model that portion of the data. We developed a way to crop the data to achieve a realistic fit. The upper portion was sufficiently linear to not need a cutoff. The lower cutoff was determined by finding the lowest value of G before the correlation coefficient of a linear fit began to decrease, which was at 1000 mg/m² (Appendix B). The

relationship to loading density was found by looking at trends in the coefficients of the linear fits. Although this model yields less information about the data as a whole, we thought it to be easy to use and understand, while still providing information about the loading density.

Code for Implementing Solutions Description

The code used to analyze the laboratory data was composed of several Python modules. All lab data was stored in an SQLite3 database called *AcuityLabData.db*. Several important Python packages were used, including pandas for data management, scipy for statistical analysis, and numpy for numerical operations. The *datahandler.py* module contains several functions for pre-processing the data before applying any statistical methods. First, *load_test()* takes in a sensor ID as an argument and simply reads in all data from one sensor contained in the SQL database and transforms it into a pandas dataframe object. *wet_dry_split()* takes in this dataframe and a specified LD value for which to split the data into its wetting and drying halves. This is accomplished by using a Savitzky-Golay filter on the RH vs. time data to smooth the data, then calculating the slope of this *RH(time)* curve at each point. Where the slope is positive, the data associated with that slope is added to a dataframe containing only wetting cycle data; where the slope is negative, the associated data is added to a dataframe containing only drying data. Next, *cycle_split()* is able to split the data frames containing only wetting or drying data into their individual cycles so that each one can be analyzed individually. This is done by measuring the time change between two data points and splitting the data where this time change is larger than 2 hours and putting that cycle's data into its own dataframe. The function then returns a list of dataframes containing the data of each cycle. Finally, *clean_data()* performs a variety of data cleanup tasks, such as removing data that is outside of the conductance sensor's range.

The actual analysis was primarily done in either *logmod_single.py*, which is capable of fitting low LD data to a logistic curve and returning the fitting parameters using scipy's *curvefit()*, as well as performing the linear approximation for higher LD data using scipy's *linregress()*. These fits are done on each cycle of each loading density for each test and returns four CSVs containing by-cycle data: files for linear model fitting parameters for the wetting data and the drying data, and files for the logistic model fitting parameters for the wetting data and the drying data. Another module, *logmod_combined.py*, does the same things as *logmod_single.py*, but does curve fitting on the aggregate of all cycles for a given loading density. Finally, *mlmod.py* contains some work performed with machine learning applied to the aggregate of all drying cycle data, such as neural network and random forest regression, but this module was not developed as extensively as the other two analysis modules. Further documentation on the workings of all modules can be found in the code that will be supplied to Luna Labs.

Error Analysis Method

One of our principal design factors was a reported range of confidence for our predicted loading density as a means to express the noise we observed in the data. We decided to include a 95% confidence interval in our final model to accomplish this goal. First, we needed to confirm that the spread of linear fit parameter values for each loading density were normally distributed in order to use the standard confidence interval calculations. We verified the normality assumption by creating Q-Q plots for our fit parameters, as well as performing the Kolmogorov–Smirnov test for normality. The Q-Q plots showed a linear trend, which indicates normally distributed data (Appendix C). Assuming normal distribution, we would be able to easily calculate the 95% confidence interval to include in our model.

Experimental Data Collection

Luna Labs Real Environment Data

Luna Labs provided us with Acuity data with 3 locations. 2 were on opposite sides of Battelle, FL. The third location was in El Segundo, CA. A final goal of Luna Labs is to be able to use a computer model to predict loading density in the real environment. As a result, we had some aspirations to verify our model with this data.

Unfortunately, environmental data has more noise and has more confounding variables than the lab data. Additionally, weather does not cycle through different humidities neatly unlike a controlled environment. Therefore, although it was never quantitatively tabulated, it is clear our confidence interval would have been even larger than in our lab data.

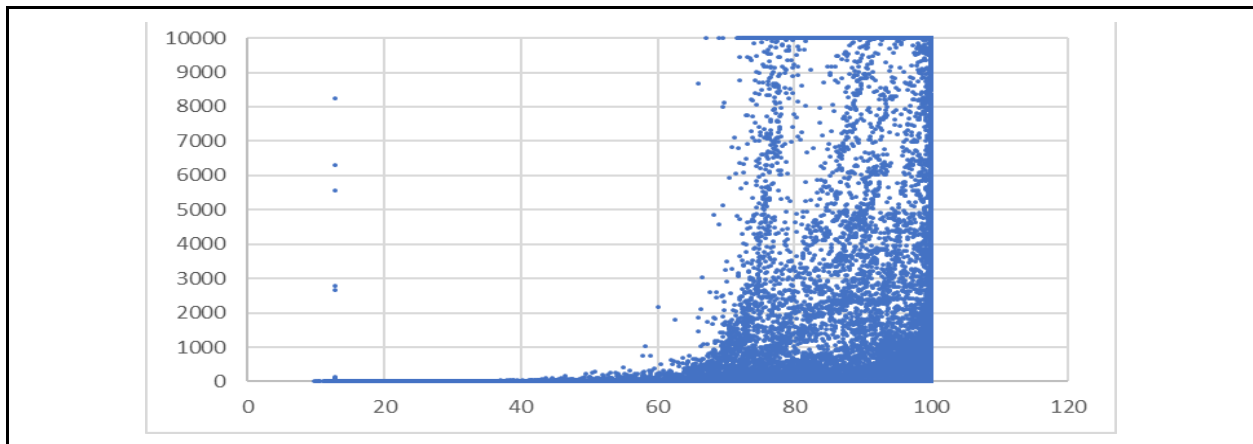


Figure 4. Conductance vs. RH for Acuity data at Battelle Ocean Site. This data shows much more variability and has fewer apparent trends than the lab experiments.

Capstone Experiment: Goals

The goal of this experiment is to conduct Acuity deployments in an outdoor environment with known loading densities. From the deployment, information about how relative humidity and temperature impact conductance for a known loading density can be discovered. This information can be compared to laboratory experiments to get a better picture of how environmental factors impact conductance.

Capstone Experiment: Acuity Sensor Preparation

The three Acuity devices used during our experimentation were labeled 00460, 00462, and 00463. Before electrolyte application, the Acuity devices had new batteries installed, the sensor surfaces were cleaned using isopropyl alcohol on a Scotch-Brite pad, and the data logging was started at approximately 1:45 p.m. on Friday March 31st, 2023.

Capstone Experiment: Electrolyte Application

The electrolyte was applied to the sensor surface using the HVLP gravity feed air spray gun located at Luna Labs. The spray gun has a nozzle size of 0.8mm, the air pressure was set to 40 psi, and the adjustment for spray pattern was turned fully clockwise to create a circular pattern for uniform distribution. During application, the spray gun was located between four (1.2m) and five (1.5m) feet away from the Acuity devices depending on the test. Similarly, the application time was between 2 and 4 seconds, depending on the test, with the goal of achieving a loading density of 500 mg/m². The electrolyte being applied was a 0.6 molar sodium chloride solution. A glass witness slide was mounted beside each Acuity device to measure the amount of deposited solution during each test. The glass witness slides were weighed before application to get a baseline measurement to compare to after application.

Capstone Experiment: First Application

The first electrolyte application occurred on March 31st at approximately 2:30 p.m. Each Acuity device was sprayed for 2 seconds at a distance of five feet. Promptly after electrolyte application, the three witness slides corresponding to each Acuity device were removed and placed in the Thermotron 8200 at a humidity of 20% and a temperature of 40°C and allowed to dry. The mass of these slides was then taken to compare to the mass before salt application. The difference in masses gave us the total amount of salt deposited and we could then calculate the loading density of the sensor based on a given area. The results of the first application are given in Table 1 below.

Slide Number	Averaged Slide Mass Pre Spray (g)	Averaged Slide Mass Post Spray (g)	Mass Difference (g)
00460	10.1213	10.1215	0.0002
00462	10.0900	10.0903	0.0003
00463	10.0765	10.0769	0.0004
Control	10.1027	10.1027	0.0000

The first attempt using the five feet two second method did not yield enough deposited salt to be statistically significant and therefore no loading density was calculated from this data. Given the time constraints, the sensors were not resprayed that day and we returned at a later date with new methods

Capstone Experiment: Second Application and Deployment

Prior to the second application attempt, the sensor faces were cleaned using isopropyl alcohol and the Scotch-Brite pads to ensure no residual salt was left on the sensors. For our second attempt, we changed the spray time to four seconds and the spray distance to four feet. The results are displayed in Table 2 below.

Slide Number	Averaged Slide Mass Pre Spray (g)	Averaged Slide Mass Post Spray (g)	Mass Difference (g)	Calculated Loading Density (mg/m ²)
00460	10.1213	10.1218	0.0005	362
00462	10.0900	10.0907	0.0007	517
00463	10.0765	10.0782	0.0017	1292
Control	10.1027	10.1028	0.0001	62

After salt application and loading density measurement, the sensors were deployed in an outdoor environment under a covered patio. This covering ensured the sensors were exposed to varying humidity and temperature levels while minimizing the impacts of other environmental factors such as wind and rain. The tests ran for one week before the measurements were checked. Upon looking at the measurements, we decided to leave the sensors out for another week due to the low humidity levels experienced during the first week. After the second week, we returned to Luna Labs after discovering Acuity 00460 was not collecting any data. Device 00460 had the previous data removed and logging was restarted before respraying. While at Luna Labs, we cleaned the sensor surface using isopropyl alcohol and the Scotch-Brite pad at 9:27 a.m. on April 20th. We resprayed 00460 while leaving the other two Acuity devices running.

Capstone Experiment: Respraying 00460 and Final Deployment

Acuity device 00460 was resprayed using a four foot and two second spray method to ensure the loading density would be similar to our first attempt. The results of this respray combined with the other two devices is displayed in Table 3 below.

Slide Number	Averaged Slide Mass Pre Spray (g)	Averaged Slide Mass Post Spray (g)	Mass Difference (g)	Calculated Loading Density (mg/m ²)	Spray Time (s)	Spray Distance (ft)
00460	10.1190	10.1194	0.0004	310	2	4
00462	10.0900	10.0907	0.0007	517	4	4
00463	10.0765	10.0782	0.0017	1292	4	4
Control	10.1017	10.1018	0.0001	52	0	0

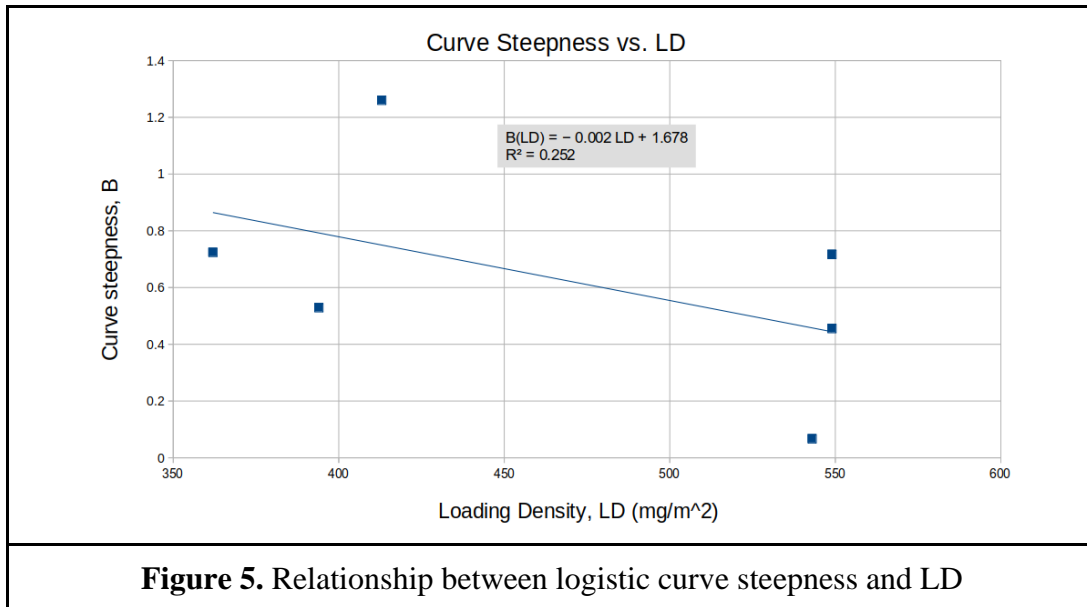
The devices were then redeployed under the covered patio and data was collected for an additional week from April 20th to April 27th before the results were analyzed.

RESULTS AND DISCUSSION

Low Loading Density Model: Logistic Curve

Among the low LD data, where full drying curves were available, there was large variability in the data. Not only was there variability between the drying curves associated with different LDs, but there was large variability in the characteristic parameters of the drying curves for individual cycles of the same LD. Within each cycle, the logistic curves fit to the data fairly well for most of the tests. However, the parameters of these logistic curve fits did not show to be a reliable predictor for chloride loading density at low LDs.

A graph for the relationship between LD and the average curve steepness of the logistic curve is shown below in Figure 5 (the same graphs for curve maximum and midpoint are in Appendix D). It is clear to see graphically and from the very low R^2 for each correlation drawn between LD and the parameters that this model does not work well, at least for when applied to only low LD data. If the full drying curves for intermediate and high loading density conditions and more drying cycles for low LDs were available, this model may show better performance.

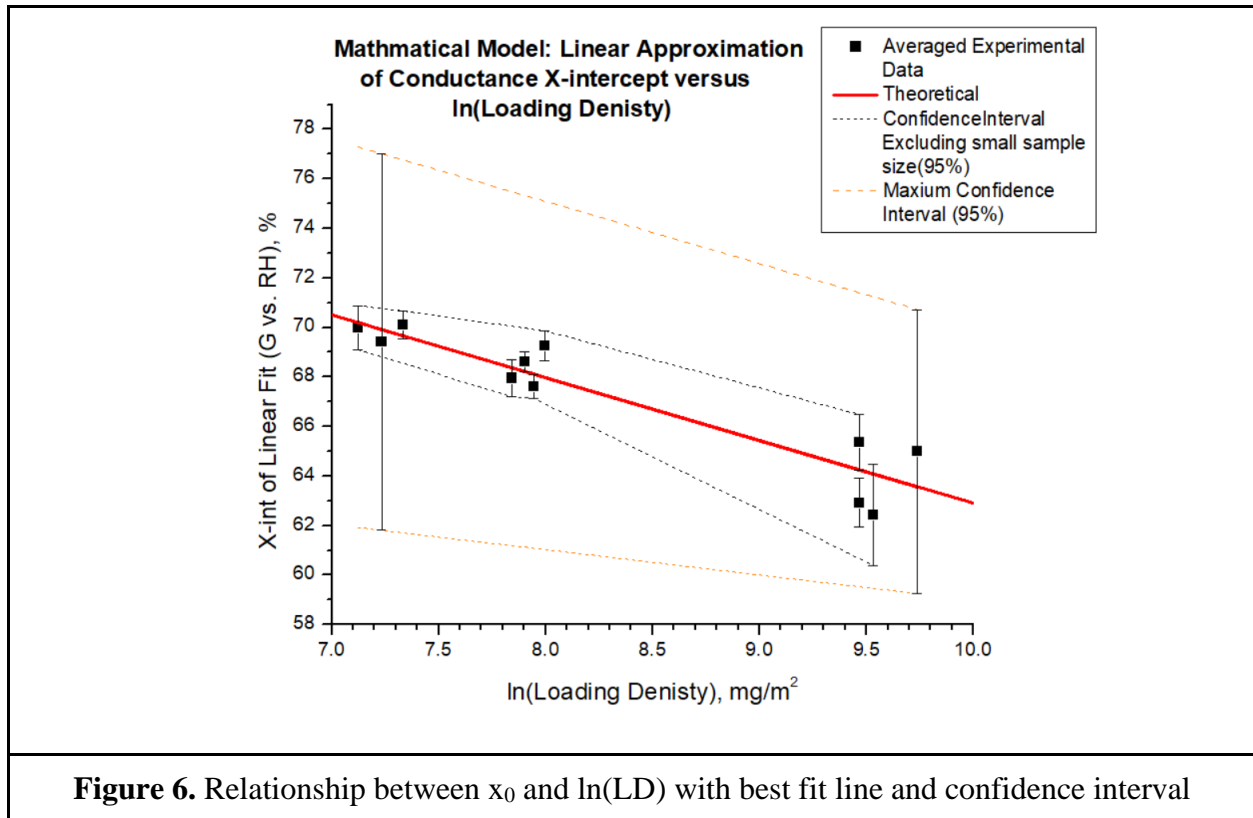


High LD Model: Linear Approximation

In contrast to the logistic curve model, the x-intercept (x_0) of the line fitting the steep linear portion of the high LD drying curves did prove to be a good predictor for chloride loading density. When plotting x_0 against the natural logarithm of the corresponding LD, a linear graph was realized with $R^2 = 0.86$ after performing a simple linear regression. By solving the equation of this linear regression line for x_0 , the equation predicting LD as a function of x_0 was found to be:

$$LD(x_0) = \exp[-0.39362 x_0 + 34.7574]$$

The graph of $\ln(LD)$ vs. x_0 , which shows this relationship can be found in Appendix E. Figure 6 shows the same relationship with the axes flipped (x_0 vs. $\ln(LD)$) to demonstrate a more detailed error analysis of the x_0 calculation. Error bars on each data point correspond to the 95% confidence interval in the x_0 for each corresponding LD. While two of the data points show very large error bars, it should be noted that these x_0 values were created from the average of two x-intercepts observed for the corresponding LDs. The drying cycles for these LDs often featured large tails in their $G(RH)$ curves that broke the linear fits or contained few data points in the linear region of interest. Thus, those cycles were not useful for this analysis.



In this form, our model for predicting chloride loading density satisfies all of our primary design goals. Judging by the high R^2 value, we can reasonably conclude that our model is accurate. While there are larger error margins that we had hoped for due to the two variable data points, we believe this can easily be rectified with generating more data at the loading densities with the largest confidence intervals. Our model is also quite simple, being a simple exponential equation with an input (x_0) that can be determined easily with a simple linear fit to one region of a drying cycle. This allows the model to be easily incorporated into future, more extensive analysis software. While the model does not include temperature, future work of lab experiments at different temperatures would allow for a temperature dependence to be added into the current model. We have also concluded that time was not a major factor in the current model as long as the wetting and drying halves are divided. Finally, our model is based on relationships found in the drying data for $G(RH)$ relationships, which contains curves with characteristics that we believe correspond to the evolution of the water layer. Thus, our model includes latent information about the water layer.

A negative linear relationship of moderate strength was found between the slopes of the linear fits and LD. While we initially did not expect the relationship to be negative, further inspection reveals that this observation lends evidence to our hypothesis that the hysteresis-like behavior of $G(RH)$ also extends to high LDs. High LDs result in the real conductance values increasing past

the maximum possible observation of the conductance sensor (10,000 μS). We hypothesize that as LD continues to rise in the high LD regime, the logistic curves corresponding to the drying cycles grow in scale by some factor. When these curves grow, the portion of the logistic curves under the 10,000 μS sensor maximum (the portion from which we can draw relationships) exhibit a lower slope. This is because, as the logistic curve is scaled in size, the conductance corresponding to the curve's inflection point also continues to rise. As a result, the portion of the total curve that is able to be observed resides in an "earlier" stage of the logistic curve where the instantaneous slope is lower. This is illustrated in Appendix F. We therefore consider the relationship between slope of the linear region and LD to be an artifact of the sensor's limitations and not the result of any physical phenomenon.

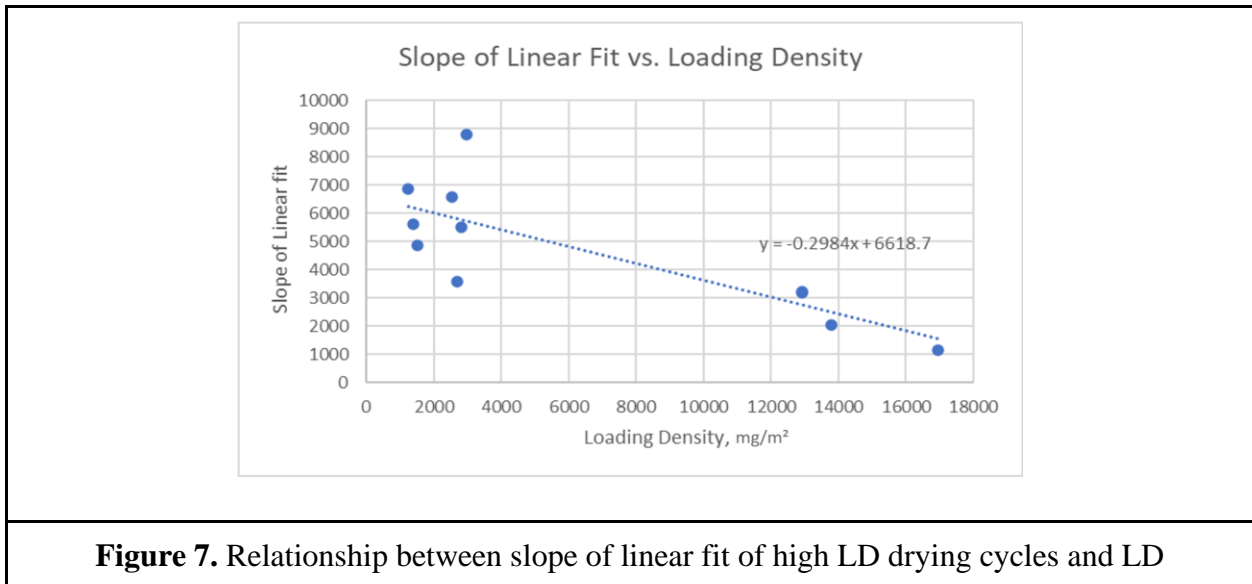


Figure 7. Relationship between slope of linear fit of high LD drying cycles and LD

Results of Verification Experiment

Due to our experiment depending on outdoor conditions, it was difficult to get enough usable data to compare to the laboratory data. Namely, the experiment depended on the relative humidity being above the deliquescence point of 76% to ensure that conductance occurred. Over the course of the three-week outdoor exposure there were only a few instances where the relative humidity was above the deliquescence point. As a result, there were not enough data points with which to make a conclusive argument for the impact of environmental data. Figure 8 below gives a representation of the data we were able to collect over the course of three weeks. It can be seen from this chart that there are few instances when the relative humidity was high enough to cause conductance.

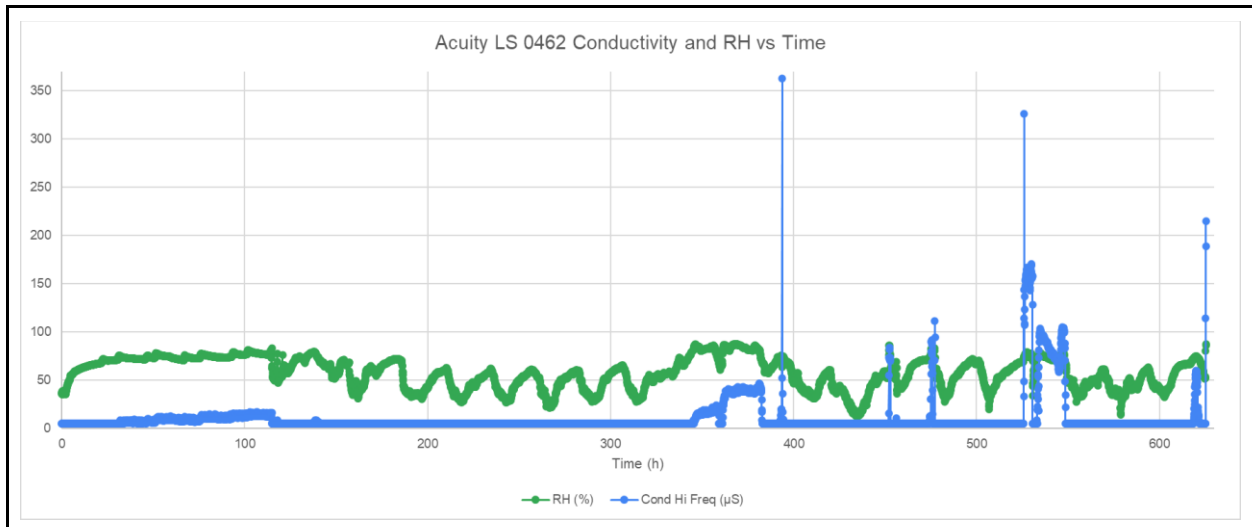


Figure 8. Conductance and relative humidity for an outdoor exposure with a loading density of 517 mg/m²

CONCLUSIONS

Laboratory data from the Luna Labs Acuity sensor was analyzed in an effort to determine and quantify a correlation between surface solution conductance and chloride loading density. A curve fit model based on changes in the relationship between conductance and relative humidity was used to develop a predictive model for chloride loading density at a constant temperature. Additionally, an outdoor experiment was performed with a known loading density at varied temperatures to gather more information about the effect of temperature on the conductance-relative humidity relationship. Based on this research, several major conclusions may be made and are shown below:

- The logistic model appears to fit the data for cycles individually, but the parameters of the fit do not correlate well to LD.
- The x-intercepts of the linear portion of high LD drying curves show a strong quantifiable relationship to LD based on the R^2 value of the model (0.86)
- The outdoor experiments showed possible evidence for temperature dependence of conductance, though many factors could result in the observed discrepancies.

These conclusions support the design goals, as we have developed a statistically accurate model that may be made more precise with further experiments as described in the recommendations. Further, our model takes into account latent information about the water layer through the use of $G(RH)$ data divided by wetting and drying cycles, and it is also time independent. Finally, our model is a relatively simple one that can be translated in many ways for implementation in more complex corrosion analysis software.

RECOMMENDATIONS

From our investigation, we have several recommendations for future work, which can be organized as recommendations for future data collection and recommendations for future analysis.

Recommendations: Future Data Collection

The two main issues that we ran into related to data collection were that the data from the tests often reached the maximum of the sensor and that it was very difficult to deploy a consistent loading density for our own experiments. Firstly, we recommend that the sensor maximum be taken into consideration for future data collection, whether that be through altering the sensitivity of the sensor itself, a much more involved process, or by choosing known loading densities that should not exceed the sensor maximum. The choice between these two proposals relies entirely on how the sensor is to be used. If the sensor will be used in lower loading density environments, then changing the sensor range is counterproductive, and the experimental methods should be changed to reflect its intended use case. However, if the sensor needs to operate at higher loading densities, it may be worthwhile to investigate an appropriate conductance sensitivity range. We hope that the results of our investigation help to determine in which direction is the best to proceed. Additionally, from our investigation, we recommend that data points be taken more often at areas of rapid change, such as the increasing and decreasing portions of the G vs. RH curves. We had to omit several relative humidity cycles from our High LD linear fit because there were two or less data points for the entire curve between the sensor maximum and minimum, so having more data points would have been useful in developing a more robust model. Finally, as a third alternative, we hypothesize that using a lower temperature for laboratory tests would also lower the maximum observed conductance value, giving a more complete curve for the same loading density.

When we were conducting our own experiment, the most difficult step in the setup was getting a consistent loading density across our repeat tests. We found that even slightly altering the

position of the sprayer could drastically change the amount of solution deposited on the sensor. From our experience, we recommend a more automated spray method for future experiments to eliminate the variation due to human interference. Towards the end of the project, we investigated automated sprayers for reptile enclosures as a possible solution or basis for design. With a more automated spray method, the spray time, distance, and direction can be much more consistent among repeat samples, increasing the amount of data available for given loading density to use in analysis.

Recommendations: Future Analysis

There are several directions of analysis that we came up with but were unable to investigate, mainly due to having the idea later on in the course of the project. Our first recommendation is to try other mathematical functions to fit the data. From our investigation, we found the logistic model to be the best choice: it had high correlation and was the simplest to understand, as each coefficient adjusted a specific feature of the graph (height, midpoint, and curvature). However, we had the idea later on to try a hyperbolic tangent function or a differential function. We did not have time to investigate these choices and thought them to be less simplistic, but future analysis could investigate whether they are a more accurate representation of the data.

We were unable to successfully implement Hubbert linearization in our model for high loading densities. However, it did work quite well for lower loading densities. Data transformation methods such as Hubbert linearization could be a useful tool for simplifying a curve fit model to be easier to use, or as a means to work around some artifacts or missing sections of the data.

One area of great interest that we came across too late in our project was the source of increasing conductance at the beginning of the drying portion, immediately after the relative humidity began to decrease from its maximum. In a talk with Dr. Charles-Granville, a postdoctoral researcher at UVA, we discerned that the increase is most likely caused by the decrease in solvent as water evaporates while the amount of solute remains the same. We thought that further investigation could give us more information about the water layer present on the sensor surface. With enough information about the water layer, analysis can take a completely different approach by determining conductivity from conductance and water layer information, which is directly related to loading density.

In addition to the completed model provided to Luna Labs, we have provided materials that can be used as a framework for future analysis. We built the program used for automatically curve fitting the data in such a way that the function used for fitting can be easily changed, in case future analysis required us to try different functions to fit the data. The program can also look at the wetting data, which did not prove to be the most valuable direction for us but is available to

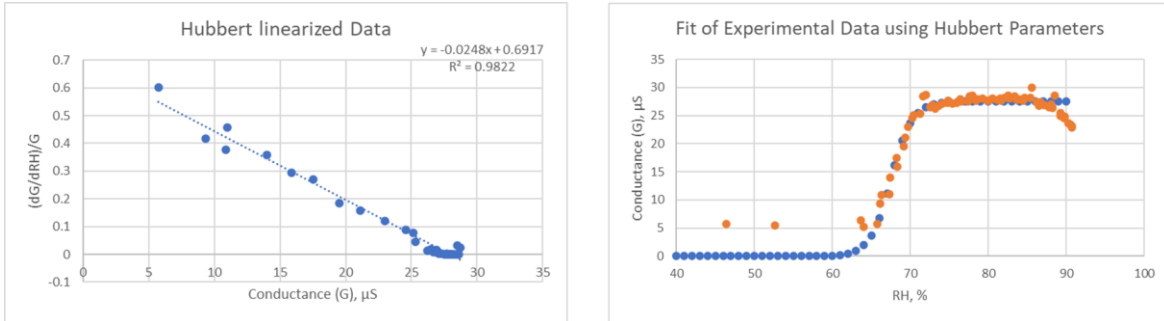
anyone who wishes to use it in the future. We worked to make our program easy to understand, change, and translate to other platforms so that the tools we developed could be used in the future.

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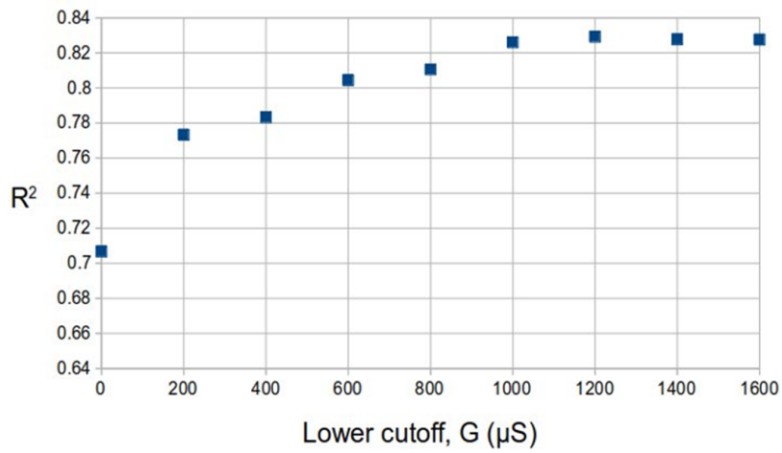
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APPENDIX

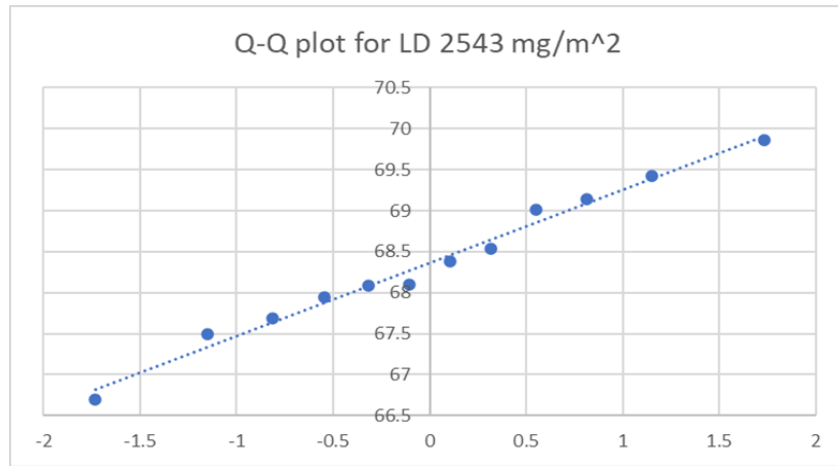
APPENDIX A: Example Graph of Hubbert Linearization Method for Curve Fitting



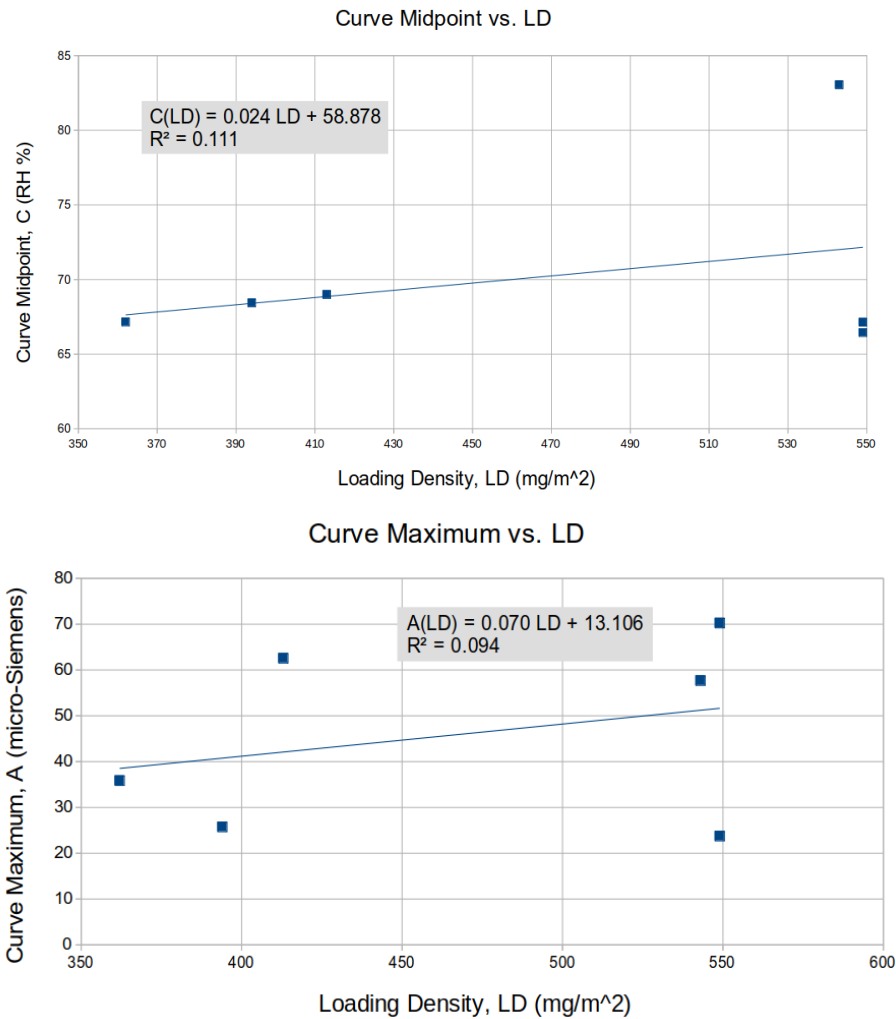
APPENDIX B: Graph of R^2 values for Linear Fit vs. Conductance Cutoff Value for High LD data



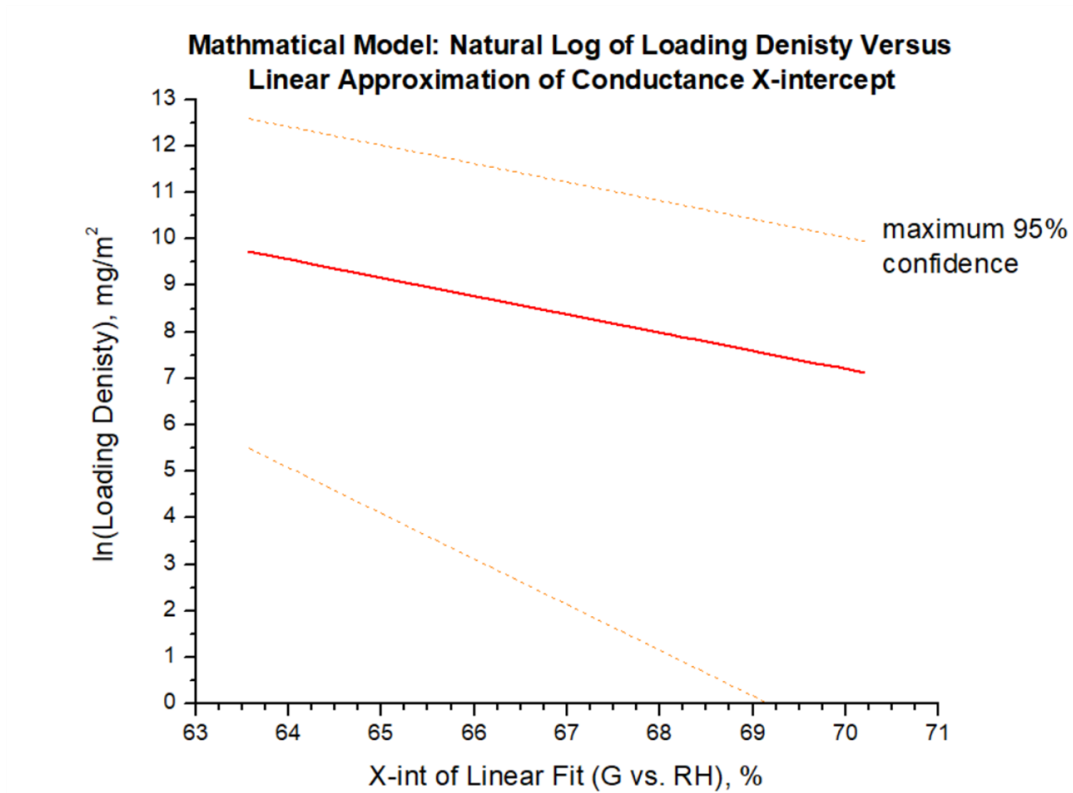
APPENDIX C: Example Q-Q plot Showing Normal Distribution for Linear Fit Parameters



APPENDIX D: Low LD Logistic Curve Parameters vs. LD



APPENDIX E: Graphical Representation of Final Linear Fit Model for High LD Data



APPENDIX F: Demonstration of Sampling Range Effect on Slope of Linear Fit

