THE INTEGRATION OF BUILDING INFORMATION MODELLING(BIM) INTO STRUCTURAL HEALTH MONITORING (SHM)

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CERTIFICATION

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DEDICATION

I dedicate this work to God Almighty and my family for their enabling support and encouragement to carry out this project.

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ABSTRACT

The long-term management of critical infrastructure requires moving beyond costly manual inspections to the adoption of continuous structural health monitoring(SHM) systems. This project successfully developed a necessary link between SHM sensor data and a building information model(BIM). The aim was to create a workflow that processes large sensor data to determine structural performance and automate the process of updating the processed data into the corresponding digital elements with the BIM environment.

The data collection from the case study was done using a locally made cost-effective accelerometer sensor. The processing of the raw sensor data was carried out using Python script to determine the peak lateral frequencies at ambient and loaded conditions, as well as the percentage shift in the frequency, which indicated a percentage shift in structural stiffness. Virtual sensors were created in the model at the location of the sensor during data collection. With the aid of Dynamo in Revit software, the processed data were automatically imported to the correct element within the model, instead of manually inputting them.

At ambient conditions, the bridge deck and staircase had a peak lateral frequency of 0.467Hz and 0.867Hz respectively, while at pedestrian loading conditions, the bridge deck and staircase had a peak lateral frequency of 0.413Hz and 0.829Hz respectively. This processed data showed that the lateral frequency of the bridge deck and staircase decreased by 11.6% and 4.38% respectively, indicating a 21.85% and 8.57% reduction in the effective stiffness of the elements respectively. The solution will improve large sensor data management by reducing data interpretation time**.** This allows structural engineers and stakeholders to gain faster, more confident insights needed for timely maintenance decisions and ensuring structural safety.

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ACRONYMS

AVT - Ambient Vibration Testing

BIM - Building Information Modelling

DFOS - Distributed Fibre Optics Sensors

DIC - Digital Image Correlation

UAV - Unmanned Aerial Vehicle

OBIA - Object-Based Image Analysis

RVS - Rapid Visual Screening

GBDT - Gradient Boosting Decision Tree

CNN - Convolutional Neural Network

GIS - Geographic Information Systems

FRF - Frequency Response Function

NDT - Non-Destructive Test

UPV - Ultrasonic Pulse Velocity

VICAS - Visual Inspection and Condition Assessment of Structures

OMA - Operational Modal Analysis

SHM - Structural Health Monitoring

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Structural Health Monitoring (SHM) is a very crucial part of maintenance and management of buildings and structures. The use of SHM in recent years is due to advancement in technology and availability of various sensors for the detection of cracks or damaged parts in structures (Abdlullahi et al.,2019) .

Awoyera et al. (2021) confirmed that within a 10 year period (2009-2019), Nigeria recorded twenty one building failures only in the year 2019 and these were mainly due to man-made errors. These building collapses in Nigeria lead to loss of lives and have adverse economic effects (Uzodinma et al., 2022). In ancient times, structures like bridges were monitored using visual inspection and manual measurements and these personnels relied on their knowledge and experience to detect a structural anomaly. These methods were subjective, time consuming and often lead to late detection of structural issues (Nagrecha, 2025). In recent years, sensors have played a pivotal role in SHM, enabling precise data acquisition and measuring necessary parameters for timely interventions to prevent failures (Sivasuriyan et al., 2024). However, a significant challenge in SHM is the management of enormous volumes of raw and processed sensor data. To this end, Building Information Modelling (BIM) has been proposed to be a powerful tool that can be utilized for effective SHM data management as well as visualization (Valinejadshoubi et al., 2017; Bahmanoo et al, 2019).

Although BIM has been in use in Nigeria for many years, its effectiveness and potentials have not been maximized (Onugwa and Uduma-Olugu, 2017). Oladiran et al. (2022) pointed out that the main barriers of the implementation of BIM in the Nigeria construction industry, are the societal beliefs among the industry players and the lack of proof of financial benefits that comes with its implementation in civil engineering projects. However in the light of several barriers like inadequate BIM professionals, BIM has also been of help to construction professionals in Nigeria. Going forward BIM needs to be introduced in universities and schools of higher learning to facilitate its widespread acceptance among young professionals (Onugwa and Uduma-Olugu, 2017). Hamma-Adama and Kouider (2018) observed that Nigerian universities have sufficient hardware but are however not technically not ready, due to lack of training software and skilled BIM tutors.

1.2 Statement of the Problem

Structural Health Monitoring (SHM) is very important in the prevention of infrastructural collapse (Alpsten, 2017). Ingle (2024) emphasized the importance of regular assessment of buildings. Traditional methods of monitoring structural condition often rely on periodic manual inspection. Pandey and Sinha (2023) emphasized the critical role of visual inspection in identifying structural deficiencies in civil construction. Bhattechurjee and Jain (2012) asserted that visual inspection might not really give precise measurements and depends on the expertise of the personnels. This method can also be slow, laborious and cost intensive. Low cost accelerometers (sensors) have been developed and used in data collection during SHM exercise in buildings (Vestroni, 2025; Lorenzoni et al., 2013 and Emadi et al., 2025). These sensor data have been Processed and integrated into Building

Information Modelling (BIM) for enhanced real-time monitoring. This project uses a low cost, user friendly system that combines sensor data with BIM environments to enhance how structural performance is assessed.

1.3 Aim and Objectives

The aim of this project is to develop and demonstrate a feasible methodology for measuring the typical vibration intensity at selected locations within a pedestrian bridge using a low-cost accelerometer sensor and integrating the data into the BIM model for visualization.

The specific objectives of this project include to;

I. Demonstrate the collection of vibration data at selected locations within the structure using low-cost accelerometer-based data acquisition system.
II. Show how the collected acceleration data can be processed using a simple script to generate the power spectral density and peak lateral frequency .
III. Demonstrate the implementation and visualization of processed data into a BIM model.

1.4 Scope of Work

The steps involved in this present study will include;

I. Collecting vibration data from selected locations within the building structure using a 3 axis accelerometer (MPU6050) .
II. Processing the collected data by generating the power spectral density and peak lateral frequency using simple scripts in Python programming language.
III. Importation of the lateral frequency values into Revit Model via Dynamo Scripts.

IV. Mapping sensor locations and associating the calculated lateral frequncy values with the particular element observed in the BIM model.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction to Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) is the process of tracking and analyzing the condition of structures like bridges and buildings over time. This is done by collecting and studying data on their responses to various factors allowing for the detection of any change or potential issues. Chen and Ni (2018) referred to SHM as a key element of cost effective strategies for condition based maintenance of a structure during its service life. It also pointed out that structural health monitoring involves tracking and evaluating a structure's condition over time using data from sensors, which helps to assess damage and performance, making it a valuable tool for maintaining engineering structures. SHM helps in assessing a structure's integrity and safety, enabling engineers to take rehabilitation measures when unexpected changes occur, such as deformation or strain (Valinejadshoubi et al., 2017).

SHM does not only come in handy in assessing recent buildings. Rossi and Burnas (2023) observed that in recent decades, the need to protect and upgrade Cultural heritage Structures(CHS) is of primary importance, due to its economic, social, cultural and environmental impact. The paper asserted that proper structural health monitoring and management of CHS are decisive measures aimed at assessing the actual state of these structures as well as an effective tool for planning cost effective and sustainable maintenance solutions.

2.1.1 Objective and Applications of SHM

Monitoring of structures provides valuable information about its health that can help in providing a decision support system for retrofits and other structural modifications (Arul and Kareem, 2020). SHM has been applied in a wide range of structures like buildings, bridges, dams, etc for damage detection, performance assessment and even for determining their remaining service life.

Jaelani et al. (2023) discussed the development of a benchmark study for bridge monitoring, focusing on Structural Health Monitoring (SHM) as a continuous damage detection strategy to optimize inspection and maintenance schedules for bridges. The case study of this research was a 30 metres long steel concrete composite bridge at the University of Bundeswehr, Munich. Various damage scenarios were applied on the bridge and the bridge was equipped with various sensors for data acquisition For the short term measurements, support forces decreased with increased support settlement and strain measurements indicated a clear relationship with temperature variations. For long term measurements, the vibration data analysis showed that natural frequencies changed due to daily temperature fluctuations. The data collected were deemed reliable and suitable for future studies on automated damage detection algorithms.

Lorenzoni et al.(2013) provided a comprehensive review of SHM applied to the Roman Arena, Verona, Italy. A structural health monitoring system was installed to evaluate the structural response of the Arena to stable, dynamic (shows, concerts) and seismic loads. In this light, multiple sensors (accelerometers) were installed at several points of the structure. A detailed crack pattern survey was also carried out to identify main cracks and damages. This was helpful in selecting the most suitable positions for placing static sensors. The monitoring system also allowed for the assessment of the effects of environmental factors on the structural behaviour of the Arena. The findings emphasized the necessity for continuous monitoring for preservation of this historical site.

Vestroni (2025) accessed the Colosseum through dynamic monitoring of the Structural health conditions. The Colosseum which was originally a robust structure, has over the years suffered collapse in the southern part of the building due to uneven settlement. The finite element method was used to analyze the Colosseum's structural behavior and modal quantities. The structure was monitored using accelerometers to measure vibrations and this data were compared with data collected from previous investigations in 2006 and 2022. The study showed that consistent model quantities over time suggested no significant damage had occurred between 2006 and 2022, but due to historical vulnerabilities, the structure requires continuous structural health assessment.

Rainieri et al. (2008) designed a system which was an application of integration between structural health monitoring and seismic early warning. This system was to be installed on The University of Naples and on a building and in a flexible retaining wall at University of Molise, about 200 km far from the first one. The two systems will be equipped with geotechnical sensors to study soil-structure interaction under dynamic loads. The SHM system was designed to monitor multiple structures across a wide area, with a distributed architecture allowing each part to operate independently. The key features of the system include; local servers near each structure for data storage, distributed knowledge to reduce data transmission, initial focus on damage detection via modal parameter changes and flexibility for future integration of new procedures using LabView environment and custom software. The system stores raw data locally for a limited time, then deletes it, while sending extracted modal parameters to the master server for analysis and visualization. During seismic events, data is flagged, stored separately, and preserved for further analysis. Local processing reduces data transmission, ensuring efficient post-earthquake operations.

Glisic and Inaudi (2012) outlined a systematic approach to using Distributed Fibre Optics Sensors(DFOS) for crack detection. A network of sensors was employed and this network allowed for the identification of crack locations and their evolution The results demonstrated that the DFOS does not only detect the presence and growth of cracks, but differentiates between active and dormant cracks, which is essential for prioritizing maintenance efforts.

2.1.2 Challenges in SHM and SHM Data Management

Patel (2024) enumerated several challenges engineers face in SHM;

I. **Data Complexity**: In structural health monitoring, engineers face the challenge of analyzing large volumes of sensor data to identify significant patterns and indicators of structural integrity. This requires advanced algorithms and a thorough understanding of the structure and potential failure modes to distinguish critical data from noise.

II. **Sensor Limitations**: Sensors in Structural Health Monitoring (SHM) have limitations like environmental influences, limited lifespan and potential incomplete capture of structural behavior and so engineers must strategically select and place sensors, ensure critical areas are monitored and plan for sensor failures and data gaps.

III. **Environmental Factors**: Environmental factors like temperature, humidity, and corrosive elements can affect both the structure and monitoring equipment. Engineers must consider these variables when analyzing data and designing monitoring systems. Challenges are amplified in harsh or inaccessible environments, where maintenance and data retrieval are more complex.

IV. **Technological Integration**: Integrating new monitoring technologies into existing structures poses challenges, which include compatibility with current systems, installation practicalities and cost considerations. Engineers must balance benefits with challenges, requiring innovative solutions and careful planning to ensure seamless upgrades and enhanced monitoring capabilities.

V. **Economic Constraints**: Economic factors significantly influence Structural Health Monitoring (SHM) implementation, with budget constraints affecting sensor quantity and quality, data collection frequency and analysis software sophistication. Engineers must balance costs with the need for accurate structural assessment, making strategic trade-offs to optimize monitoring effectiveness within budget limits.

Developing more robust algorithms that can handle the uncertainties associated with sensor data and environmental conditions (Ostachowicz et al., 2019). The paper emphasized on the optimization of sensor placement for structural health monitoring (SHM), highlighting the importance, challenges as well as methodologies for optimization. Effective sensor placements enhance the efficiency of SHM systems, though the complexity of the structures, the variability of environmental conditions and need for real-time data acquisition can be limitations. As a result, the paper highlighted some methodologies and approaches for an optimized sensor placement which include mathematical programming, heuristic methods and metaheuristic algorithms. Various case studies were used to demonstrate the application of these optimization techniques in real world scenarios.

2.2 Various Technologies Used for SHM

Nonis et al. (2013) observed that qualitative visual inspection of bridges were inadequate in monitoring the condition of bridges To address this, the paper investigated the use of three dimensional (3D) digital image correlation (DIC) .3D DIC is a non- contact, full field, optical measuring technique that uses digital cameras to measure surface geometry, displacement and strain. DIC was shown to locate non-visible cracks in concrete, quantify spalling and measure bridge deformation. These techniques were first demonstrated in the laboratory. On a reinforced concrete beam the DIC measured strain was shown to agree well when compared to a fiber optic strain gauge. Although it was stated that it can be improved on in terms of reduction of noise produced in the computation.

Ozbek (2022) explored the application of high resolution laser scanners for smart maintenance and health monitoring of buildings and infrastructure This paper discussed the use of high resolution laser scanners for capturing detailed 3D point cloud data of buildings and infrastructure. It also highlighted the potential of laser scanning technology for smart maintenance enabling early detection of defects and anomalies. The study discussed how laser scanning can enable informed decision making for maintenance and repair, coupled with the cost effectiveness and improved efficiency, accompanying its usage.

Fernandez et al. (2015) presented a novel approach to assessing urban structural damage using Unmanned Aerial Vehicles (UAVs) and advanced image analysis techniques.The study utilized UAVs in capturing high resolution images of damaged urban areas, enabling rapid and accurate assessment of structural damage. It also discussed the application of Object-based image analysis (OBIA) techniques in identifying and classifying damaged structures. Integrated in this study, was a semantic reasoning framework used to improve the accuracy of damage assessment, thus enabling the identification of complex damage patterns. The paper highlighted the potential of the proposed approach in supporting informed decision making in disaster response and recovery. It also suggested future research directions including the integration of additional data sources and development of more sophisticated semantic reasoning frameworks.

Kumari et al. (2022) explored the application of machine learning algorithms for Rapid Visual Screening (RVS) of reinforced concrete buildings, to assess seismic vulnerability. By leveraging Artificial Intelligence techniques, the research was aimed at reducing human bias and uncertainties in vulnerability assessment. RVS methods rely on expert opinions, pushover analyses and post seismic event data to predict potential damage. A web application was developed using the Django framework to implement a Gradient Boosting Decision Tree (GBDT) trained model. The results demonstrated the potential of AI methods in identifying vulnerable structures reducing seismic hazards and supporting decision making in post-disaster crisis management.

Yang (2025) presented a comprehensive review of Artificial Intelligence (AI) advancements in Structural Health Monitoring (SHM), emphasizing AI's potential to overcome the inefficiencies, inaccuracies, and high costs of traditional monitoring methods. This paper highlighted that AI could significantly enhance detection accuracy, improve predictive maintenance, and reduce operational expenses. It also detailed how AI addresses economic concerns by enabling faster damage detection, with machine learning and cointegration methods detecting damage within 10-20 hours, quicker than traditional approaches and by reducing reliance on costly wired sensors through automated data processing via Convolutional Neural Networks (CNNs) and leveraging low-cost or non-contact data sources like images and videos via Deep Learning (DL) with Unmanned Aerial Vehicles (UAVs). Despite these advances, it concluded by identifying key challenges which include; handling large volumes of heterogeneous data, improving the "black box" interpretability of AI models, ensuring real-time processing with limited computational resources, and addressing the scarcity of labeled damage data. Overcoming these challenges is crucial for the widespread practical deployment of AI in SHM.

Francioni et al. (2015) presented an integrated approach for assessing slope stability in an open pit mine. The study combined remote sensing techniques with Geographic Information Systems (GIS) in the analysis of an open pit mine. Kinematic and numerical methods were also employed to assess slope stability, considering factors such as rock mass properties, discontinuity orientations and ground water conditions. The research focused on the Carrara district in Italy. Remote sensing data such as aerial photographs, satellite images or LiDAR data were used to characterize the study area. GIS was used to analyze and integrate various date sources including geological, geotechnical and topographic information.

Doebling et al. (1998) provided an overview of vibration- based methods for locating and detecting damage in Structures. The paper reviewed methods that use changes in vibration characteristics to detect and locate damages These methods include modal-based methods, frequency response function (FRF) methods and time-domain methods. The model method uses changes in the model. parameters (natural frequencies, mode shapes modal damping) to detect damage. The frequency response function method analyzes changes in FRFs to detect damage. Time-domain methods analyze time-series data to detect damage. The paper also highlighted challenges such as noise, non- linearity and modeling error that can affect the accuracy of this damage detection technique.

Irshad (2022) presented a dissertation for structural assessment of three sub-station buildings. In this project, a site assessment for each of these buildings was first carried out before several structural elements were marked for testing using Non-Destructive Test (NDT) techniques. The Ultrasonic Pulse Velocity (UPV) and rebound hammer tests were the techniques used. For the three sub-station buildings, some structural elements were marked for testing and from using the UPV test technique, they all had a doubtful quality. After testing these same elements using the rebound hammer, the results were partially satisfactory after comparison with its design strength as at the year of construction. This study recommended ways of improving these building health and provided a bill of quantity (BOQ) for several materials to be used.

Bhattacharjee and Jain (2012) explored the use of Visual Inspection and Condition Assessment of Structures (VICAS) methodology and tools. Primarily, visual inspection might not really give precise measurements and depends also on the expertise of the personnels. With respect to that, this paper proposed a methodology for visual inspection and condition assessment that incorporates a fuzzy system. Condition indices (CI) obtained for a test element are used to compute corresponding structural condition indices and used as decision criteria for development of maintenance and repair schemes.

Rainieri et al. (2020) observed Operational Modal Analysis (OMA) as a valuable non-destructive technique for assessing and monitoring the health of civil structures, particularly bridges, by analyzing their response to ambient vibrations. This method is appealing due to its cost-effectiveness, speed, and non-interference with structural use, though it requires sensitive, low-noise measurement equipment. OMA has been widely used for validating and updating numerical models of bridges during commissioning or after retrofitting, helping to characterize baseline structural behavior and support maintenance decisions. The Italian Ministry of Transportation has recommended OMA for analyzing existing bridges to reduce modeling uncertainties and aid in maintenance and strengthening interventions. Advances in data acquisition and processing have led to the development of automated OMA techniques, enabling continuous monitoring and remote damage detection, which is crucial given that many existing bridges are subjected to loads exceeding their original design specifications. Case studies demonstrate OMA's application in predicting fundamental frequencies of RC arch bridges, validating finite element models of steel-concrete composite bridges, and assessing the vibration serviceability of footbridges under human-induced excitations. Ultimately, the goal was to implement robust, automated, and continuous modal-based SHM systems for timely and accurate damage detection in bridges, even when damage is hidden or occurs unexpectedly.

2.2.1 Sensor Technologies Used for SHM

Rossi and Bournas (2023) proposed various SHM techniques which were categorized into traditional and innovative methods. Traditional methods include static and dynamic monitoring while innovative methods include fibre optic sensors(FOS) and smart sensing technologie (piezoelectric sensors and self sensing materials, that can provide real time data on structural health).

Lynch (2006) provided a comprehensive overview of wireless sensors and sensor networks specifically designed for structural health monitoring. The review categorized various types of sensors used in SHM including Strain sensors, displacement sensors and vibration sensors and how each of them can be used for the exercise. The paper also discussed the advantages of using wireless sensor networks for SHM, highlighting their ability to reduce installation costs and improve data collection efficiency: Discussed also, were the several challenges associated with the implementation of these wireless sensors in SHM and the various suggestions on how sensor technologies can be improved for the exercise in the future.

Emadi et al. (2025) proposed the use of low cost sensors in monitoring structural health. The study was aimed at underscoring the use of these low cost sensors together with the expensive commercial sensors for efficient SHM. An accelerometer was developed in the form of a long short-term memory (LSTM) model and used to access a bridge by placing it at several nodes, together with some commercial sensors. The data collected after testing were analyzed and interpreted using an Artificial Intelligence tool. Proper validation of these results produced by the modeled accelerometer was also discussed. Although there was the problem of temporary calibration of the low-cost sensors, it still passed as a very cost effective method for SHM.

Cassese et al. (2021) explored the use of Cement-based smart composites (CSCs) which are emerging as promising self-sensing materials for civil Structural Health Monitoring (SHM) due to their piezoresistive properties. By incorporating conductive fillers, CSCs change electrical resistivity under mechanical stress, allowing for strain detection. These composites offer advantages over traditional sensors, including material compatibility, reduced installation complexity, and lower costs. While extensive research has focused on material fabrication and optimization, further studies are needed on their application to large-scale structures. Challenges remain in ensuring consistent measurement stability, achieving mechanical compatibility with host structures, and addressing environmental impacts like temperature and moisture.

Table 2.1: Some worldwide SHM systems

Country	Structure	Year	No of sensors	Seismic zone	Seismic type	Main features
Canada	Pipelines	2004	N.A.	No	FOS	N.A.
Denmark	Wind turbine	2002	N.A.	No	FOS,MEMS accelerometers	N.A.
USA	Golden Gate Bridge	2000-06	64 nodes	Yes	Wireless accelerometers	The largest wireless sensor network for SHM
China	Donghai Bridge	2006	8	Yes	GPS Antennas	GPS-based SHM system
Sweden	Gröndal Bridge	2004	≥ 30	No	FOS, LVDT	Comparison FOS-LVDT
Portugal	Historical Structures	2005	≤ 10	Yes	Accelerometers	SHM of historical structures
Italy	School of Engineering Tower	2006	≤ 30	Yes	Accelerometers	Automated OMA

Source : (Rainieri et al., 2008)

2.3 Building Information Modelling (BIM)

Borrmann et al. (2018) defined a Building Information Model (BIM) as a detailed digital model of a building. It not only shows the 3D shape of the building's parts with a lot of precision but also includes things you can't physically touch, like rooms, different areas, how the project is organized, and timelines. When building professionals implement Building Information Modelling technology (BIM), buildings can be designed and constructed to promote effective human interaction, leading to improved occupant experience and overall well-being (Chinonyerem et al., 2025). This paper was aimed at exploring BIM's role in enhancing human interaction among BIM tools. In carrying out the study a questionnaire survey was done, then descriptive statistical methods and Relative Importance Index (RII) were used to analyze data and rank significance. This study was carried out in Lagos, Nigeria.

Mohammed et al. (2020) systematically mapped the integration of BIM and IoT (Internet of Things) in the construction industry over a six-year period (2015-2020). This paper pointed out that within the study years, the integration of BIM and loT was characterized by a noticeable increase in publications, peaking in 2018. The majority of studies (67.27%) focused on construction operation and monitoring, followed by facility management (21.83 %).

According to (Wang et al. 2016), BIM is instrumental in optimizing energy and selecting eco-friendly materials, which supports more responsible construction practices. The paper also highlighted that one of the key benefits of BIM is its ability to facilitate better collaboration among project stakeholders. BIM provides a shared digital platform that enables real-time collaboration and data driven decision making, which can significantly reduce errors and miscommunications during the construction process. Furthermore, BIM enhances the visualisation capabilities of building designs. These findings highlighted the potential of BIM in achieving sustainability in the built environment.

Gragnaniello et al. (2024) explored how structural health monitoring (SHM) systems can be designed and set up using BIM methodologies" The paper highlighted that one of the significant advantages of integrating BlM with SHM is the ability to perform real-time monitoring of structural conditions. This allows for early detection of potential issues allowing for timely intervention. The paper provided examples of how BlM has been successfully implemented in various projects to enhance structural health monitoring.

Bryde et al. (2013) enumerated the advantages that BIM brings to construction projects. BIM facilitates better communication and collaboration among project stakeholders. 3D visualization of projects through BIM allows stakeholders to better understand the design and functionality of the building before construction begins, reducing misunderstandings and errors. BIM also helps minimize delays and reduce overall project cost. BIM enhances better risk management and also provides a good analysis when it involves creating buildings that are environmentally friendly. These findings underscores the importance of incorporating BIM in construction projects.

2.3.1 Integration of BIM into SHM

A very significant challenge in Structural Health Monitoring (SHM) is the enormous volume of raw and processed data generated by sensor systems (Valinejadshoubi et al., 2017). The paper showed how Building Information Modelling (BIM) can be integrated into SHM to serve as a powerful tool for SHM data management. The paper examined how sensors can be created and visualized within the building components in the BIM model.

Bahmanov et al. (2019) addressed the challenge of efficiently managing and interpreting data from Vibration-Based Damage Identification (VEDI) in structural health monitoring (SHM) of civil engineering structures The paper proposed that to enhance the efficiency of SHM, BIM should be utilized for visual data management. The study was conducted on a three-storey steel scaled structure tested in both pristine and damaged state: It involved acquiring sensor data (acceleration data), processing it too obtain modal properties of the structure and integrating this data into the BIM model, for visualizing the current conditions of the structural elements based on a predefined color-coding scheme.

Rodriguez Polania et al. (2025) discussed the integration of Building Information Modelling (BIM) methodologies in monitoring and assessment of bridges to enhance efficiency and effectiveness of Structural Health Monitoring (SHM) systems. The paper presented a data management approach that utilizes BIM to create a database for bridge monitoring procedure. It also discussed how BIM can be integrated in SHM systems for real-time collaboration among stakeholders as well as the usefulness of BIM in providing a visualization of the structural condition of the bridge.

Qin et al. (2025) presented a novel approach for integrating BlM in real time visualized monitoring and assessment of bridge health with a focus on butterfly arch bridges. Various sensors were utilized in monitoring critical parameters. The data from these sensors were transmitted to a central system for analysis. The structural operation condition of the bridge was analyzed and the performance evaluation was done by the BIM-Based structural health monitoring system (SHM). This approach showed a great development in SHM of bridges.

Rodrigues et al. (2019) discussed the development of a web application aimed at managing historical buildings using Building information Modelling (BIM) technology. The application was also aimed at creating a management system that connects to a 3D BIM model, to provide automated and digitised information for various tasks. The developed methodology included several phases including data analysis, BIM modeling, database development, web application development and result analysis. The case study for this application was Casa de Santo António, a heritage building in Ilhavo, Portugal which was built in the 1930s.

Singh and Sadhu (2020) asserted that BIM is a powerful data management tool that can be utilized as a base platform to analyze and visualize long term monitoring data. This paper proposed a method of visualizing structural health monitoring information within BIM using Autodesk Revit. Accelerometer sensors were used for data collection and virtual sensors were modelled within Revit to mimic sensors installed on the real structure. MATLAB online portal was used for system identification scripting, to aid decision making. This method enhances software interoperability and frequent communication, which are required in civil infrastructure projects.

Sresakoolchai et al. (2025) explored the innovative application of accelerometers and machine learning techniques together with BIM to enhance railway safety and efficiency: The accelerometers were used for collection of real-time data, which were processed and analyzed using supervised machine learning algorithms to classify and predict potential tight and wide gauge event. BIM was integrated to serve as a platform for data management as well as provide visual representation of the monitoring exercise. This proposed method is beneficial due to better and faster detection and classification of track defects.

Khodeir et al. (2016) discussed the integration of Heritage Building Information Modeling (HBIM) tools in the context of sustainable retrofitting of heritage buildings in Egypt. The paper defined HBIM as an extension of BIM tailored towards presenting and managing historical structures. Sustainability applied in the retrofitting (upgrading) of these bullings was concerned with making them energy efficient, which was cited to be a challenge, because it is difficult to balance historical values with energy efficiency. The paper described how HBIM has been applied in various retrofitting projects, stating their improvements.

Liu et al. (2025) provided a comprehensive review of the integration of BIM, Internet of things (IoT) and Geographic Information System (GIS) technologies in construction resource monitoring. The paper provided various research on BIM-IoT, BIM-GIS and IoT-GIS integration. It emphasized on the importance of BIM-IoT-GIS integration which included; real-time data collection (IoT), enhanced data visualization (GIS and BIM), improved decision making and increased efficiency.

2.3.2 BIM Softwares and Visual Programming

Various softwares used for implementing BIM is enumerated in table 2.2 below

Table 2.2 : Various Softwares used for BIM

Software	Developer	Operating system(s)	License
Allplan Architecture	Nemetschek Group	Windows	Proprietary
Archicad	Graphisoft	Windows, macOS	Proprietary
AutoCAD Architecture	Autodesk	Windows	Proprietary
Autodesk BIM 360	Autodesk	Web-based	Proprietary
Autodesk Civil 3D	Autodesk	Windows	Proprietary
Autodesk Revit	Autodesk	Windows	Proprietary
Bonsai (Blender BIM)	Open-source	Windows, macOS, Linux	GNU GPL
BricsCAD	Bricsys nv	Windows, Linux, macOS	Proprietary
CATIA	Dassault Systèmes	Windows, Unix (server)	Proprietary
Cadwork	Cadwork informatik AG	Windows	Proprietary
Cadwork Engineer	Cadwork informatik AG	Windows	Proprietary
Chief Architect	Chief Architect, Inc.	Windows	Proprietary
CodeBook	CodeBook International	Windows	Proprietary

Software	Developer	Operating system(s)	License
DataCAD	Microtecture Inc., Cadkey Inc., DATACAD LLC	Windows	Proprietary
Digital Project	Gehry Technologies	Windows	Proprietary
Dynamo	Autodesk	Windows	Apache 2.0
FINE MEP	4M	Windows	Proprietary
FreeCAD BIM Workbench	Open-source	Linux, macOS, Windows	GPL-2.0-or-later
Graphisoft BIM Server	Graphisoft	Windows, macOS	Proprietary
Graphisoft BIMx	Graphisoft	Windows, macOS, iOS, Android	Proprietary
Graphisoft MEP Modeler	Graphisoft	Windows, macOS	Proprietary
IntelliCAD	IntelliCAD Technology Consortium	Windows	Proprietary
MPDS4	CAD Schroer	Windows and Solaris	Proprietary
MicroStation	Bentley Systems	Windows	Proprietary
Autodesk Navisworks	Autodesk	Windows	Proprietary
OpenRoads Designer[6]	Bentley Systems	Windows	Proprietary
OpenStudio	National Renewable Energy Laboratory (NREL)	Windows, macOS, Linux	BSD
Prokon	Prokon Software Consultant	Windows	Proprietary
Quantapoint	Quantapoint, Inc.	Windows	Proprietary
Reflex	Reflex Systems Ltd.	Windows	Proprietary
Revizto	Revizto SA	Windows, macOS, iOS and Android	Proprietary
RFEM	Dlubal Software	Windows	Proprietary

Software	Developer	Operating system(s)	License
RIB Software	Schneider Electric	Windows	Proprietary
Rhinoceros 3D - Grasshopper 3D	McNeel & Associates	Windows, macOS	Proprietary
STAAD	Bentley Systems	Windows	Proprietary
Sefaira	acquired by Trimble Inc.	Windows and MacOS	Proprietary
Tekla Structures	Trimble	Windows	Proprietary
Sketchup	Trimble	Windows, macOS, iPadOS	Proprietary
Vectorworks	Nemetschek Group	Windows, macOS	Proprietary
VisualARQ	Asuni CAD	Windows	Proprietary

Source : (Wikipedia, 2025)

However for SHM, Autodesk Revit is mainly used because it aids visual programming using tools like Dynamo.

Matos et al. (2023) explored the use of Revit software for maintenance management of an existing building by application of Building Information Modelling (BIM). The paper enumerated the various steps involved in modeling the case study: Civil Engineering Department Building, University of Aveiro and incorporating a maintenance system, by fusing Excel data and Revit. This was made possible through Dynamo, an and-in in the Revit software. Another add-in, sheetLink was also used as a means of communication between Revit software and excel database. This approach properly implemented, notifies a facility manager of any form of predictive maintenance required by the structure.

Thabet and Lucas (2019) discussed the use of Dynamo for model-based delivery of facility asset data, highlighting its significance in enhancing facility management processes.

Dynamo serves as a powerful tool for linking BIM with facility management systems. It automates the extraction of asset management data from the BIM model. The paper also highlighted the visual programming capabilities of Dynamo, which enable users to create complex workflows without extensive programming knowledge. Examples of how Dynamo has been applied to real-world scenarios were also discussed.

Matos et al. (2020) proposed a methodology that utilizes BIM to assess building performance and prioritise maintenance actions through Key Performance Indicators (KPI). The study aimed at extending service life of building components involved building information collection (Interviews and inspections), building life cycle cost estimation and automated calculation of Building Performance Indicator (BPI) using Revit and Dynamo. The BPI value calculated for the case study indicated a deterioration level of some of the building components and a color-coding system was applied to the BIM model to visually represent the urgency of maintenance needs .

CHAPTER THREE

METHODOLOGY

3.1 Research Approach

This project was applied to a case study and it involved measurement, processing and analysis of experimental data obtained. This approach was adopted instead of long-term structural health monitoring or damage detection because the latter were not feasible considering the time frame of the project. There is also an increased cost in carrying out long term structural health monitoring due to the need for more sensors and a constant power supply as well as a more laborious data processing and analysis .

3.2 Ambient Vibration Testing (AVT)

Ambient Vibration Testing (AVT) was used to establish a non-destructive, quantitative health baseline for the pedestrian bridge by analyzing its dynamic signature. AVT was selected as the field measurement protocol because it uses natural, low-level excitations (such as light wind, micro-seismic activity, and thermal effects) to excite the bridge's natural vibration modes. This is the most effective way to determine the structure's intrinsic properties.

To ensure the highest quality data for a pure baseline reading:

1. **Timing:** Data acquisition was performed during late night hours to guarantee zero pedestrian traffic and minimize all external disturbances.

2. **Sensor Placement:** The custom sensor was rigidly mounted on the bridge deck to maximize the capture of the first and most critical mode of vibration.
3. **Data Parameters:** The sensor logged data at a constant sampling rate of 3.3Hz for a continuous duration of 30 minutes.

3.3 Vibration Data Acquisition System

The main device used for the data acquisition during this project was a three-axis accelerometer. This accelerometer relies on a Micro-Electro Mechanical System (MEMS) design. This sensor was used because it can be readily and electronically installed on inaccessible structural elements (Haritos, 2009). These accelerometers can be wired powered or powered using a battery. Although the downside to using battery powered accelerometer sensors is periodic battery replacement (Haritos, 2009), it was used for this study since just one accelerometer was used and the data collection was within a short time frame. DwyerOmega (2025) explained that an accelerometer is designed to measure static and dynamic acceleration. Static acceleration can be linked to gravity, friction etc while dynamic acceleration is due to non-uniform forces like vibration or shock. It also gave various types of accelerometers, which include;

1. **Piezoelectric Accelerometers**: This works by measuring acceleration, vibration or shock by utilizing the piezoelectric effect.
2. **Piezoresistance Accelerometers**: This works by varying their resistance based on the acceleration they experience.

3. **Capacitive Accelerometers**: This consist of a capacitor with a movable plate suspended between two fixed plates. It measures acceleration, vibration or tilt by detecting changes in capacitance.
4. **Triaxial Accelerometers**: This accelerometer measures acceleration in three orthogonal directions (X, Y and Z). This feature enables it to measure all the vibrations affecting the object being observed. This project makes use of this type.

For the low cost accelerometer used in this project, below are the major components;

1. **MPU6050**: This is the main accelerometer sensor. It helps to measure acceleration, velocity orientation, displacement and many other motion related parameters of a system (Joseph, 2022).
2. **ESP32**: This is the microcontroller that carries out data processing. It also has an Analog-Digital Converter (ADC).
3. **OLED Display**: This component is the screen through which the data can be seen as collection is ongoing.
4. **Lithium battery**: This is used for power supply since the accelerometer is battery powered.
5. **Powerbank Module**: This is used to charge the battery.

3.3.1 Vibration Data Collection Procedure

Due to the aim of this experiment, only one accelerometer was used for collecting acceleration data from the case study. Various locations were selected for this exercise. The data collection process involved;

1. Assemblage of accelerometer sensor.
2. Selection of several key locations within the case study.
3. The sensor was securely placed at the predetermined point.
4. The data logger of the sensor was started and the time for this data collection was recorded. The sensor started collecting data after it had connected to the nearby wifi.
5. The data logging is monitored online through thingspeak.mathworks.com webpage.
6. After a stipulated time, the sensor is put off and the data for a particular location is downloaded and cleared from the webpage before the same process is repeated.

3.3.2 Vibration Data Transfer and Organization

Raw acceleration data collected is usually in analog form, prompting the need to inculcate an analog-to-digital converter in the microcontroller of the accelerometer. The role of an ADC is to convert continuous analog signals into digital signals, representing the signal's amplitude as a series of numerical values (Haraoubia, 2019). Since the data collected exist in the webpage mentioned earlier, after each data logging session, it is downloaded in a CSV(Comma-Separated Values) file format, where it has been arranged into several columns. The columns include the time/data of collection, Accel_X_g, Accel_Y_g and Accel_Z_g.

However, to be able to easily retrieve data collected at different locations, the data logger is cleared online after the data pertaining to a point has been downloaded.

3.4 Signal Processing Methodology

Raw acceleration data cannot be used directly. They are usually in analog form, prompting the need to inculcate an analog-to-digital converter in the microcontroller of the accelerometer. The role of an ADC is to convert continuous analog signals into digital signals, representing the signal's amplitude as a series of numerical values (Haraoubia, 2019). It requires a series of signal processing steps to isolate the structural response from measurement artifacts and noise. A Python script was used to perform the following steps sequentially.

3.4.1 Python Programming

Python is a versatile and widely used programming language that can be applied to various domains such as web development, automation and data analysis (Coursera, 2023). Its general purpose nature, simplicity and readability makes it an ideal language for both beginners and experienced developers. Python is backed by library support, so there's no need to build anything from scratch as there is most likely a library that can already do it (GeeksforGeeks, 2025).

Python was used for data processing instead of MATLAB and Microsoft Excel because:

1. MATLAB was more complex to learn as a beginner.
2. Microsoft Excel has limited capabilities for complex data analysis and is less efficient for the large dataset of acceleration. However for a small dataset and less complex analysis, Microsoft Excel can easily be used.

The raw acceleration data has been organized into columns and the stored CSV file was imported into python for processing. For this operation, two libraries were very essential;

NumPy and Pandas. NumPy facilitates efficient numerical operations on large quantities of data while Pandes is a library for working with data (handling missing data, performing operations on rows and columns and transforming data) (Codecademy).

3.4.2 Detrending and DC Offset Removal

The raw signal contains a constant offset primarily due to gravity (1g), which is a zero-frequency (DC) component that must be removed. This process centers the signal around a true zero mean, preventing the DC component from dominating the final frequency spectrum.

The mathematical operation used is the removal of the mean ($\overline{a}$) from the raw acceleration data (a_{raw}):

$$a_{detrended}[n] = a_{raw} - \overline{a} \qquad \text{(Equation 3.1)}$$

Where:

a_{raw} is the raw acceleration data at time step n, $\overline{a}$ is the mean (average) value of the entire acceleration signal and $a_{detrended}[n]$ is the signal with the DC offset removed, centered at zero.

3.4.3 Digital Low-Pass Filtering

To ensure that only the low-frequency structural response is analyzed, high-frequency noise (e.g., electronic interference, wind noise) was removed using a digital filter. A **Butterworth Filter** was selected for its flat response in the critical passband.

A Butterworth filter with a cut-off frequency (fc) of 1.5 Hz was applied. This cutoff is safely above the anticipated structural frequencies but below typical environmental noise. The filter's design is governed by its magnitude squared transfer function:

$$|H(j\omega)|^2 = \frac{1}{1+(\frac{\omega}{\omega_c})^{2N}} \qquad \text{(Equation 3.2)}$$

Where;

N is the filter Order, ω is the signal frequency (in radians per second, $\omega=2\pi f$) and ω_c is the Cutoff Frequency.

In the Python code, the filter is implemented using **scipy.signal.filtfilt**, which applies the filter forward and backward. This critical step eliminates phase distortion (time shift) in the filtered signal, which is necessary to preserve the true time relationship of the acceleration peaks.

3.4.4 Frequency Domain Analysis (Fast Fourier Transform)

The cleaned, time-domain acceleration signal was transformed into the frequency domain using the Fast Fourier Transform (FFT), specifically employing the **Periodogram method**. This converts the signal from acceleration versus time to vibrational energy versus frequency. The core concept is the **Discrete Fourier Transform (DFT)**, of which the FFT is a computationally efficient algorithm. The DFT converts N time samples into N frequency components:

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-j2\Pi kn/N} \qquad \text{(Equation 3.3)}$$

Where:

x[n] is the filtered acceleration signal in the time domain, X[k] is the frequency spectrum (a complex number) at frequency index k and N is the total number of samples.

The Periodogram estimates the **Power Spectral Density** $S_{xx}(f)$, which represents the distribution of power across the frequency components, often calculated as proportional to the magnitude squared of the Fourier Transform $X(f)$:

$$S_{xx}(f) \propto |X(f)|^2 \qquad \text{(Equation 3.4)}$$

The Measured Baseline Natural Frequency **(**f_{AVT}**)** is then determined by identifying the frequency (f) at which the $S_{xx}(f)$ curve reaches its maximum peak. This frequency peak represents the fundamental mode of vibration of the bridge.

3.5 Power Spectral Density (PSD)

Power Spectral Density (PSD) is a fundamental and powerful tool in vibration analysis, enabling the precise characterization of a signal's power or energy distribution across its various frequency components (Hutchinson; Fiveable; SVANTEK). Unlike Root Mean Square (RMS) acceleration, which provides a single, overall measure of vibration intensity in the time domain, PSD transforms the raw time-domain data into the frequency domain. This transformation reveals the underlying sinusoidal components that constitute the complex vibration signal, providing a detailed view of the energy distribution over the frequency spectrum (Hutchinson; Vibration Research, 2018).

Conceptually, the PSD is derived from the Fourier Transform of a signal, which decomposes the complex vibration waveform into its constituent sine and cosine waves at various frequencies. The PSD then quantifies the average power (or energy per unit frequency) contained at each frequency band. For practical applications involving finite, discrete, and often noisy data, various methods are employed to estimate the PSD. Among these, the Welch method is widely utilized due to its robustness and ability to provide a smoothed spectral representation by averaging multiple short-time periodograms (Fiveable; SVANTEK). The units of PSD are typically expressed as the square of the input signal's units per Hertz (e.g., for acceleration data), indicating the power density at a given frequency (Vibration Research, 2018). The integral of the PSD curve over a frequency range yields the mean square value of the signal, which is directly related to the RMS value (Hutchinson; Fiveable; Ansys).

3.5.1 Relevance to this Project

In the context of this project, analyzing the Power Spectral Density offers crucial and complementary insights:

1. **Identification of Dominant Frequencies:** By plotting the PSD, distinct and prominent peaks emerge at specific frequencies. These peaks directly indicate the frequencies at which the building or its components are vibrating most significantly. In structural engineering, these dominant frequencies often correspond to the inherent natural frequencies of the structure itself or the primary excitation

frequencies originating from external dynamic loads (Hutchinson; SVANTEK; National Instruments). This provides a foundational understanding of the building's dynamic characteristics .

2. **Understanding Vibration Sources:** Analyzing the frequency content through PSD plots can significantly aid in inferring and confirming the potential sources of observed vibrations. For example, if a strong peak in the PSD aligns with known operational frequencies of local machinery, typical frequency ranges associated with traffic (e.g., specific vehicle types, road irregularities), or common human-induced frequencies (e.g., walking, jumping), it establishes a stronger and more informed link between the measured vibration and its probable cause (Hutchinson; Vibration Research, 2018).
3. **Characterizing Building Dynamics:** The natural frequencies of a building are fundamental properties determined by its mass and stiffness. Identifying these frequencies provides a critical understanding of how the building is predisposed to respond to various dynamic loads. While this specific project does not aim for full modal analysis (which would involve determining mode shapes and damping ratios from multiple synchronized sensors) or long-term damage detection based on frequency shifts, knowing the natural frequencies is an essential step in characterizing the building's dynamic signature (National Instruments).
4. **Supporting RMS Interpretation:** The PSD effectively complements the overall RMS value by illustrating where the total vibration energy (quantified by RMS) is concentrated within the frequency spectrum. For instance, a high RMS value might be predominantly driven by a strong, low-frequency component stemming from

heavy traffic. This would be clearly visible as a significant peak in the PSD plot at that specific low frequency, providing a more nuanced interpretation of the overall vibration intensity (Hutchinson).

By integrating PSD analysis, this project progresses beyond merely quantifying how much a building vibrates to also understanding at what frequencies it vibrates, thereby significantly enriching the overall assessment and visualization of the building's typical dynamic response.

3.6 BIM Integration and Visualization

This section outlines how BIM was integrated in the structural health monitoring process to import the processed data into the model, as well as show a visual representation of the measured vibration intensity on the selected points within the case. This process involves;

1. **Preparing the Revit Model for Data Input:** Before the importation of the vibration data into the Revit (BIM) model, it was essential to prepare the Revit file, to aid easy syncing of the data with the intended location on the model.
2. **Developing the Building Model:** The structural model of my chosen case study pedestrian bridge was generated in Autodesk Revit 2019. The focus of this modeling phase was to accurately represent the key structural elements like bridge deck, piers, staircase, as these are critical pathways for vibration transmission. The model provided a clear geometric context of measurements carried out.
3. **Establishing Measurement Locations in BIM:** To serve as digital reference points for the physical sensor placements, the corresponding locations within the Revit model were established. The measurement points were represented as small Generic

Model components like spheres, placed precisely at the XYZ coordinates where the physical accelerometer was mounted, because using dedicated points often offers more precise control for visualization. Each digital placeholder had a unique identifier to match with the collected data.

3.7 Creating a Dedicated Shared Parameter

To link the quantitative RMS acceleration data directly within the relevant elements of my Revit model, a custom data field called "Measured_Frequency" was created. This field allows the measured vibration values to be consistently stored, displayed, scheduled, and exchanged as an integral part of the intelligent building model. Additional custom shared parameters named “SHM_Freq_Shift_Percentage” and “SHM_Inference” were also created.

3.8 Using Dynamo for Automated Data Import

Dynamo is a visual programming environment in Revit, that automates the importation of the processed external vibration data (Frequency) into the model, instead of manually inputting them.

The following steps were taken to import the processed data into Revit using Dynamo scripts.

1. **Setting up the Dynamo Workflow:** A new Dynamo script was initiated from within my Revit project.
2. **Importing the Vibration Results:** The first step in Dynamo was to bring in the processed data. **File Path** node was used to point to an external CSV file, which contained columns like “Test Location”, “Measured_Frequency”,

"SHM_Freq_Shift_Percentage" and "SHM_Inference". Subsequently, **Excel.ReadFromFile** node was employed to import this tabular data directly into Dynamo's workspace.

3. **Matching Data to Model Elements:** A critical phase involved accurately matching each frequency value and percentage shift to its corresponding digital location in the Revit model. The imported data was processed to extract the "Test Location" for each measurement (Location). Then, using Dynamo node **Select Model Elements by ID**, the specific Revit elements (my sensor points) that perfectly corresponded to these IDs were identified and selected. This step highlighted the importance of maintaining consistent naming conventions between the field notes, data files, and the BIM model.
4. **Assigning Data to Parameters:** With the data matched to the elements, the **Element.SetParameterByName** node was used to take the extracted RMS acceleration value and rebound number value from the imported data and write it directly into the "Measured_Frequency", "SHM_Freq_Shift_Percentage" and "SHM_Inference" shared parameters for each corresponding Revit element. This action dynamically updated the BIM model with the measured vibration performance.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Instrumentation Overview

This section formally introduces the locally produced accelerometer used for dynamic testing.

4.1.1 Custom Accelerometer Design

The Structural Health Monitoring (SHM) system employed a custom-fabricated low-cost accelerometer unit based on the MPU6050 to measure tri-axial acceleration. The system was designed for simplicity and longevity, recording continuous data at a fixed sampling rate of **3.3Hz**.

As detailed in the Methodology, this constrained the analysis to frequency modes below the Nyquist limit(1.65Hz), allowing the study to focus specifically on the bridge's low-frequency lateral stability and serviceability.

The sensor unit’s electronic layout and packaging are presented below.

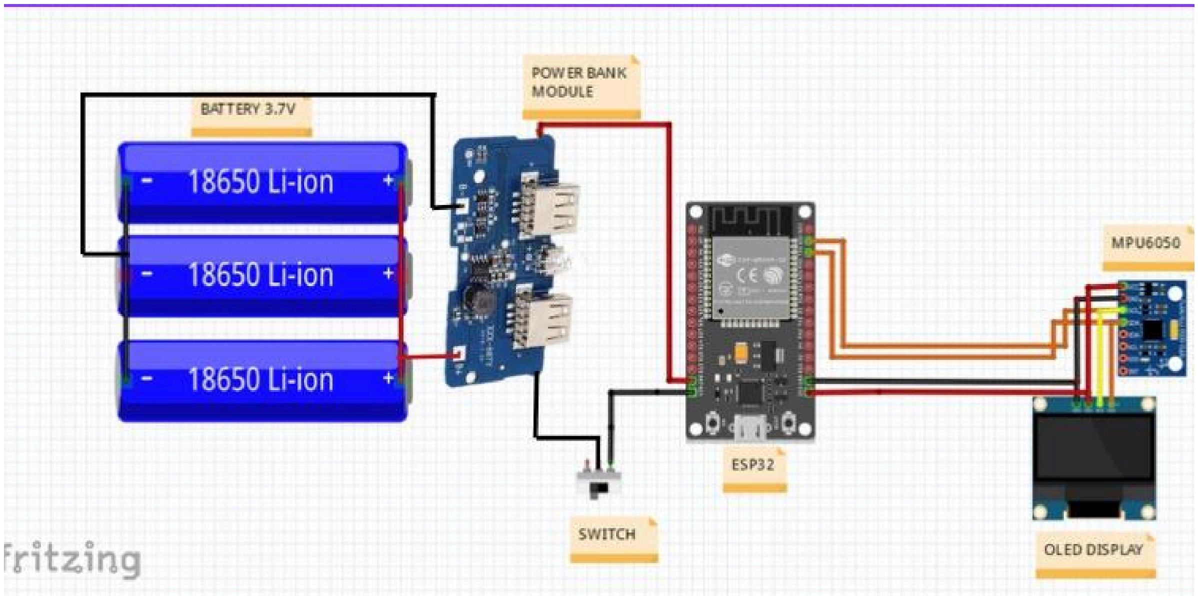


Plate 4.1 : Circuit Diagram of the accelerometer sensor

Plate 4.2 : Image of the coupled accelerometer sensor

4.2 Experimental Results

This section presents the measured natural frequencies derived from the Fast Fourier Transform (FFT) analysis for all tested locations under both Ambient Vibration Testing (AVT) and Loaded conditions.

4.2.1 Bridge Deck Analysis

The deck, representing the primary structural element, provides the critical stiffness baseline.

Table 4.1: Processed Bridge deck Vibration

Test Condition	Location	Measured Frequency	Percentage Shift from Baseline
AVT (Baseline)	Bridge deck	0.467Hz	N/A
Loaded	Bridge deck	0.413Hz	11.6%

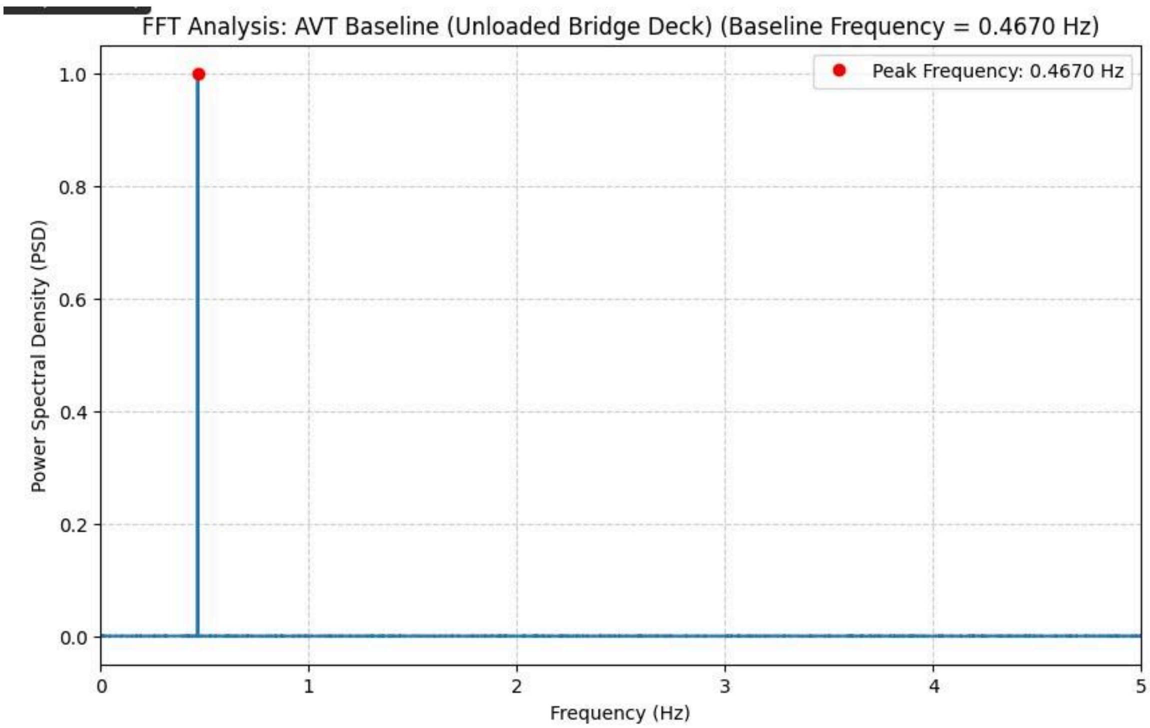
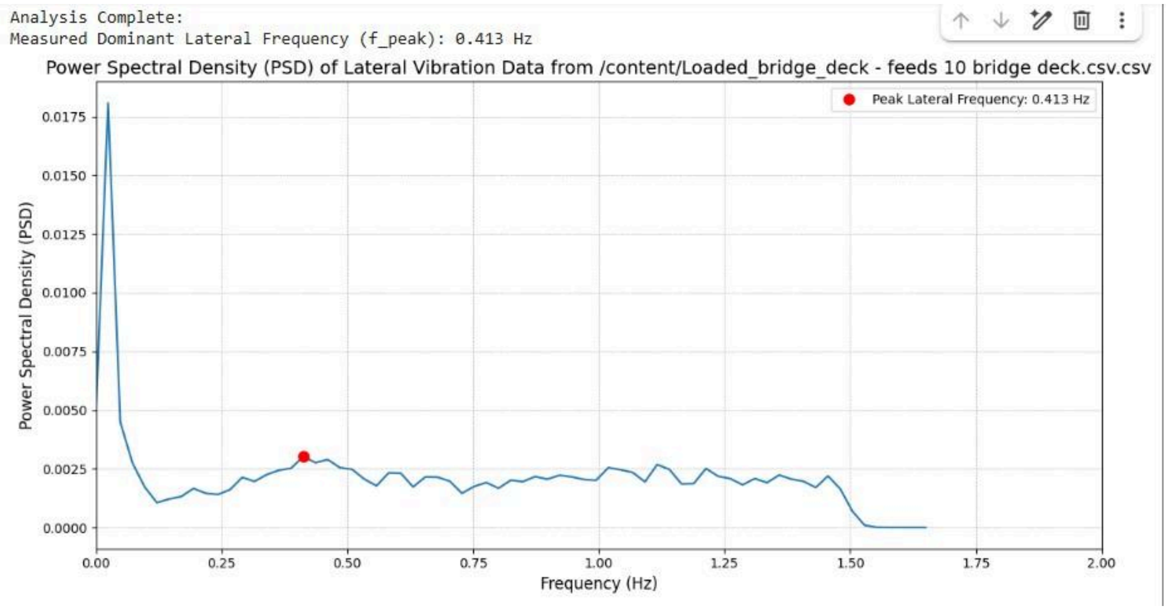


Figure 4.1 : Plot of Power Spectral Density against Frequency for the bridge deck(Baseline)



```
Analysis Complete:
Measured Dominant Lateral Frequency (f_peak): 0.413 Hz
```

Figure 4.2 : Plot of Power Spectral Density against Frequency for the bridge deck(Loaded)

4.2.2 Staircase Analysis

The staircase was analyzed to assess the dynamic performance of the connection points and its propensity for human-induced resonance.

Table 4.2 : Processed Staircase Vibration

Test Condition	Location	Measured frequency	Percentage Shift From Baseline
AVT (Baseline)	Staircase	0.867Hz	N/A
Loaded	Staircase	0.829Hz	4.38%

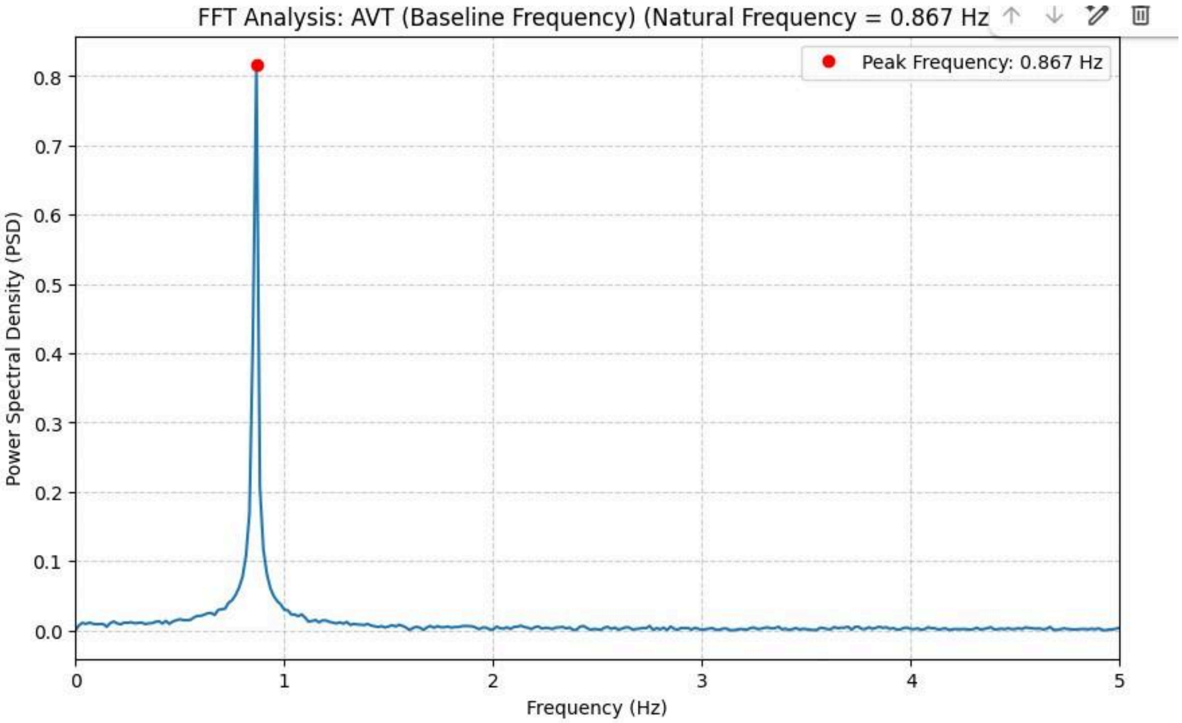
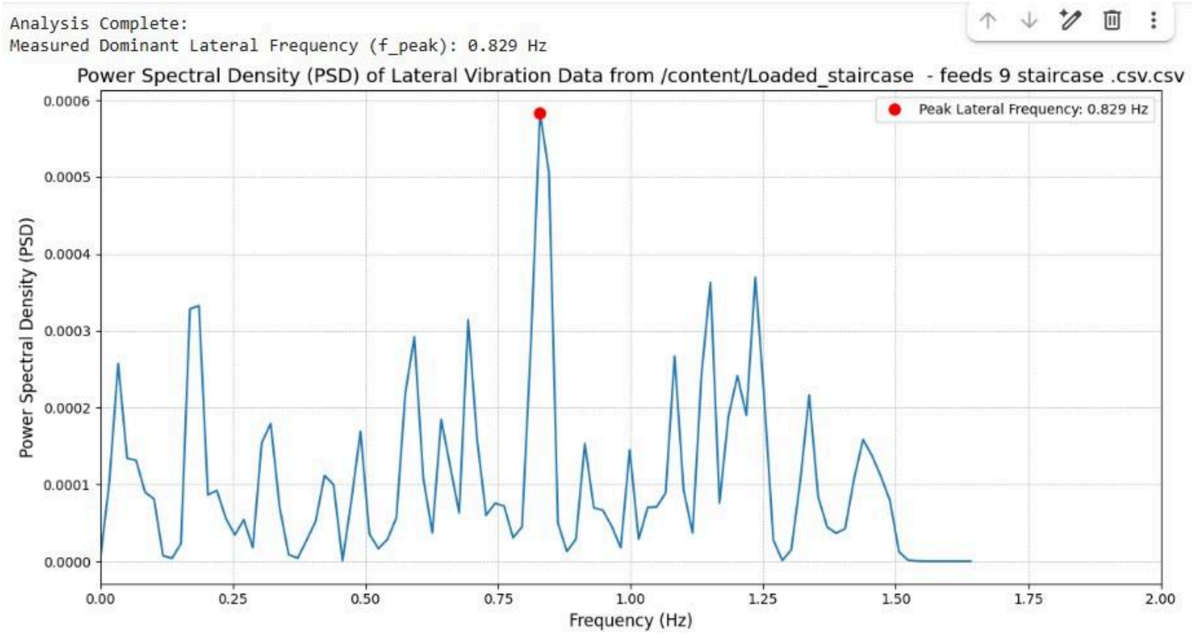


Figure 4.3 : Plot of Power Spectral Density against Frequency for the staircase (Baseline)



```
Analysis Complete:
Measured Dominant Lateral Frequency (f_peak): 0.829 Hz
```

Figure 4.4 : Plot of Power Spectral Density against Frequency for the staircase (Loaded)

4.3 Discussion of Structural Health Inference (Stiffness Degradation)

Before analyzing the measured frequency shifts, it is essential to establish the engineering criteria for structural health. Structural Health Monitoring (SHM) relies on the fundamental principle that the bridge's natural frequency (f) is proportional to the square root of its stiffness (K), as shown in the equation

$$f \, \alpha \sqrt{\frac{K}{M}} \qquad \text{(Equation 4.1)}$$

This relationship implies that stiffness is proportional to the square of the frequency i.e $K \, \alpha \, f^2$.

1. **Bridge Deck:** The lateral frequency of the bridge deck decreased by 11.6% under pedestrian loading, indicating a 21.85% reduction in effective stiffness due to human-structure interaction.

2. **Staircase:** The lateral frequency of the bridge deck decreased by 4.38% under pedestrian loading, indicating a 8.57% reduction in effective stiffness due to human-structure interaction.

Both results are standard and expected as it is a typical behaviour in flexible pedestrian structures, where the presence of moving pedestrians induces a frequency shift (softening effect) compared to the unloaded condition.

4.4 Building Information Modelling

The final stage of this project was visualizing the quantitative findings from the vibration analysis on the bridge's model done using Revit. The various steps taken are stated below.

1. **Mapping the Measurement Locations:** To begin the process, the position of the sensor during field measurement was mapped out using virtual sensors created in Revit.
2. **Creating Shared Parameters:** To successfully transfer the processed data in the CSV file to the virtual sensors, shared parameters "Measured_Frequency", "SHM_Freq_Shift_Percent" and "SHM_Stiffness_Shift_Percent" were created in the model and transferred to the virtual sensors
3. **Automated Data Import Using Dynamo:** Importing the processed data from the CSV file into the virtual sensors on the model was done using Dynamo, a visual programming addin in Revit. This involved two steps

a. **Data Preparation and Splitting**: In this phase, various nodes shown in figure 4.5, were used to bring in data from the CSV file. The data were also split into different categories of processed data as shown in the **watch** nodes.

b. **Outpu**t: This phase involved selecting the family of the virtual sensor created in revit and linking the split data to the virtual sensor corresponding to the test location. This was done using the nodes shown in figure 4.6.

The result of this visual programming is an automatic import of these processed data into the model (as shown in figure 4.7 and 4.8) , preventing the need for manually inputting them.

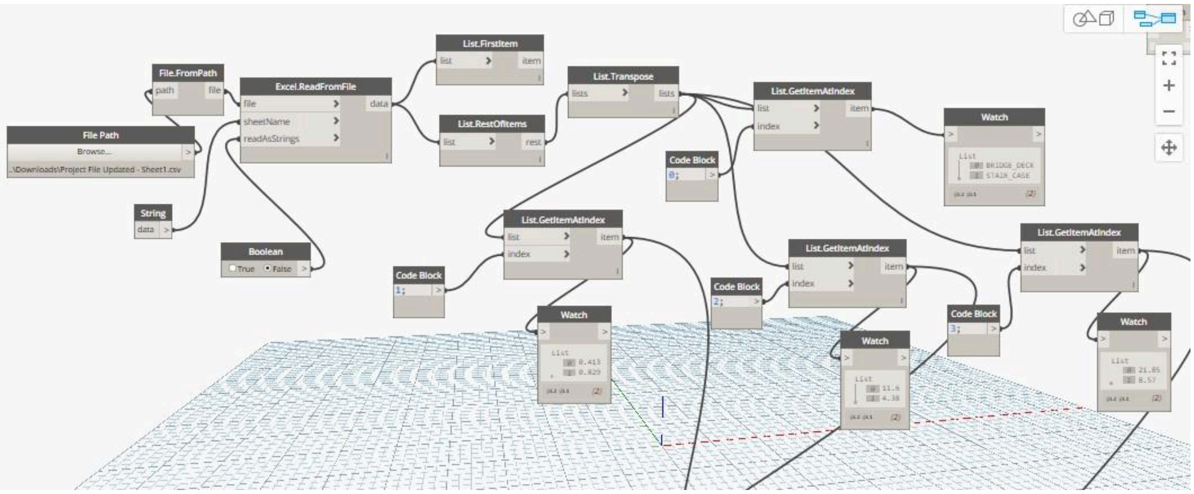


Figure 4.5 : Visual Programming for Data Preparation and Splitting

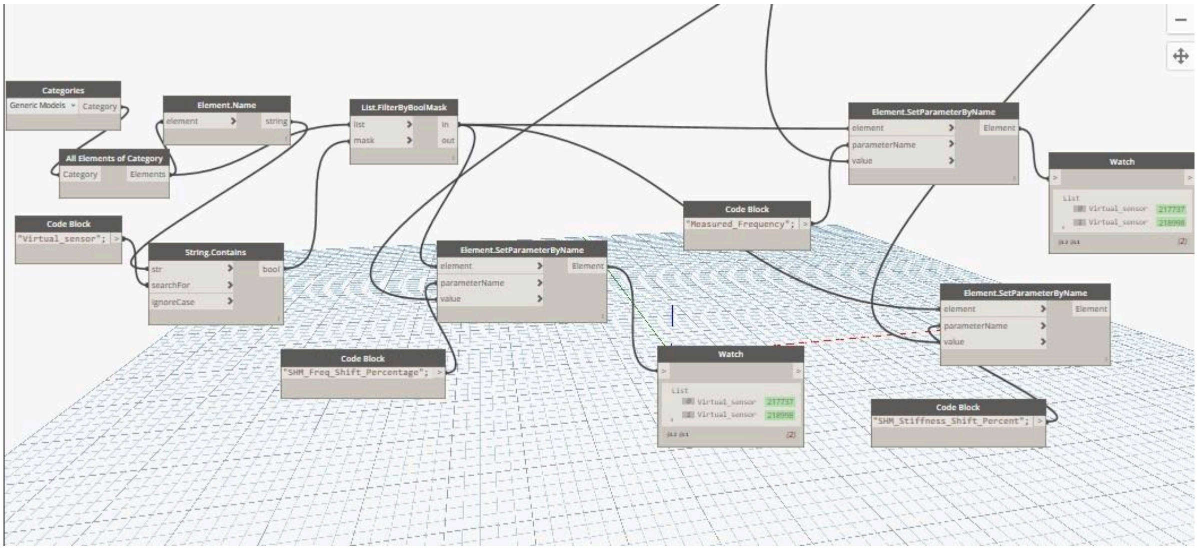
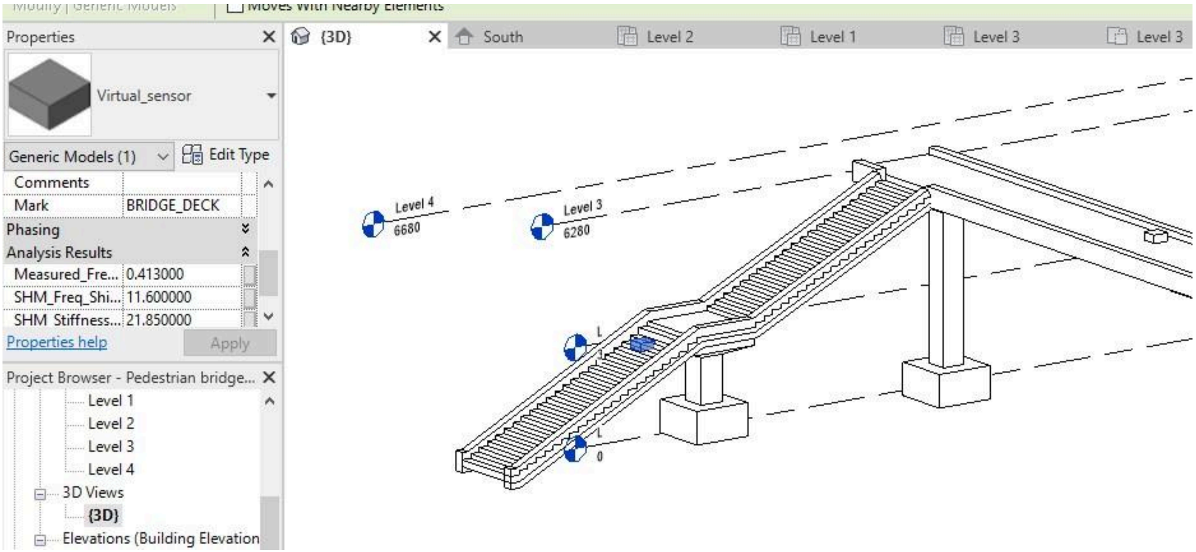


Figure 4.6 : Visual Programming for Data Output

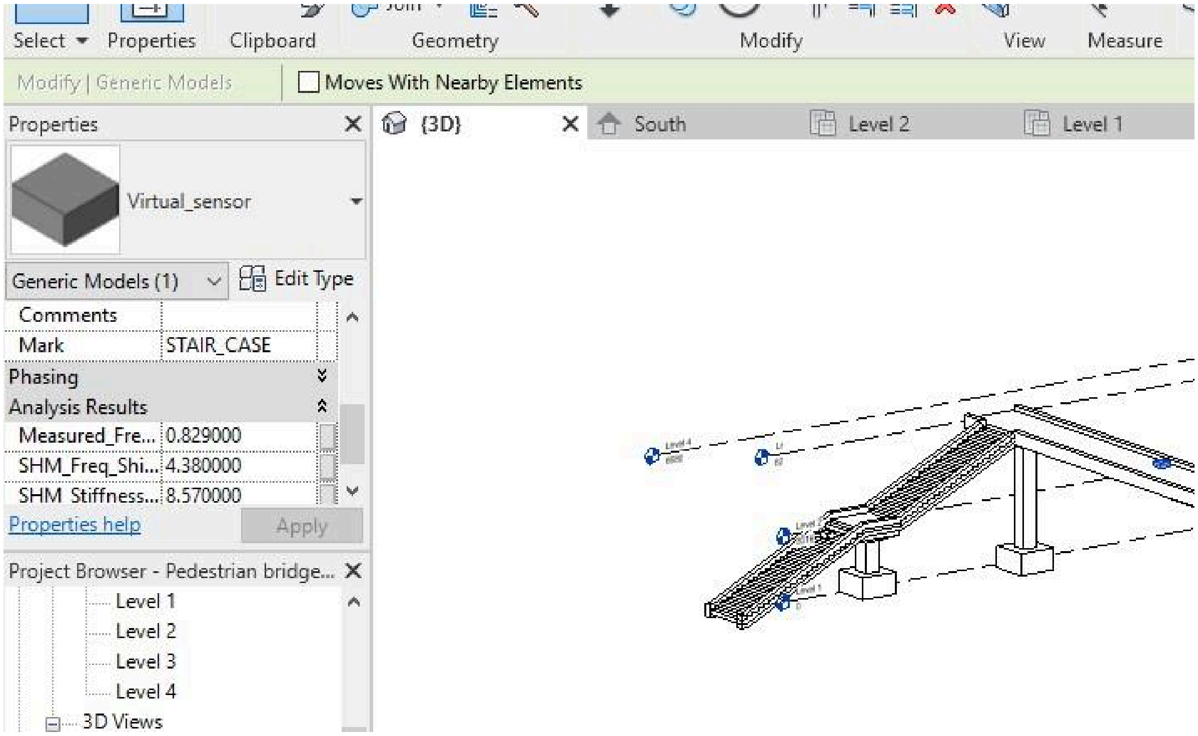


Virtual_sensor

Generic Models (1)

Comments	
Mark	BRIDGE_DECK
Measured_Fre...	0.413000
SHM_Freq_Shi...	11.600000
SHM_Stiffness...	21.850000

Figure 4.7 : Transferred Bridge Deck Data



Virtual_sensor

Generic Models (1)

Comments	
Mark	STAIR_CASE
Measured_Fre...	0.829000
SHM_Freq_Shi...	4.380000
SHM_Stiffness...	8.570000

Figure 4.8 : Transferred Staircase Data

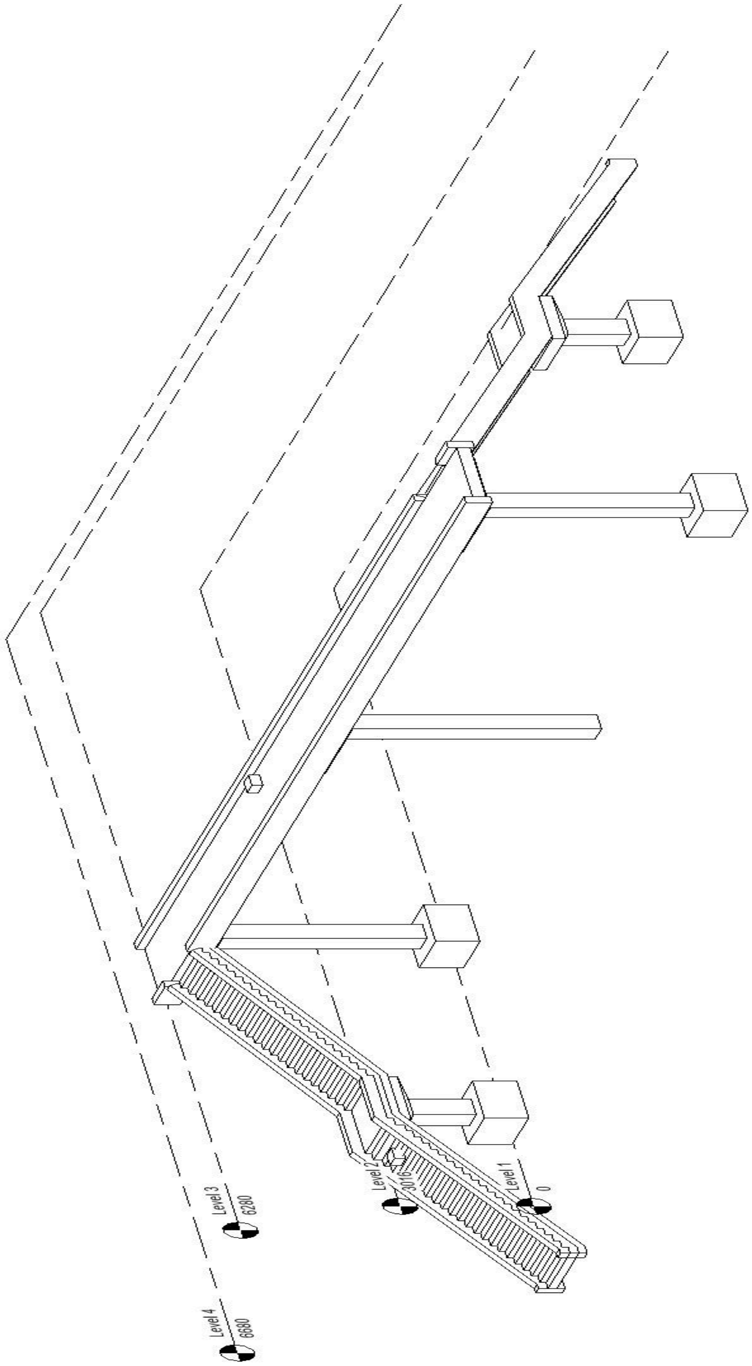


Figure 4.9 : Image of the Model with Mapped Virtual Sensors

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 CONCLUSION

This project has successfully demonstrated a cost-effective and feasible methodology for integrating Structural Health Monitoring(SHM) data into a building information model, which addresses the common challenge of sensor data management and visualization. A low-cost accelerometer sensor (MPU6050) was used for vibration data collection and the raw data was processed using custom Python scripts, which generated the Power Spectral Density and hence the peak lateral frequency. Importation of the processed data into the Revit model using Dynamo scripts successfully linked the quantitative structural health metrics to the corresponding structural elements (bridge deck and staircase). This integration provided a clear, visual representation of the structure's health, thereby offering a more proactive and effective digital framework for structural maintenance and informed decision making regarding structural safety and longevity.

5.2 RECOMMENDATION

The results show that this proposed methodology proves to be an effective way of monitoring structures. However to extend the practicality of this method, the following recommendations are proposed;

1. **Develop a Continuous Monitoring System**: Since the feasibility has been demonstrated, a system that will allow continuous, real-time data collection should be developed. This will require implementing reliable, low-power data transmission

and storage solutions to overcome complexities like time frame, power supply and data processing.

2. **Integrate Automated Anomaly Detection**: In this method, we rely on manual inspection of the visualized data. To improve on this, Machine Learning (ML) or other advanced algorithms can be incorporated into the Python processing, to automatically identify deviations and generate alerts for potential structural distress.
3. **Enhance User Interoperability and Accessibility**: To improve access and visualization of the model to stakeholders, the visualization platform can be transitioned to a web-based or cloud-based environment. This would as well facilitate collaboration in real-time without needing specialized BIM softwares.

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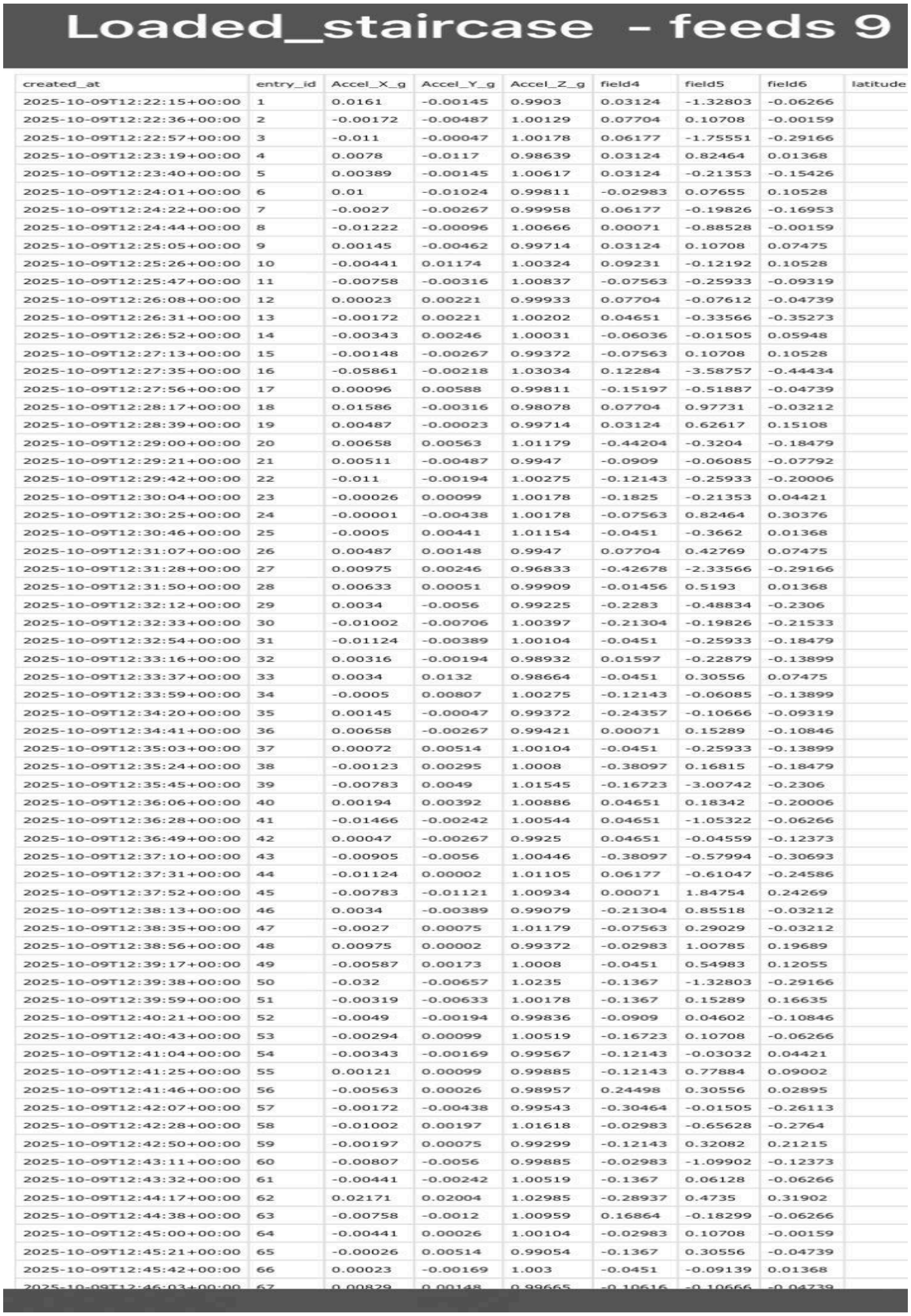
APPENDIX

Raw Acceleration Data



Loaded_staircase - feeds 9

created_at	entry_id	Accel_X_g	Accel_Y_g	Accel_Z_g	field4	field5	field6	latitude
2025-10-09T12:22:15+00:00	1	0.0161	-0.00145	0.9903	0.03124	-1.32803	-0.06266	
2025-10-09T12:22:36+00:00	2	-0.00172	-0.00487	1.00129	0.07704	0.10708	-0.00159	
2025-10-09T12:22:57+00:00	3	-0.011	-0.00047	1.00178	0.06177	-1.75551	-0.29166	
2025-10-09T12:23:19+00:00	4	0.0078	-0.0117	0.98639	0.03124	0.82464	0.01368	
2025-10-09T12:23:40+00:00	5	0.00389	-0.00145	1.00617	0.03124	-0.21353	-0.15426	
2025-10-09T12:24:01+00:00	6	0.01	-0.01024	0.99811	-0.02983	0.07655	0.10528	
2025-10-09T12:24:22+00:00	7	-0.0027	-0.00267	0.99958	0.06177	-0.19826	-0.16953	
2025-10-09T12:24:44+00:00	8	-0.01222	-0.00096	1.00666	0.00071	-0.88528	-0.00159	
2025-10-09T12:25:05+00:00	9	0.00145	-0.00462	0.99714	0.03124	0.10708	0.07475	
2025-10-09T12:25:26+00:00	10	-0.00441	0.01174	1.00324	0.09231	-0.12192	0.10528	
2025-10-09T12:25:47+00:00	11	-0.00758	-0.00316	1.00837	-0.07563	-0.25933	-0.09319	
2025-10-09T12:26:08+00:00	12	0.00023	0.00221	0.99933	0.07704	-0.07612	-0.04739	
2025-10-09T12:26:31+00:00	13	-0.00172	0.00221	1.00202	0.04651	-0.33566	-0.35273	
2025-10-09T12:26:52+00:00	14	-0.00343	0.00246	1.00031	-0.06036	-0.01505	0.05948	
2025-10-09T12:27:13+00:00	15	-0.00148	-0.00267	0.99372	-0.07563	0.10708	0.10528	
2025-10-09T12:27:35+00:00	16	-0.05861	-0.00218	1.03034	0.12284	-3.58757	-0.44434	
2025-10-09T12:27:56+00:00	17	0.00096	0.00588	0.99811	-0.15197	-0.51887	-0.04739	
2025-10-09T12:28:17+00:00	18	0.01586	-0.00316	0.98078	0.07704	0.97731	-0.03212	
2025-10-09T12:28:39+00:00	19	0.00487	-0.00023	0.99714	0.03124	0.62617	0.15108	
2025-10-09T12:29:00+00:00	20	0.00658	0.00563	1.01179	-0.44204	-0.3204	-0.18479	
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2025-10-09T12:30:04+00:00	23	-0.00026	0.00099	1.00178	-0.1825	-0.21353	0.04421	
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2025-10-09T12:31:50+00:00	28	0.00633	0.00051	0.99909	-0.01456	0.5193	0.01368	
2025-10-09T12:32:12+00:00	29	0.0034	-0.0056	0.99225	-0.2283	-0.48834	-0.2306	
2025-10-09T12:32:33+00:00	30	-0.01002	-0.00706	1.00397	-0.21304	-0.19826	-0.21533	
2025-10-09T12:32:54+00:00	31	-0.01124	-0.00389	1.00104	-0.0451	-0.25933	-0.18479	
2025-10-09T12:33:16+00:00	32	0.00316	-0.00194	0.98932	0.01597	-0.22879	-0.13899	
2025-10-09T12:33:37+00:00	33	0.0034	0.0132	0.98664	-0.0451	0.30556	0.07475	
2025-10-09T12:33:59+00:00	34	-0.0005	0.00807	1.00275	-0.12143	-0.06085	-0.13899	
2025-10-09T12:34:20+00:00	35	0.00145	-0.00047	0.99372	-0.24357	-0.10666	-0.09319	
2025-10-09T12:34:41+00:00	36	0.00658	-0.00267	0.99421	0.00071	0.15289	-0.10846	
2025-10-09T12:35:03+00:00	37	0.00072	0.00514	1.00104	-0.0451	-0.25933	-0.13899	
2025-10-09T12:35:24+00:00	38	-0.00123	0.00295	1.0008	-0.38097	0.16815	-0.18479	
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2025-10-09T12:36:06+00:00	40	0.00194	0.00392	1.00886	0.04651	0.18342	-0.20006	
2025-10-09T12:36:28+00:00	41	-0.01466	-0.00242	1.00544	0.04651	-1.05322	-0.06266	
2025-10-09T12:36:49+00:00	42	0.00047	-0.00267	0.9925	0.04651	-0.04559	-0.12373	
2025-10-09T12:37:10+00:00	43	-0.00905	-0.0056	1.00446	-0.38097	-0.57994	-0.30693	
2025-10-09T12:37:31+00:00	44	-0.01124	0.00002	1.01105	0.06177	-0.61047	-0.24586	
2025-10-09T12:37:52+00:00	45	-0.00783	-0.01121	1.00934	0.00071	1.84754	0.24269	
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2025-10-09T12:38:35+00:00	47	-0.0027	0.00075	1.01179	-0.07563	0.29029	-0.03212	
2025-10-09T12:38:56+00:00	48	0.00975	0.00002	0.99372	-0.02983	1.00785	0.19689	
2025-10-09T12:39:17+00:00	49	-0.00587	0.00173	1.0008	-0.0451	0.54983	0.12055	
2025-10-09T12:39:38+00:00	50	-0.032	-0.00657	1.0235	-0.1367	-1.32803	-0.29166	
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2025-10-09T12:40:21+00:00	52	-0.0049	-0.00194	0.99836	-0.0909	0.04602	-0.10846	
2025-10-09T12:40:43+00:00	53	-0.00294	0.00099	1.00519	-0.16723	0.10708	-0.06266	
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2025-10-09T12:44:38+00:00	63	-0.00758	-0.0012	1.00959	0.16864	-0.18299	-0.06266	
2025-10-09T12:45:00+00:00	64	-0.00441	0.00026	1.00104	-0.02983	0.10708	-0.00159	
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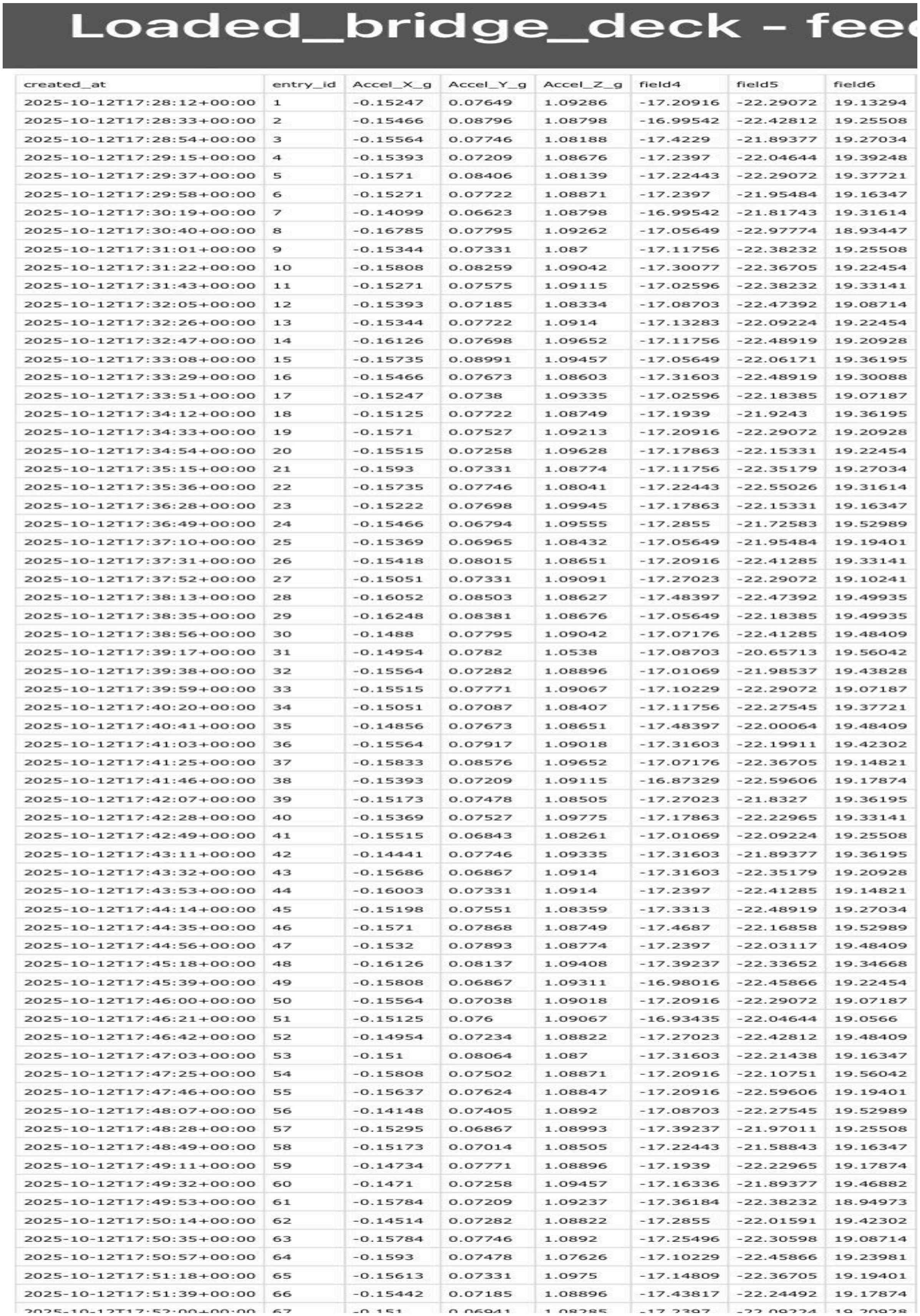
2025-10-09T12:45:42+00:00	66	0.00023	-0.00169	1.003	-0.0451	-0.09139	0.01368	
2025-10-09T12:46:03+00:00	67	0.00829	0.00148	0.99665	-0.10616	-0.10666	-0.04739	



Loaded_bridge_deck - fee

created_at	entry_id	Accel_X_g	Accel_Y_g	Accel_Z_g	field4	field5	field6
2025-10-12T17:28:12+00:00	1	-0.15247	0.07649	1.09286	-17.20916	-22.29072	19.13294
2025-10-12T17:28:33+00:00	2	-0.15466	0.08796	1.08798	-16.99542	-22.42812	19.25508
2025-10-12T17:28:54+00:00	3	-0.15564	0.07746	1.08188	-17.4229	-21.89377	19.27034
2025-10-12T17:29:15+00:00	4	-0.15393	0.07209	1.08676	-17.2397	-22.04644	19.39248
2025-10-12T17:29:37+00:00	5	-0.1571	0.08406	1.08139	-17.22443	-22.29072	19.37721
2025-10-12T17:29:58+00:00	6	-0.15271	0.07722	1.08871	-17.2397	-21.95484	19.16347
2025-10-12T17:30:19+00:00	7	-0.14099	0.06623	1.08798	-16.99542	-21.81743	19.31614
2025-10-12T17:30:40+00:00	8	-0.16785	0.07795	1.09262	-17.05649	-22.97774	18.93447
2025-10-12T17:31:01+00:00	9	-0.15344	0.07331	1.087	-17.11756	-22.38232	19.25508
2025-10-12T17:31:22+00:00	10	-0.15808	0.08259	1.09042	-17.30077	-22.36705	19.22454
2025-10-12T17:31:43+00:00	11	-0.15271	0.07575	1.09115	-17.02596	-22.38232	19.33141
2025-10-12T17:32:05+00:00	12	-0.15393	0.07185	1.08334	-17.08703	-22.47392	19.08714
2025-10-12T17:32:26+00:00	13	-0.15344	0.07722	1.0914	-17.13283	-22.09224	19.22454
2025-10-12T17:32:47+00:00	14	-0.16126	0.07698	1.09652	-17.11756	-22.48919	19.20928
2025-10-12T17:33:08+00:00	15	-0.15735	0.08991	1.09457	-17.05649	-22.06171	19.36195
2025-10-12T17:33:29+00:00	16	-0.15466	0.07673	1.08603	-17.31603	-22.48919	19.30088
2025-10-12T17:33:51+00:00	17	-0.15247	0.0738	1.09335	-17.02596	-22.18385	19.07187
2025-10-12T17:34:12+00:00	18	-0.15125	0.07722	1.08749	-17.1939	-21.9243	19.36195
2025-10-12T17:34:33+00:00	19	-0.1571	0.07527	1.09213	-17.20916	-22.29072	19.20928
2025-10-12T17:34:54+00:00	20	-0.15515	0.07258	1.09628	-17.17863	-22.15331	19.22454
2025-10-12T17:35:15+00:00	21	-0.1593	0.07331	1.08774	-17.11756	-22.35179	19.27034
2025-10-12T17:35:36+00:00	22	-0.15735	0.07746	1.08041	-17.22443	-22.55026	19.31614
2025-10-12T17:36:28+00:00	23	-0.15222	0.07698	1.09945	-17.17863	-22.15331	19.16347
2025-10-12T17:36:49+00:00	24	-0.15466	0.06794	1.09555	-17.2855	-21.72583	19.52989
2025-10-12T17:37:10+00:00	25	-0.15369	0.06965	1.08432	-17.05649	-21.95484	19.19401
2025-10-12T17:37:31+00:00	26	-0.15418	0.08015	1.08651	-17.20916	-22.41285	19.33141
2025-10-12T17:37:52+00:00	27	-0.15051	0.07331	1.09091	-17.27023	-22.29072	19.10241
2025-10-12T17:38:13+00:00	28	-0.16052	0.08503	1.08627	-17.48397	-22.47392	19.49935
2025-10-12T17:38:35+00:00	29	-0.16248	0.08381	1.08676	-17.05649	-22.18385	19.49935
2025-10-12T17:38:56+00:00	30	-0.1488	0.07795	1.09042	-17.07176	-22.41285	19.48409
2025-10-12T17:39:17+00:00	31	-0.14954	0.0782	1.0538	-17.08703	-20.65713	19.56042
2025-10-12T17:39:38+00:00	32	-0.15564	0.07282	1.08896	-17.01069	-21.98537	19.43828
2025-10-12T17:39:59+00:00	33	-0.15515	0.07771	1.09067	-17.10229	-22.29072	19.07187
2025-10-12T17:40:20+00:00	34	-0.15051	0.07087	1.08407	-17.11756	-22.27545	19.37721
2025-10-12T17:40:41+00:00	35	-0.14856	0.07673	1.08651	-17.48397	-22.00064	19.48409
2025-10-12T17:41:03+00:00	36	-0.15564	0.07917	1.09018	-17.31603	-22.19911	19.42302
2025-10-12T17:41:25+00:00	37	-0.15833	0.08576	1.09652	-17.07176	-22.36705	19.14821
2025-10-12T17:41:46+00:00	38	-0.15393	0.07209	1.09115	-16.87329	-22.59606	19.17874
2025-10-12T17:42:07+00:00	39	-0.15173	0.07478	1.08505	-17.27023	-21.8327	19.36195
2025-10-12T17:42:28+00:00	40	-0.15369	0.07527	1.09775	-17.17863	-22.22965	19.33141
2025-10-12T17:42:49+00:00	41	-0.15515	0.06843	1.08261	-17.01069	-22.09224	19.25508
2025-10-12T17:43:11+00:00	42	-0.14441	0.07746	1.09335	-17.31603	-21.89377	19.36195
2025-10-12T17:43:32+00:00	43	-0.15686	0.06867	1.0914	-17.31603	-22.35179	19.20928
2025-10-12T17:43:53+00:00	44	-0.16003	0.07331	1.0914	-17.2397	-22.41285	19.14821
2025-10-12T17:44:14+00:00	45	-0.15198	0.07551	1.08359	-17.3313	-22.48919	19.27034
2025-10-12T17:44:35+00:00	46	-0.1571	0.07868	1.08749	-17.4687	-22.16858	19.52989
2025-10-12T17:44:56+00:00	47	-0.1532	0.07893	1.08774	-17.2397	-22.03117	19.48409
2025-10-12T17:45:18+00:00	48	-0.16126	0.08137	1.09408	-17.39237	-22.33652	19.34668
2025-10-12T17:45:39+00:00	49	-0.15808	0.06867	1.09311	-16.98016	-22.45866	19.22454
2025-10-12T17:46:00+00:00	50	-0.15564	0.07038	1.09018	-17.20916	-22.29072	19.07187
2025-10-12T17:46:21+00:00	51	-0.15125	0.076	1.09067	-16.93435	-22.04644	19.0566
2025-10-12T17:46:42+00:00	52	-0.14954	0.07234	1.08822	-17.27023	-22.42812	19.48409
2025-10-12T17:47:03+00:00	53	-0.151	0.08064	1.087	-17.31603	-22.21438	19.16347
2025-10-12T17:47:25+00:00	54	-0.15808	0.07502	1.08871	-17.20916	-22.10751	19.56042
2025-10-12T17:47:46+00:00	55	-0.15637	0.07624	1.08847	-17.20916	-22.59606	19.19401
2025-10-12T17:48:07+00:00	56	-0.14148	0.07405	1.0892	-17.08703	-22.27545	19.52989
2025-10-12T17:48:28+00:00	57	-0.15295	0.06867	1.08993	-17.39237	-21.97011	19.25508
2025-10-12T17:48:49+00:00	58	-0.15173	0.07014	1.08505	-17.22443	-21.58843	19.16347
2025-10-12T17:49:11+00:00	59	-0.14734	0.07771	1.08896	-17.1939	-22.22965	19.17874
2025-10-12T17:49:32+00:00	60	-0.1471	0.07258	1.09457	-17.16336	-21.89377	19.46882
2025-10-12T17:49:53+00:00	61	-0.15784	0.07209	1.09237	-17.36184	-22.38232	18.94973
2025-10-12T17:50:14+00:00	62	-0.14514	0.07282	1.08822	-17.2855	-22.01591	19.42302
2025-10-12T17:50:35+00:00	63	-0.15784	0.07746	1.0892	-17.25496	-22.30598	19.08714
2025-10-12T17:50:57+00:00	64	-0.1593	0.07478	1.07626	-17.10229	-22.45866	19.23981
2025-10-12T17:51:18+00:00	65	-0.15613	0.07331	1.0975	-17.14809	-22.36705	19.19401
2025-10-12T17:51:39+00:00	66	-0.15442	0.07185	1.08896	-17.43817	-22.24492	19.17874
2025-10-12T17:52:00+00:00	67	-0.151	0.06941	1.08285	-17.2397	-22.09224	19.20928

Python Code

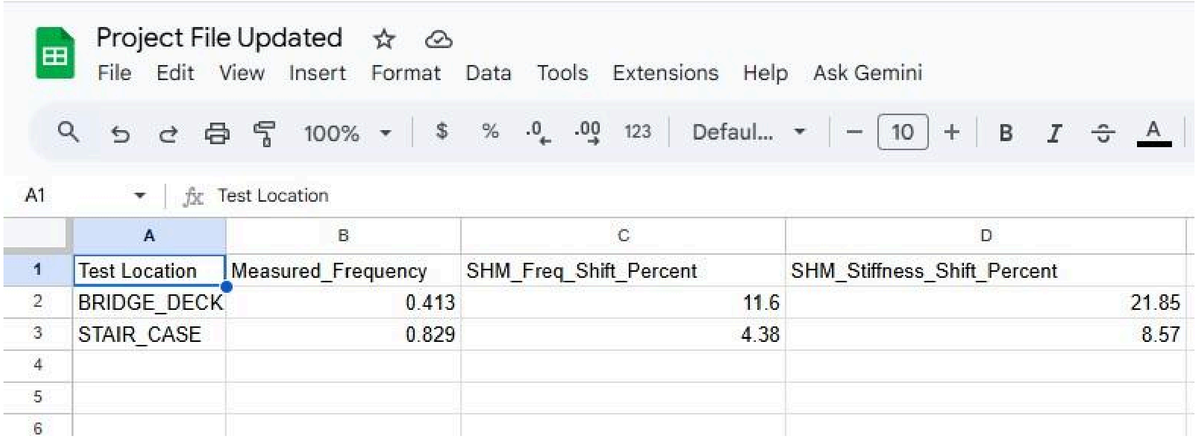
```python
import numpy as np
import pandas as pd
from scipy.signal import periodogram, butter, filtfilt
import matplotlib.pyplot as plt
# --- CONFIGURATION (UPDATE DATA_FILE ONLY) ---
# 1. Name of your CSV data file (e.g., 'avt_night_baseline.csv' or 'loaded_traffic.csv')
DATA_FILE = 'your_bridge_data.csv'
# 2. FIXED Sensor sampling rate in Hertz (from custom sensor design)
SAMPLING_RATE_HZ = 3.3
# 3. FIXED Cutoff frequency (must be below 1.65 Hz Nyquist limit)
CUTOFF_FREQ_HZ = 1.5
# --- DATA LOADING AND CLEANING ---
try:
    # Load the entire CSV file
    df = pd.read_csv(DATA_FILE)
    # CRITICAL CHANGE: Extract the acceleration data from the FIFTH column (index 4)
    # The first column is index 0, so the fifth column is index 4.
    a_raw = df.iloc[:, 4].values
except FileNotFoundError:
    print(f"ERROR: Data file '{DATA_FILE}' not found. Please check the file name and path.")
```

```
    exit()
except Exception as e:
    # Catching general errors like incorrect column indexing if the file is structured unexpectedly
    print(f"An error occurred during data loading (Check column index 4): {e}")
    exit()
# 1. Detrending (DC Offset Removal)
# This removes the mean value, eliminating the static 1g gravity offset
a_detrended = a_raw - np.mean(a_raw)
print(f"Data Loaded and Detrended (Mean removed: {np.mean(a_raw):.4f} units)")
# --- SIGNAL PROCESSING (FILTERING) ---
# Butterworth Low-Pass Filter Design (5th order is standard)
order = 5
nyquist = 0.5 * SAMPLING_RATE_HZ
Wn = CUTOFF_FREQ_HZ / nyquist  # Normalized cutoff frequency
if Wn >= 1:
    print("\nWARNING: Cutoff frequency is too high for the 3.3 Hz sampling rate. Please check config.")
    a_filtered = a_detrended
else:
    # Design the filter
    b, a = butter(order, Wn, btype='low', analog=False)
```

```
    # Apply the filter forward and backward (filtfilt) to eliminate phase distortion
    a_filtered = filtfilt(b, a, a_detrended)
    print(f"Signal filtered with {order}th order Butterworth filter (Cutoff: {CUTOFF_FREQ_HZ} Hz)")
# --- FREQUENCY ANALYSIS (FFT) ---
# Calculate the Power Spectral Density (PSD)
# FIX APPLIED: Changed 'hanning' to 'hann' to resolve the KeyError.
f, S_xx = periodogram(a_filtered, fs=SAMPLING_RATE_HZ, window='hann', scaling='density')
# Find the peak frequency (focusing on frequencies above 0.1 Hz to ignore baseline noise)
mask = f > 0.1
f_peak = f[mask][np.argmax(S_xx[mask])]
S_peak = S_xx[mask][np.argmax(S_xx[mask])]


print(f"\nAnalysis Complete:")
print(f"Measured Dominant Lateral Frequency (f_peak): {f_peak:.3f} Hz")
# --- PLOTTING RESULTS ---
plt.figure(figsize=(12, 6))
plt.plot(f, S_xx, color='#1f77b4')
plt.plot(f_peak, S_peak, 'o', color='red', markersize=8, label=f'Peak Lateral Frequency: {f_peak:.3f} Hz')
plt.xlim(0, 2.0) # Confining the view to the measurable range (Nyquist limit is 1.65 Hz)
```

```
plt.title(f'Power Spectral Density (PSD) of Lateral Vibration Data from {DATA_FILE}', fontsize=14)

plt.xlabel('Frequency (Hz)', fontsize=12)

plt.ylabel('Power Spectral Density (PSD)', fontsize=12)

plt.grid(True, which='both', linestyle='--', linewidth=0.5)

plt.legend()

plt.tight_layout()

plt.show()



print("\nSuccess! Use this f_peak value as your f_lateral, baseline or f_loaded.")
```

CSV File



Test Location	Measured_Frequency	SHM_Freq_Shift_Percent	SHM_Stiffness_Shift_Percent
BRIDGE_DECK	0.413	11.6	21.85
STAIR_CASE	0.829	4.38	8.57