EPiC Series in Computing
Volume 79, 2021, Pages 1–10
Proceedings of ISCA 34th International Conference on
Computer Applications in Industry and Engineering

Detecting Vibration Frequencies of Concrete Structures via RFID Tags

Janita Aamir[1] Barrett Durtschi[2], Andrew Chrysler[2], and Paul Bodily[1]

[1] Department of Computer Science, Idaho State University, Pocatello, Idaho, U.S.A
[2] Department of Electrical Engineering, Idaho State University, Pocatello, Idaho, U.S.A
{aamijani,durtbarr,chryandr,bodipaul}@isu.edu

Abstract

Radio-Frequency Identification (RFID) technology is widely used for localization detection in the Internet of Things (IoT) applications. RFID is low-cost and has many real world applications in areas such as health care, library systems, inventory tracking, and object detection. This paper presents a possible application of RFID in smart infrastructure. We present an algorithm to detect the vibration frequencies of precast concrete structures during transportation. Measuring the current and future frequency values helps to prevent possible damage during transportation. This experiment makes use of a shake table to simulate movement in a concrete structure to which RFID tags are attached. While the shake table is running, values like Peak Received Signal Strength Indicator (RSSI) and phase angle are recorded. Analysis on these data is then performed using fast Fourier transform (FFT) and linear regression. The linear regression model is able to predict frequency values by looking at the peaks per second for data sets that were recorded using the experimental setup. We use 10-fold cross validation to demonstrate that the linear regression model is able to predict vibration frequency with high accuracy (RMSE = 0.591 Hz).

1 Introduction

Precast concrete structures have a high risk of damage during transportation to the construction site. The damage occurs due to high levels of frequency in concrete caused by a moving vehicle. Damage to the precast concrete can cause millions of dollars to repair. In addition, vibration detection is important to enhancing the safety measures in infrastructure projects. Therefore, it is not only important to detect but also predict frequency values of precast concrete. Successful vibration detection can be groundbreaking for the infrastructure industry, as it can prevent potential damage to the concrete by stopping the structure from reaching its frequency limit. One of the methods that can be used for vibration detection is through Radio Frequency Identification (RFID) technology. The main goal of this research is to evaluate different vibration detection and prediction algorithms using RFID tag readings as an input.

Vibration detection using RFID technology is a novel approach and has only been researched within the past decade. Traditional forms of vibration detection can be very costly and may require wired connections, making them harder to install and maintain [1]. In real-world practical examples, such as the transportation of precast concrete, it is important to use vibration detection techniques that are less costly and easier to maintain. RFID-based systems are wireless technology and are fairly economical. They are comprised of only 2 components which are the RFID tags and readers/antennae. The RFID components make use of electromagnetic fields to track RFID tags that are often attached to different objects. The RFID readers are mobile; therefore, they can be mounted on a wide range of objects either indoors or outdoors [2].

For this experiment, we mounted a concrete structure onto the shake table and attached an RFID tag to it. The RFID antenna was placed independent of the shake table. The known frequency values of the shake table allow us to determine how close the predicted values (derived by our models from RFID data) are to the actual frequencies at which the concrete structure was moving at the time the data was collected. The data collected included values such as the peak Received Signal Strength Indicator (RSSI), the phase angle, and the Unix time stamp. Our methods include applications of the fast Fourier transform (FFT) and a linear regression model. We use 10-fold cross-validation to evaluate the performance of our linear regression model and calculate root mean squared error (RMSE) of predicted frequency values for this model.

2 Related Works

Related work has examined vibration sensing using off-the-shelf RFID systems. Given that RFIDs can only detect low-level frequency values, researchers have used an RFID-based system, Tag-Sound, along with Universal Software Radio Peripheral (USRP) platforms to explore the harmonics for vibration sensing [1]. This vibration sensing system can measure both high-frequency values (>1Hz) and also low amplitude values (<2mm). Their findings indicate that even with high-frequency values, Tag-Sound is able to detect sub-hertz vibration frequency values with high accuracy.

Similar research presents the use of ultra high frequency (UHF) RFID-based vibration frequency sensing tags [3]. They make use of tilt/vibration switches that repeatedly turn ON/OFF when vibration is applied to the sensors. Researchers obtained the number of readings per second and found that those readings were proportional to the vibration frequencies. The overarching goal of this study is the same as this research, but the methods and algorithms used are different.

Both of the research papers above talk extensively about finding vibration frequency values using RFID technology. However, they do not go in-depth into how their findings can be used in practical deployments.

Another study investigates vibration measurement and the importance of time synchronized wireless sensor network [4]. In this study, an IEEE 802.11-standard-based wireless device is used along with the timing synchronization function (TSF). The main goal of this research is to ensure that different wireless nodes maintain consistency on the common time line and have no time delays in the readings. The increasing popularity of the wireless sensor networks makes it necessary to analyze any weaknesses in the system and improve the accuracy of the system's readings.

In the infrastructure industry, there has been immense research done to detect the long-term damage in concrete structures using methods like Vibration-Based Damage Detection (VBDD). The following two studies work with real-world, practical examples. The first study looks at using VBDD techniques to maintain the structural health of precast concrete box girders [5].

Their work aims to prevent bridge failures. The bridge condition is assessed through detecting low levels of damage using sensors (accelerometers and strain gauges) and the mode of vibration. For this experiment, the researchers remove a piece of precast, pre-stressed concrete box girder from a bridge. On the piece of concrete, they analyze corrosion and damage over time using different VBDD methods. Their findings indicate that Change in Mode Shape (CMS) method is the most reliable approach for damage detection, as it gave the clearest results over a wide range of damage locations.

Comparably, research done by Lyapin et al. [6] aims to find the damage in concrete columns through vibration analysis techniques. The researchers look at damage localization results with the different positions of the mono-axial accelerometer sensors along the concrete column. They find that increasing the number of measurement points for the sensors can lead to a proportional increase in localization accuracy.

Both of the studies above are notably useful in detecting long term damage on precast concrete. However, the studies differ from our work in that their aim was to detect existing damage in concrete whereas our aim is to predict future frequency values to prevent potential damage to the precast concrete during transportation. Vibration detection technology enables us to detect any damage during transportation that may be overlooked.

3 Methods

The following sections walk through the experimental setup of the shake table, the concrete structure, and the RFID technology. We then present our analysis of the data recorded from the experimental setup and the algorithms that are used to determine frequency values.

3.1 Experimental Setup

Our experiments utilized a UHF RFID Reader, a RFID Reader Antenna, and a Confidex Survivor RFID tag. A cinder-block was used as a proxy for precast concrete. An electric shake table was used with the capability of moving at frequencies of 1-7 Hz at a displacement of 1 inch. Our experiment took measurements over RFID data such as RSSI and phase angle by a program made with Octane SDK in the C# language[1]. The preliminary tests did acquire information of the shake table using a data acquisition program (e.g., exact displacement), but these were not used in the final analysis.

3.1.1 Setup

Initially, a different setup using two antennae was used. One antenna was mounted onto the table using a wooden brace while another antenna was placed off the table at the same height and distance away from the concrete and RFID tag. Eventually, tests changed to incorporate a single antenna/tag configuration that was used throughout the testing phase of this experiment. A photo of the setup can be seen in Figure 1. This experiment uses a single target tag which is shaken at frequencies ranging from 0-4 Hz. Only 0-4 Hz is analyzed because higher frequencies made the shake table unstable. The instability comes from two factors. First, in the room made of large concrete, the pad that the table was sitting on had a slight downhill slope. Even with brakes, if the frequency was too high, the table would move resulting in a change of distance from the antenna to the RFID tag. Another factor that could have contributed to the table being unstable was the amount of weight holding down the table. On a flat surface with a

[1] https://support.impinj.com/hc/en-us/articles/202755268-Octane-SDK

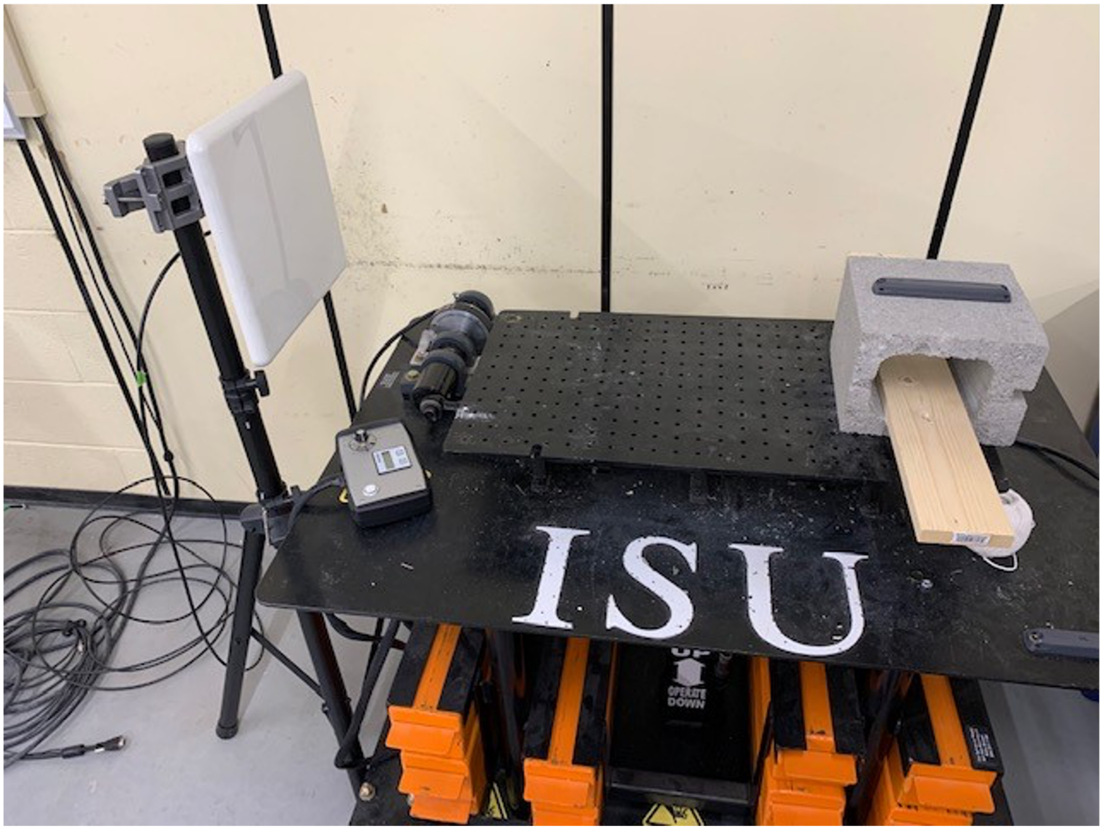

Figure 1: Actual setup of experiment with antenna on the left and concrete (with RFID tag), mounted to the shake table. The grey strip seen on the concrete is the RFID tag. The orange bars beneath the table are weights that make the shake table sturdy.

high frequency the table would move slightly, but the movement is so small that it can be considered negligible. With these two factors combined however, the table would move too dramatically, thus limiting our testing range from 0-4 Hz. The diagram in Figure 2 identifies key measurements of objects in the experimental setup with respect to the shake table. The cinder-block dimensions measure 6 x 8 x 8 inches. The antenna is placed off the table to make its position independent of the shake table's location while moving.

3.1.2 Testing Environment

All tests were performed in the Civil Engineering Liquids and Fluids Laboratory at Idaho State University. The details of the testing environment have the potential of directly impacting the back scatter with RFID readings. For all tests, the wheels of the shake table were immobilized, and multiple weights made the table sturdy (with the exception of going over 5Hz); The sturdiness of the table in this case means the wheels remain in their initial position and the distance between the antenna and the tag remains constant. The shake table was moved to the middle of a large classroom and leveled to make sure the moving surface was flat. The classroom had a concrete floor and sheetrock walls. This classroom consisted of work desks and heavy civil

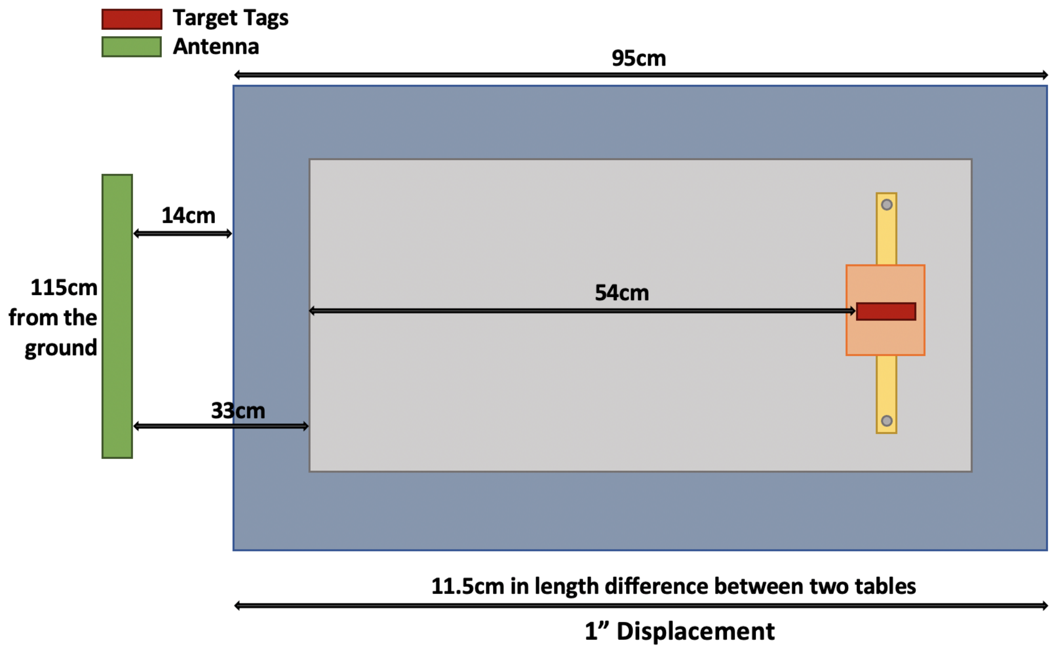

Figure 2: Diagram showing distances between equipment used in the experiment setup.

engineering lab equipment. The extraneous lab equipment was located around the perimeter of the room while the desks were pushed as close to the walls as possible. On the perimeter of the room were also shelves with metal components that were used in conjunction with the extraneous lab equipment. This environment roughly represents the environment where precast concrete might be assembled.

3.1.3 Tests

Tests were performed by starting the Octane SDK software and then proceeding to activate the shake table. The shake table moved for approximately one minute after which the SDK software ended. The information from the program was exported to an Excel file and the process repeated. In total there were five tests, one for each of the frequencies 0, 1, 2, 3, and 4 Hz [2].

3.2 Data sets and Analysis

After collecting the data from the lab experiments, the data was cleaned by removing data outliers. Before graphing data sets, the Unix timestamp was converted to seconds elapsed. The Unix timestamp values were converted by taking the first recorded reading and subtracting that first reading from the following timestamps. For any further calculations or alterations, the first 150 and the last 150 readings of the data set were ignored; this helped to remove any possible noise during start-up and cool-down phases and ensure that the shake table reached

[2]Datasets are accessible via https://tinyurl.com/shaketabledata

its preset frequency. Failure to remove the first and last 150 readings from the set can lead to inaccurate results because the shake table needs to reach the set frequency when started and also needs to slow down from its set frequency when stopped.

For each of the five data sets, two graphs were produced. One graph was for 'peak RSSI' against seconds elapsed and the second graph was for 'phase angle' against seconds elapsed. The peak RSSI values alone can facilitate vibration detection since peak RSSI values are a measurement of how well the RFID tags receive signals from the access point. This value tells us the distance from the antenna to the tag. Peak RSSI and frequency have a direct relation; the higher the frequency, the higher the density for the peak RSSI values.

We employed three different vibration frequency estimation approaches of which we found one that worked effectively. The first approach was to use a fast Fourier transform (FFT) algorithm on the collected data set to transform the time data set into a frequency data set. The result is displayed on a graph that contains one or more peaks indicating the intensities of different frequency values. In this experiment, our desirable outcome was a frequency peak appearing on or close to the preset frequency of the shake-table. This approach, however, requires a constant time interval between each reading from the RFID tags. RFID tags generally take readings at quick and random intervals, hence it was necessary to come up with an alternative solution to this problem.

The data set was altered such that all readings had an equal time interval of 3 milliseconds. We synthesized a data set of readings at equal intervals by fixing regular intervals and interpolating the peak RSSI values at those equidistant intervals. The interpolated peak RSSI values were calculated using closest peak RSSI readings from the raw data set. The function used was as follows:

$$interpolatedpeakRSSI = (\frac{peakRSSI_2 - peakRSSI_1}{timestamp_2 - timestamp_1})(synthTimestamp) + y - intercept \quad (1)$$

The graphs that were then produced using FFT still possessed a lot of noise. Since FFTs work best when there is a clear and consistent pattern of the data sets, the focus was shifted towards another approach. Our second approach was to use the lomb-scargle periodogram from the scipy.signal.lombscargle library in Python [7]. The lomb-scargle periodogram is similar to the FFT in that it estimates a frequency spectrum but with the difference that it can be used on data sampled at irregular time intervals. The graphs produced from this approach also contained noise and the results were similar to the FFT. Our hypothesis is that the noise is produced due to the scatter from the walls and the extraneous lab equipment. Looking at the graphs for the peak RSSI values, a clear pattern can be seen as the graphs got denser with an increase in frequency (see Figure 3). More density in the graphs meant that the number of peaks also increased. This indicates a direct relation between the number of peaks and frequency values. As such, we hypothesized that looking just at the raw number of peaks per second in the graph could be an accurate predictor of the frequency. Therefore, our third approach was to write a Python program that calculates the number of peaks for each of the five original data sets. This program made use of the scipy.signal library [7]. The peaks were then plotted on the initial graphs as seen on Figure 3. From the analysis, it is clear that as the graph becomes denser, the number of peaks increase as well. This hypothesis was further analyzed by calculating the number of average peaks per second for each of the five data sets. Table 1 shows the average number of peaks per second for all five data sets.

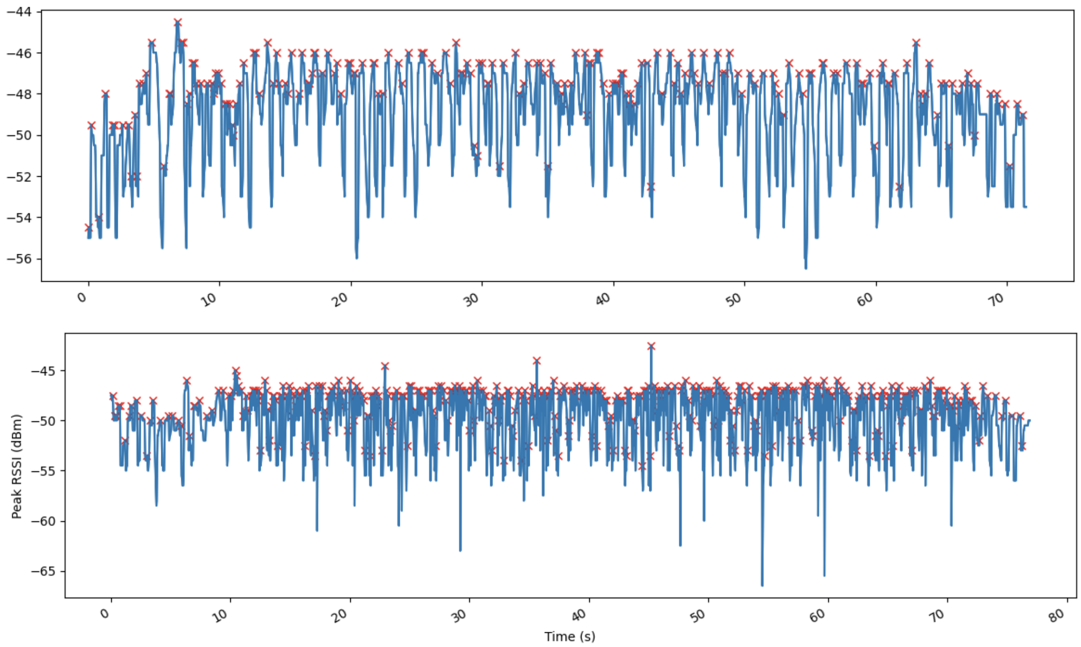

Figure 3: The top graph shows the peak RSSI vs seconds elapsed for 1 Hz vibration. The bottom graph shows the peak RSSI vs seconds elapsed for 4 Hz vibration. Note that the number of peaks per second increases proportional to the vibration frequency. The blue lines indicate the peak RSSI values and the red x's on the graphs indicate peaks.

Table 1: Average number of peaks per second by shake table frequency

Frequency Hz	**Peak Calculations**		
	Total Peaks	***Total Seconds***	***Peaks/Second***
0	192	62.46969	3.073
1	202	71.46965	2.826
2	284	74.20540	3.827
3	376	72.47507	5.188
4	481	76.90152	6.255

[a]Using the values above, a linear regression model was found and plotted.

4 Results

From the calculated data in Table 1, a steady increase in values can be seen as the frequency values increase. Hence, we decided to compute a linear regression model for these values. The x-axis represents the frequency values, and the y-axis represents the number of peaks per second. The linear regression model enables us to predict the behavior of a dependent variable based on the value of the independent variable. In our case, our dependent variable is the number of peaks per second and the independent variable is frequency. This linear regression model enabled us to get a close prediction of frequency by calculating and feeding in the peaks per second of a particular data set. On the linear regression model, our actual response can be slightly away from the estimated regression line or it may also be on the line.

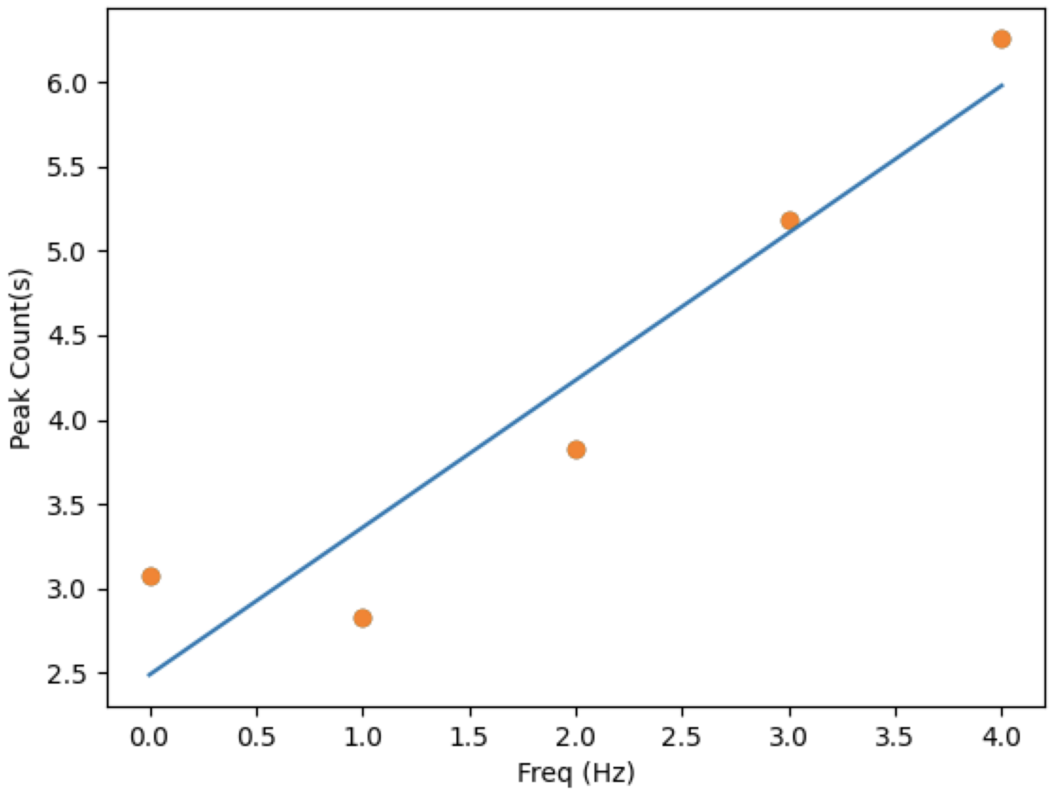

Figure 4: Linear Regression Model for all five data sets. The linear regression line is represented by blue, and the actual peaks/second values are represented by the orange dots.

In order to ensure the accuracy of our model, the 10-fold cross-validation technique was computed with the help of the sklearn.model_selection library in Python [8]. Although the linear regression model enabled us to get a close prediction of frequency values, the 10-fold cross-validation further demonstrated how accurately our model predicts frequency values. The 10-fold cross-validation is used to evaluate and predict values from data sets by partitioning the data into training and testing sets. For the cross-validation technique, the number of peaks for the data set were calculated again. This time, the peaks were not calculated for the whole data set at once; instead, the peaks per second were calculated in one-second windows for all five of the original data sets. Instead of moving the windows over a full second, they were slid over by half a second to the next section of the data set values such that the windows overlapped. All peak values were then collected into a single data file which contained the number of peaks per second and the given frequency value corresponding to each peak count. The data was then shuffled for partitioning to ensure that the frequency values are not in any particular order. To partition our data into training and test sets, the data was separated into 10 smaller subsets. Out of the 10 subsets, 9 are used for training the model by found regression values, and 1 is used for testing or validating the predictive model. The number of peaks per second for our testing set was then fed into the model to get a prediction for frequency. The cross-validation method was repeated 10 times with each having a unique testing set. The results for the 10 folds were then recorded to estimate the value of the overall root mean squared error.

To calculate the root mean squared error by using the formula in 2. On average we expect that we would be able to predict the vibration frequency within an RMSE value of 0.591 using the method described. The RMSE results from the 10-fold cross validation are given below:

Table 2: The RMSE value based on the predicted and target values using cross-validation

RMSE Formula	**RMSE Value**
$\sqrt{\frac{1}{10}\sum_{i=1}^{10}(predicted_i - target_i)^2}$	0.591

Looking at the 10-Fold cross-validation box-plots in Figure 5, we see that the linear regression model serves to predict vibration frequency with high precision and accuracy. This is because the median, representing prediction values, for each of the five box-plots increases linearly with frequency.

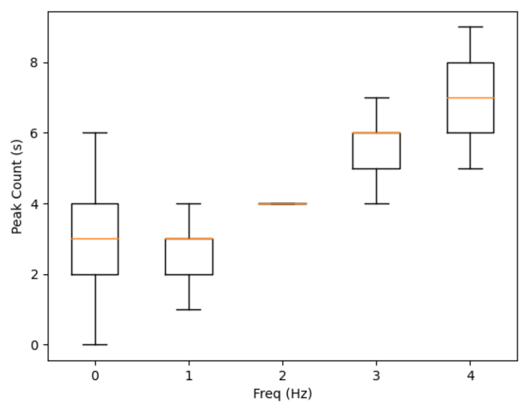

Figure 5: 10-fold cross validation box-plot. The median of the box-plot indicates a linear relation between the frequency values and peak count.

The trend in the box-plot shows a fairly strong correlation between vibration frequency and peaks per second calculation meaning that we can use peak count per second calculation to predict vibration frequency.

Future Work and Discussion/Conclusion

The research presented in this paper is meant to be deployed practically. Hence, in order to investigate the practical application of these methods in real world scenarios, we plan to collaborate with Concrete and Asphalt Lab which is part of Civil Engineering Department at Idaho State University. The lab has all the necessary equipment to test and determine the mechanical properties of concrete.

In addition, we plan to use diverse and more complex algorithms to further improve the frequency predictions. These can include recurrent neural network (RNN) algorithms that can help make frequency predictions with greater accuracy. They use their internal memory to store information from the input values, which aids in making fairly close predictions on future values.

In this paper, our goal is to effectively detect vibration frequencies in precast concrete structures; predicting frequency values would prevent any potential damage to the concrete structures during transportation. To achieve our goal, we analyze different algorithms that can effectively detect vibration frequencies in precast concrete structures with the help of RFID technology. Some algorithms like the FFT and the lomb-scargle periodogram were not an effective solution to the problem considering the inconsistent pattern of the data set along with the varying time intervals. Linear regression model, on the other hand, does not require constant time-intervals or a consistent pattern in the data set. The method that we used seems to be more resistant to back scatter or noise. It makes use of Peak RSSI values and their time stamp from data sets and makes predictions by calculating the peaks per second values for all five data sets. It calculates the total number of peaks and divides them by the total seconds of the data set. The 10-fold cross-validation is then used for further analysis of the model. Along with predictions of frequency values with the help of the linear regression model, the 10-fold cross-validation further calculates the accuracy level by finding the RMSE value (0.591 Hz) for the model.

References

[1] P. Li, Z. An, L. Yang, P. Yang, and Q. Lin, "RFID harmonic for vibration sensing," *IEEE Transactions on Mobile Computing*, pp. 1614–1626, 2019.

[2] F. Chetouane, "An overview on RFID technology instruction and application," *IFAC-PapersOnLine*, vol. 48, no. 3, pp. 382–387, 2015.

[3] D. Feng, T. Higuchi, Y. Kobayashi, S. Takeda, K. Kagoshima, and M. Umehira, "Measurement of a novel UHF RFID based battery-less vibration frequency sensing tag," in *2018 International Symposium on Antennas and Propagation (ISAP)*. IEEE, 2018, pp. 1–2.

[4] Y. Uchimura, T. Nasu, and M. Takahashi, "Time synchronized wireless sensor network for vibration measurement," in *SICE Annual Conference 2007*, 2007, pp. 2940–2945.

[5] Z. Zhengjie, L. Wegner, and B. Sparling, "Structural health monitoring of precast concrete box girders using selected vibration-based damage detection methods," *Advances in Civil Engineering*, vol. 2010, pp. 1–21, 05 2010.

[6] A. Lyapin and Y. Shatilov, "Vibration-based damage detection of the reinforced concrete column," *Procedia Engineering*, vol. 150, pp. 1867–1871, 12 2016.

[7] P. Virtanen, R. Gommers, T. E. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright *et al.*, "Scipy 1.0: fundamental algorithms for scientific computing in python," *Nature methods*, vol. 17, no. 3, pp. 261–272, 2020.

[8] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg *et al.*, "Scikit-learn: Machine learning in python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.