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Review Article

Vibration-Based Failure Diagnosis of Warren Truss Structures Using Supervised Machine Learning Techniques

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Abstract

This article explores advancements in damage detection and structural diagnostics for steel bridges by proposing an integrated analysis method for failure patterns and structural feasibility validation. The approach incorporates the correlation between damage causes and vibrational data classified by intensity levels. Using a supervised machine learning framework, training datasets are developed by analyzing structural behavior identified through specific vibration characteristics, specifically examining the Warren Truss type. It explored a system that diagnosed failure sequences based on vibration-classified structures within the steel bridge frame. The system generated data on the feasibility conditions by analyzing the vibration characteristics of structural elements with varying levels of damage. This vibration classification could be used as a reference for structural maintenance and repair. Machine learning diagnosis involved investigating bridge collapses to identify the types of elements and their positions within the structure, with forecasts serving as the basis for interference detection. Identifying and classifying vibration patterns in bridge structures focuses on assessing their response to potential damage and dysfunctions to ensure their safety and long-term durability. This involves using vibration-based structural health monitoring (SHM) systems that detect anomalies or changes in the dynamic behavior of bridges. The primary objective is correlating specific vibration signatures with structural defects, such as fatigue cracks, material degradation, or connection failures. This assessment categorized structural degeneration into three levels: moderate (30%), urgent (50%), and severe/critical (≥70%). The findings of the assessment group informed the design of management strategies, technical maintenance plans, and overall structural performance improvements for Warren Truss Bridges. Factual values and ductility measurements were also considered. The study provided a more detailed summary of relevant research outcomes and the developmental stages of a recent vibration-based diagnostic system for future research.

Keywords

Fatigue Analysis, Machine Learning (ML), Warren Truss, Diagnostic, Structural Health Monitoring

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1. Introduction

The development of a system for diagnosing and monitoring bridge integrity through vibration signals is intended to assess structural conditions for maintenance purposes and to prevent potential collapse. This study analyzed data from the sudden failure of several steel bridges due to various factors, aiming to derive valuable insights for enhancing future bridge designs. Given the unexpected collapse of numerous steel bridges, there is an urgent need for a non-destructive and practical diagnostic tool capable of accurately evaluating a bridge's structural integrity to help prevent similar incidents. The diagnostic tool conducted a feasibility analysis by simulating various rapid-collapse scenarios in steel bridges, assessing element damage, and predicting the maximum strain on the compromised components. [1, 2].

Steel bridge collapses have occurred in various countries for multiple reasons, including more than 500 instances in the United States [3], 2,130 incidents of destruction in India [4], and several others across different nations. The data indicates that the most frequent causes of structural damage to bridges include crack propagation, fatigue, corrosion, design flaws, construction errors, natural disasters, collisions, and plastic buckling. Failure mode diagnoses due to bridge element deterioration commonly utilize vibration response analysis to assess the structural integrity. Figure 1 illustrates a collapsed bridge in Indonesia caused by element decay and overload.

Figure 1. *The steel bridge collapsed in Indonesia; (a) Kutai Kertanegara (2011), (b). Babad Widang, Lamongan (2018). (c). Parawang, Riau (2023); Aceh, (d). Pematang Panggang, Palembang (2019).*

The Kutai Kartanegara Bridge, a 710-meter steel structure, collapsed in 2011 due to construction errors, deficiencies in connections and clamps, as well as structural elements. Prior to its collapse, signs of deterioration such as cracks, corrosion, and damage to bridge components were observed. Similarly, the Babad Widang Bridge in Lamongan failed in 2018, primarily due to overloading and structural weaknesses. The Parawang Bridge, measuring 382 meters in total length with three spans, collapsed in 2023 as a result of corrosion in support members, cracks in critical structural components (diagonals), and overloading. Likewise, the Panggang Bridge in Palembang experienced failure due to overloading and significant damage to vital structural elements, particularly the bottom chord. Similar incidents have occurred globally, where steel bridges failed due to structural deficiencies. These recurring issues highlight the need for a robust diagnostic system capable of evaluating damage feasibility and assigning damage ratings to steel bridges based on specific technical and design scenarios. Such a system would utilize vibration mode analysis to detect structural faults.

The study identified distinct patterns of damage during structural collapses by meticulously analyzing data correlations, damage classifications, and their severity levels. Leveraging an advanced datasheet, Supervised Machine Learning (SML) models were trained to enable precise diagnostic assessments for bridge structures with comparable designs. These findings underscore the transformative potential of SML in structural health monitoring, particularly for Warren truss bridges subjected to critical loading conditions. Emerging advancements in machine learning algorithms and sensor technologies present a unique opportunity to enhance diagnostic accuracy further. By integrating high-resolution sensor data, critical load simulations, and fatigue analysis, future research can develop more robust predictive models capable of detecting subtle signs of structural distress well before catastrophic failures occur. This approach will not only improve the precision of existing diagnostic techniques but also address complex interactions between load dynamics and structural vulnerabilities that are often overlooked. Such innovation is vital for ensuring the safety and longevity of critical infrastructure.

2. Failure Modes and Patterns Diagnostics for Feasibility of Steel Warren Truss Bridge

The Failure Modes and Patterns Diagnostics approach focuses on identifying and understanding the mechanisms behind system or component failures by analyzing detected failure patterns or modes. This process typically utilizes advanced data analysis methods, including vibration monitoring, spectrum analysis, and other inspection techniques, to identify early signs of potential failure and guide corrective actions. The data generated from vibration characteristics, aligned with the fatigue levels of structural elements, serves as reference data for machine learning models or statistical algorithms, enabling more precise predictions. In the context of steel bridges, each structure has a natural frequency at which it vibrates when subjected to external forces. By analyzing the vibration response, engineers can assess how these forces affect the structural integrity of the bridge, identifying areas of high or low stress during vibration. If external vibrations coincide with the bridge's natural frequency, resonance can occur, leading to amplified vibrations and accelerated deterioration.

A bridge maintenance system that can accurately detect these critical conditions will enable rapid and precise diagnosis of potential failures. The implementation of real-time monitoring through vibration sensors integrated with the Internet of Things (IoT), the Global Positioning System (GPS), and the Global Navigation Satellite System (GNSS) has the potential to continuously provide real-time data. However, applying such technology across an entire bridge requires significant investment, as well as ongoing monitoring and maintenance efforts [5-8]. Additionally, failure due to phenomena such as plastic buckling in support points, beams, and diagonals further complicates maintenance and requires precise diagnostic tools. [9, 10]. Therefore, while real-time monitoring systems offer substantial benefits, they must be balanced against the costs and logistical challenges involved in their deployment.[11]. The diagnostic approach for failure pattern recognition using classified vibration signals, taking into account the degree of damage to the structural components of the Warren truss.

The diagnostic approach for failure pattern recognition, using classified vibration signals. Data on the characteristics of various types of element damage are collected by introducing controlled artificial damage based on a measured volume. The damage criteria are derived from research and observations of failures, with several elements subjected to maximum strain, particularly near the support points, significantly influencing stress concentration and crack propagation. [12, 13]. The characteristic data was used to develop a diagnostic system based on the typicality and similarity of damage, as described in studies [14-16]. For each type of steel bridge structure, under varying damage conditions and severity levels, the SML diagnostic system requires failure mode data categorized by the type of element damage at different classification levels. To accurately draw conclusions from the SML system's training data, the analysis system needs reference data, consisting of numerical values or data related to vibration. Preliminary research utilized a laboratory-scale prototype of a Warren truss bridge to investigate its dynamic response, as illustrated in Figure 2.

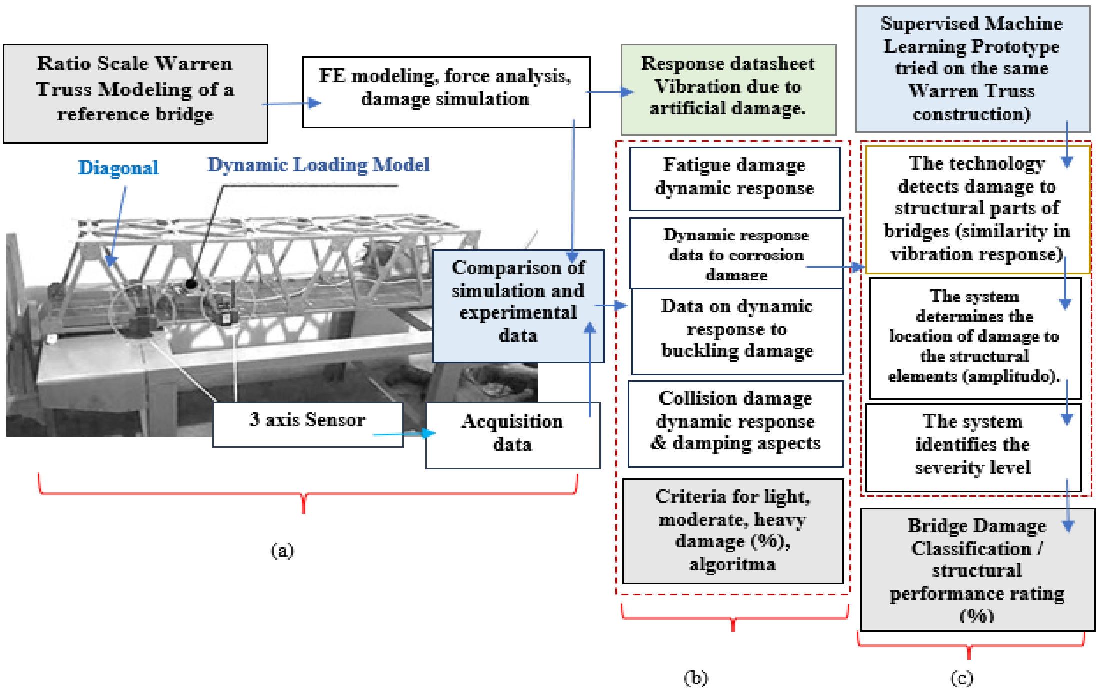


Figure 2. (a). Modeling and Datasheets (b). Validation, Fusion, and Algorithms (c) Supervised Machine Learning (SML), [16].

2.1. The Failure of an Individual Component and Its Propagation

The unintended collapse of steel Warren truss bridges has occurred in several countries, including the United States, China, Japan, and India, leading to numerous fatalities, significant financial losses, and prolonged disruptions to access in affected areas [9, 20-25]. Real-time monitoring systems to observe bridge conditions by detecting positional and structural changes. Findings from these monitoring efforts suggest that the root cause of damage and collapse in steel bridges may often stem from the failure of a single component, which then propagates throughout the entire structure [26, 27].

Fatigue propagation in materials due to cyclic loading develops over time. Continuous loading cycles can lead to the accumulation of damage within the material, ultimately resulting in structural failure. At this stage, cracks will propagate over time, potentially leading to complete failure of the material. Key components such as transferal beams and stringers at mid-span, secondary elements located at diagonal positions in the upper chord, and variations in treatments for fatigue, corrosion, and cracking have been highlighted in studies [28, 29]. Vibration response-based failure detection has been developed to identify damage levels caused by localized element failures, which could not be easily classified into the typical categories of mild, moderate, or severe/critical. The complexity in determining appropriate artificial treatments in the fatigue degradation simulation process arises from varying damage criteria, element positions, and the underlying causes. These treatments are applied to adjust the mechanical properties, such as the reduction in stiffness of elements during prototype testing, in order to provide an overview of the structural balance changes due to the applied loads.

Based on recent advancements in vibration-based Structural Health Monitoring (SHM), vibration patterns in bridge structures are analyzed using advanced techniques to detect potential damage and validate both durability and safety. Structural defects, such as cracking or reductions in stiffness, are identified through SHM systems, providing critical insights. Additionally, this technology enables the integration of SHM data with Digital Twin frameworks, enhancing the management and monitoring of structural integrity in bridges, [30]. Anomaly detection algorithms are employed to observe variations in bridge vibration responses, often caused by material degradation or failure at connections. These methods enable early identification of structural changes through shifts in dynamic behavior [31]. The specific vibration signatures are associated with distinct damage types, improving the localization and severity assessment of structural issues, [32, 33].

2.2. Challenges of Steel Truss Bridge Failure Pattern Diagnostic Systems

The condition monitoring of bridge structures, traditionally conducted through visual inspection of each structural element, has progressively been replaced by vibration response monitoring. However, the implementation of this approach has not yet reached a level of precision and efficiency. Vibration response-based diagnostic and monitoring systems have been developed to explore feasibility through more practical and cost-effective methodologies. Currently, a feasibility analysis is being conducted through several phases, beginning with the visual inspection of the bridge condition, followed by an evaluation of the structural elements. Subsequently, modeling is performed using the Finite Element Method (FEM) with software such as Deform, ABAQUS, SAP2000, ANSYS, and others. This is then followed by a comprehensive analysis involving numerical, statistical, and experimental methods, [16, 17]. Vibration response monitoring has gradually replaced the visual inspection of individual bridge elements for assessing the condition of bridge structures. The method developed involves vibration response-based diagnostic and monitoring systems, aiming to enhance feasibility through more practical and cost-effective phases and methodologies. The feasibility analysis was conducted through several stages, starting with visual observations of the bridge's condition and inspections of the structural elements.

The SML algorithm-based feasibility assessment system for bridge structures aims to generate data on element damage, identify damage locations, and evaluate the feasibility ratings of structural health of Warren truss steel bridges, limited to similar types of structures, requiring substantial numerical data and trends in vibration behavior that relate to various structural characteristics. The SML approach develops an analytical model through the use of a data sheet, a significant challenge system is the consistent acquisition of vibration trend data across multiple bridges. The development of the SML model involves the preparation of reference data based on measured vibrations obtained from various levels of damage with fatigue degradation on structural elements at critical locations identified through numerical analysis, in order to diagnose the damage level of the bridge. The analysis revealed four primary types of damage; fatigue that exceeded the maximum strain, corrosion of support elements, maximum tension in the diagonal rods, and plastic buckling. [18, 19].

The technical preparation was significantly enhanced through a comprehensive evaluation of each variable, which contributed to the development of a more effective design methodology. This thorough analysis ensured that key factors were carefully considered, resulting in an optimized approach that aligns with best practices in the field.

3. Literature Review

Over the past decade, advancements in bridge damage detection and monitoring have increasingly leveraged vibration response-based systems. These systems aim to provide timely identification of structural issues, enhancing the safety and longevity of bridges. Despite significant progress, applying comprehensive damage rating systems remains a challenge. Current methodologies often lack the detailed descriptions necessary to establish practical criteria for assessing bridge damage severity. Specifically, the integration of vibration mode analysis to quantify stress components remains underutilized, limiting the ability to identify early-stage damage or degradation patterns effectively. The SML has emerged as a promising tool for structural diagnostics. SML facilitates the identification of degradation-prone components whose failure may propagate through the structure. However, the effective application of SML in bridge damage detection relies heavily on high-quality training data. For steel bridge elements, data reflecting damage volumes must first be reconstructed into precise vibration response characteristics, ensuring that the SML model can discern subtle degradation trends.

While research into SML-based diagnostic systems continues to expand, gaps remain in linking theoretical models with actual applications. Specifically, the practical challenges of reconstructing vibration response data and correlating it with structural stress and damage thresholds have not been comprehensively addressed. This research seeks to address these gaps by developing an approach to integrate reconstructed vibration characteristics into SML frameworks, enabling more accurate and efficient damage diagnostics for steel bridges. Such advancements are critical for ensuring rapid, data-driven decision-making in structural health monitoring systems.

Table 1 presents the occurrence of local element failures under artificial treatment, referencing actual bridge structures to suggest potential improvements for monitoring systems and steel frame bridge design enhancements, particularly for Warren Truss structures. The progress in detecting failure modes based on vibration response is further elaborated in the Results Analysis and Recommendations section, as shown in Table 1.

Table 1. *Summarizes achievements in developing failure modes detection based on the vibration response of steel frame bridges.*

Author, (Year)	**Structure/ steel truss-type**		**Methodology**	**Results Analysis and Recommendations**
	Truss Type	**Dimensions (PxLxT) (m)**		
Sukamta, et. al, 2022,[16].	Warren Truss and Modelling	Reference bridge dimensions (53.0, 9.0, and 5.0 m) with scale and ratio 1:23.	Laboratory scale Steel truss bridge modeling involves static and dynamic loads for responsiveness measurements, finite element (FE) modeling, and damping ratio measurements.	Changes in vibration response were computed by comparing natural frequencies to experimental data, and the degree of divergence and reduction in damping were used as indicators of element deterioration within a 10% tolerance. The higher the amplitude, the more severe the damage.
Giacomo Caredda et. al., 2005, [17]	Railway/ Steel Truss	21, 2.8, 2.3	Simulating failure patterns on a computer by applying artificial treatments to predict the occurrence of element damage, especially at locations that trigger the propagation of structural damage, measuring bending moments, 3D simulations, artificial damage to the main structure (transfer beam, axis (z, x), the longitudinal beam of the middle bridge, and artificial treatment of the secondary structure (z, y) at its center indicate and sides of the bridge with two elements.	Maintenance was carried out based on the results of an analysis of expected damage to the most critical elements, which have the potential to accelerate damage propagation and degrade structural balance. The maximum bending force caused element breakage at the major structure's center point, necessitating a stronger top connection. Bridge sections with damage to two or more components in the center have a higher connection bending moment; continuous parts are preferred over connection types on long spans. Damage to a particular component may cause collapse.
B. Barros, et. al, 2023, [34]	Pedestrian bridge with rivet connection steel truss	15.6, 5.8, 2.5	Visual inspection, corrosion observation, laser scanning test, 3D model, vibration test, and FEM modeling will be carried out in three stages. (1). Identification, visual investigation, FE modeling, numerical approaches, and algorithms, (2). Measurement of vibration response failure patterns (3). Prediction of elemental damage.	The natural frequency measurement test data from five measurement sites (11,813 Hz) and the largest (31,813 Hz) show that pitting corrosion was the cause of failure, resulting in concentrated damage. Corrosion generates a sequence of breaks, propagating damage throughout the bridge structure. The algorithm's outputs reveal the presence of degraded and potentially harmful substances (propagation).

Author, (Year)	Structure/ steel truss-type		Methodology	Results Analysis and Recommendations
	Truss Type	Dimensions (PxLxT) (m)		
Santiago Lopes, 2023, [35]	Truss, warren, prat	Span variation and collapsed proportion	Investigating the causes of the Warren Bridge destruction. Pratt categorizes the causes of damage and collapse by determining the span and its largest percentage of truss warrens.	The causes of damage and collapse were classified as 50% design and maintenance errors, 25% maintenance errors, 6% construction errors, 13% collisions, and 6% environmental and flooding-related incidents.
Jiajia Hao, et. al, 2022, [36]	Warren Truss	8.0, 0.6, 0.6	Developing an algorithm (deep learning) uses a variety of approaches to identify damage from an architectural and structural perspective, as well as mathematical (numerical) approaches and simulations that compare predicted data to actual data. Artificial damage scenarios comprise one, two, and three elements.	The detection accuracy of an intentionally controlled vibration experiment reached 99.6%, identifying a correlation between element degradation and a decrease in elasticity. Calculating the precise location of damage using the number of conditioned elements was an excellent reference for developing algorithms. The central point was the most dispersed damage.
Mohamad Ibrahim Zaed Ammar, et. al, 2017, [37]	Warren Truss	77.0, 6.0, .6.0	Simulation with ANSYS and SAP2000 generates corrosion treatment and dynamic load variations on the structure, predicts the magnitude of the highest stress, particularly at the midpoint location, maximum strain, a 200 KN load was measured using an accelerometer at speeds ranging from 20 to 40 km/h.	The influence of dynamic loads and damping measurements on steel bridge constructions: the natural frequency measurement was 100 Hz, and the changes that occurred at the treatment location were less than 100 Hz. The vibration response on pitting corrosion elements differed between the bottom and diagonal elements.
Marianna Crognale, et. al, 2021, [38]	Railway, Truss/Pratt rivet	The bridge's total length measured 170 meters, split into two 42.2-meter spans with sides measuring 21.48 and 21.12 meters.	Focuses on fatigue and corrosion, identifying critical points and elements, artificial treatment in the form of fatigue, corrosion, and cracks on structural elements on the bottom and diagonal sides, modeling with SAP 2000, treatment by reducing element cross-sections, deflection testing, and decreased element stiffness.	The SAP2000 assessment of the appearance of element vibration response tendencies by monitoring changes in deflection values and decreasing structural stiffness indicates that damage occurs when the deflection exceeds 0.3 and the main rod stiffness diminishes. Corrosion and fissures in component joints also had significance.
Andro Bunce, et. al, 2024, [39]	Warren Truss, (foot bridge/ highway	The spans measure 34 and 36 meters long, 2.5 meters wide, and 2.5 meters height.	The monitoring and diagnostic system was developed by generating vibration response datasheets for two actual Warren truss steel bridges from the same period. The response data would be employed for training the Failure Pattern Diagnostic Model SML. Testing of concrete bridges was also conducted.	The vibration response data from two steel bridges revealed a data similarity of 93–96%, comparable vibration patterns, and the same structure, suggesting that the data could potentially be used as a Datasheet to train a diagnostic system model on other bridges of the same construct. The vibration response values for steel and concrete bridges differ considerably.
Patricia Vanova, et. al, 2022, [40]	Warren Truss	Warren Truss Bridge Prototype Model (2.0, 0.5, 0.5 m)	artificial damage scenarios in the form of deep fatigue cracks with variations in damage to several bridge elements, FEM, ABAQUS simulations, and differences in mass and stiffness will reduce the frequency, identifying element characterization and structure.	The materials and models used were adjusted to approximate the condition of the steel truss Warren bridge, enhanced using numerical equations and measurements compared to the intact condition, and the level of damage that affected the stiffness. The dynamic response complying, response differences were observed for crack or damage depths exceeding 30%.
Sudath C. Siriwardane, et. al, 2015, [41]	Truss Bridge/ railway	Span 160 m, railway	The study was divided into three phases: comprehensive bridge construction, visual observation, material testing with load variations, element modeling, FE, and SAP2000, and measuring element vibra-	According to Finite Element (FE) analysis data, at the damage location, each element measured an average natural frequency of 4.72–9.1 Hz, and when compared to the vibrations measured at the damaged element's location, the damage

Author, (Year)	Structure/ steel truss-type Truss Type	Dimensions (PxLxT) (m)	Methodology	Results Analysis and Recommendations
			tions while compensating for bridge damage.	location was determined to be 10 to 16 meters to the left of the reference.
T. susanto, et. al, 2014, [42]	Truss Bridge/ railway bridge/ steel	Span 30 m	Creating a replica of the Porong Bridge railway bridge in East Java, Indonesia, simplifies the acquisition of vibration responses. Modeling with CSI Bridge v15, and investigating the vibration response characteristics of damage parameters that comply with a ten percent decrease in element cross-section.	The ensuing vibration response data may indicate oscillations indicating a loss in stiffness and relative appropriateness. To identify the precise location of essential elements. The element adjacent to the center location has the greatest probable potential of causing damage.
Azim, et. al, 2021, [43]	Truss Bridge/ railway bridge/ steel	32.92, 5.32, 5.32	FEM simulations, numerical analysis, and variable loading were used to assess vibration responses on elements under normal conditions, and when fake damage was applied, response variations were associated with damage severity. Artificial treatment with a factor that decreases the elasticity value of elements that have suffered 30–60% artificial damage.	The damage treatment reduces the stiffness value in the vertical rod by the same amount as the decrease in elasticity; in the adjacent diagonal plane, the changing elasticity is 50%. Model-based analysis indicates deterioration by comparing vibration response and stiffness variations, particularly on components that indicate significant corrosion and fractures.
Thiri Phyoe, et. al, 2014, [44]	Warren Truss bridge/ highway	36.57, 2.7.3, 9.1	The variables examined include alterations to truck loads on the highway and train loads on the railway; the assessment of the dynamic response of various bridge sections; and assessing the amount of deflection. Damping ratio (1–5%).	Vibrations in each element were dynamically evaluated based on the volume of ratifying cars; the bridge's middle encountered the most deflection; the damping ratio was inversely proportional to the acceleration response
Mehrisadat Makki Alamdari, Et. al, 2017, [45]	Truss Bridge	Span 1.200	Data acquisition interprets the vibration response by modeling a 1200-meter-long steel bridge, observing 800 arch supports (jacks), and accounting for transportation frequency. Structure degradation.	The consequences of observations on long-span bridges by applying structural damage, the changes in normal and distorted signals were identified and utilized to predict structural degradation and bridge viability.
Alireza Entezami, et. al, 2017, [46]	Steel Structure	Steel frame structure on a laboratory scale	Analyzing the bridge's feasibility despite considering the elements in sensitive locations, predicting the remaining element service using the auto-regressive (AR) technique, and formulating the vibration response using SML with stated restrictions. includes consequences of environment.	Damage to steel structures was effectively recognized and located; the intensity of the environmental influence and potentially the quantitative number of damaged elements were collected and utilized to calculate the remaining expected lifespan of materials and structures.
Seyed Saman Khedmatgozar Dolati, 2021, [47]	Steel Bridge	Steel bridge with structure variations.	Discusses the numerous applications of non-destructive testing (NDT) approaches, such as the viability of steel bridge structures, vibration response, and the use of drones and cameras to identify damage. Visual inspection of elements for corrosion, delamination, cracks, reduction in cross-section, foremost surface area.	The entirety of the NDT method provides a technique for detecting damage generated by cracks, propagation, and interior cracks utilizing eddy currents. Ultrasonic testing (UT) generates complete data on damage, particularly in the surface area, assesses the extent of corrosion, and produces a different response on damaged structures than on normal structures.
Lorenzo Bernardini, et. al, 2021, [48]	Warren Truss	21.42, 4.5, 3.71	Using 3D FE simulation, on a Warren truss model bridge to cause fictitious damage to the lower elements, such as cross girders and diagonal sides. Measuring with two dynamic responses: continuous wavelet (CWT) and Huang-Hilbert.	Detection of vibration response patterns to identify defective elements with the potential to propagate cracks and collapse under the influence of high loads. Corrosion lowers load-bearing capability, especially at the bottom diagonal element connections. Damage to ele-

Author, (Year)	Structure/ steel truss-type		Methodology	Results Analysis and Recommendations
	Truss Type	Dimensions (PxLxT) (m)		
				ments subjected to significant loads will affect the entirety of the structure.
Tran, M. Q, et. al, 2023, [49]	warren truss	1.230, 20.06, 11.0 (m) divided into 7 span structures	Damage to steel bridge structures was investigated using artificial intelligence (AI). FEM modeling, determining the damping ratio's influence and comparing it to the natural frequency of each bridge span model. Artificial damage ranges from 40 to 50 percent.	Generates FEM data, numerical vibration response with simulated damage treatment on elements (40–50%), and element characteristics. Damage might be acknowledged in the dynamic response due to the reduced stiffness of the major components.
Samim Mustofa, et. al, 2018, [50]	warren truss	70.77, 6.0, 6.0 (m)	The element damping ratio will be used to determine the presence of strain, followed by FE modeling and changes in damping values to identify element damage. Diagonal components have a significant impact on structural performance.	Element damping data was collected, particularly at the diagonal element structural position; local damage data revealed changes in element stiffness, which were supported by modeling and energy calculations; and response patterns were used to track local damage by implementing a variety of parameters.
Wang S., et, al, 2023, [51]	Suspension bridge/ railway	1.120, 16.0	The influence of train air speed on structures on long-span bridges was explored using FEM modeling and parameters ranging from modest to fast train speeds.	High train speeds, combined with maximum load weight, have an extensive effect on the vibrational responses of bridge structures. The impact of the train's wind speed exceeds its weight, as evidenced by vibration response data along the diagonal structural elements.
O. Bouzas, et. al, 2022, [52]	Steel Bridge/truss	48.1, 6.5, 7.5	Inspection of NDT testing, aspects, geometry, and materials holistically, FE, reliability assessment, visual inspection, laser scanning, ultrasonic, vibration tests, and numerical analysis.	Completely defined element characteristics, plastic behavior of materials, approach to maximum service limits, calibration error 2.04%, reliability prediction by applying NDT, and maximum structural lifesaving capabilities were discovered.
Ali M, et. al., 2018, [53]	Warren Truss	Modeling (5.5, 0.65, 0.65) refers to AS/NZS1163: 2009	The bridge monitoring system, which featured Warren truss steel frame modeling, was subjected to a hammer test with measured intensity to simulate damage to elements at precise points corresponding to the maximum load. FE models and statistical analysis.	Damage treatment was conducted by reducing the strength of the connection with different variations and the number of elements, and statistical analyses indicate the condition and location of damage; to comprehend the Warren Truss Bridge's complex structure.

According to Table 1, the data classified by the methodology generally aligns with each other. In terms of phases, similar methods were employed, with sampling used to define a series of datasheets based on vibration responses aimed at identifying the most severe damage. Datasheets were developed for SML-based analysis algorithms by identifying damage in locations with potential structural significance.

3.1. Development of Datasheet for Diagnostics of Warren Truss

The datasheet was compiled and an assessment of the viability of bridges with similar structures was conducted using data collected from observations of collapse and damage to bridge elements. The data collection process required extensive time to generate training datasets for the SML model. Visual evidence, specifically of damage to structural components on each bridge under investigation, was necessary to identify the area most prone to further damage propagation. Bridges were inspected visually using a digital camera mounted on a drone, particularly for high structures, those located in steep terrain, and those spanning major rivers. Direct visual inspection posed significant risks to inspectors, often requiring complex safety protocols. Therefore, drones were employed for aerial inspections, and underwater drones were utilized for seat inspections to gather more comprehensive data. Visual data obtained from digital cameras at reported damage sites were compared with observational data collected from previously inspected bridges, [40, 54]. The vibration behavior was assessed through sensor measurements and data acquisition, allowing for the estimation of the similarity proportion in both condition and feasibility, [55].

A bridge monitoring and diagnostic system is being developed by utilizing SML. Measurements from bridges with analogous structures are leveraged to build a comparative dataset. Data collected from instances of structural failure and deterioration are analyzed to create a comprehensive dataset, aiding in the assessment of the structural integrity of other bridges with similar designs. Visual documentation, highlighting damage to particular sections of each examined bridge, is utilized to pinpoint areas most susceptible to damage propagation. Elevated bridge structures, steep terrains, and large rivers present challenges for direct visual inspection, which may pose risks to personnel and necessitate complex safety protocols. As a result, drones equipped with digital cameras are deployed for aerial inspections, while underwater drones are utilized for underwater section examinations, enabling the collection of more comprehensive data. Visual data captured by digital cameras at identified damage locations are then compared with observational data from previously studied bridges to enhance the analysis of structural integrity, [56, 57]. The initial frequency may be compared to the frequency of damaged components in the previous bridge. Vibration behavior was measured using sensors, and data was collected to estimate the similarity in conditions and assess feasibility, [58].

3.1.1. Classification Rating of Bridge Condition

Research and failure evaluations will examine the damage level factors with degradation of 30%, 50%, and 70%, along with the treatment of prototype material elements. A reduction in stiffness or elasticity could significantly influence the extent of damage resulting from artificial deterioration. [43-45, 49]. The Percentage may be utilized as a parameter to represent different types of damage, including cracks, fatigue, or corrosion, which could potentially weaken structural elements and propagate further. The approach to classifying bridge conditions and establishing damage criteria varies across countries. Damage ratings are typically determined according to standards set by the relevant government authorities or technical ministries, [59].

The assessment and maintenance guidelines for steel bridges assign ratings to bridge structures based on specific conditions. These ratings are frequently referenced in SML analysis to generate criteria data corresponding to each rating level.

Table 2 provides a summary of the grading standards for the suitability and damage conditions of steel bridges across several countries, detailing the criteria used to evaluate their condition and suitability for continued service.

Table 2. *Classification Rating of Bridge Condition criteria in several countries, [Summarize by The Author].*

Countries	Bridge Condition Criteria Level	Range Rating
Indonesia	0-5 bridge condition group	5
Amerika (U.S)	0-9 Eligibility condition cluster	10
Korea	A-E Eligibility Condition Group	5
China	CS 1- CS 5 Rating condition/Status	5
Jepang	A,B,C,E1,E2,M,S Ratings	6
Germany	1= Very Good, 2 = Good, 3 = Satisfactory, 4= Poor, 5 = Very Poor	5
Malaysia	0-5 Rating condition/Status	5
UK	1-5 Damage Severity Condition, A to E, Increased level/rating	5

Table 2 provides an assessment of the bridge's condition based on the level of elemental damage. The primary components of concern include pillars, which, when experiencing up to 30% damage, may begin to lose their ability to support vertical loads. Damage to cross beams can result in uneven load distribution, while damage to the deck, particularly in the range of 30%-50%, may affect the dynamic response of the bridge under moving loads. Instability, in this context, refers to phenomena such as excessive deformation, where damaged bridge components may exhibit permanent deformations, such as tilted pillars or sagging decks. Load redistribution caused by damage can lead to certain components bearing loads far exceeding their capacity, ultimately triggering systemic failure. Additionally, dynamic response alterations due to damage can modify the natural frequency of the bridge, potentially resulting in resonance and excessive vibrations when subjected to dynamic loads. At the moderate level (30%), elemental damage remains tolerable but begins to show signs of reduced structural capacity. Intensive monitoring is required to prevent further progression. At the urgent level (50%), load redistribution becomes significant, with remaining components bearing increased loads, accelerating the rate of damage and posing a risk of localized failure. At the severe/critical level (≥70%), damage at this stage indicates a loss of primary functionality in the affected elements, potentially leading to progressive collapse if not addressed promptly. The grouping of ratings by percentage of element damage is preferred for FE analysis, as well as for references to numerical and artificial damage treatments.

The percentages associated with various structural elements were analyzed to assess the extent of damage caused by external phenomena such as fatigue, buckling, and corrosion, by measuring the affected areas [60]. Corrosion detection devices, which display different colors based on the condition of the corroded regions, were utilized for this purpose [61]. The SML datasheets specify damage to individual elements exhibiting critical conditions due to corrosion, with beam connections susceptible to collapse, and dynamic response patterns with defined characteristics [48, 62]. Vibration data collected from installed sensors, along with mechanical property testing, Scanning Electron Microscopy (SEM), and X-Ray Fluorescence (XRF) analysis, were employed to correlate material characteristics with vibration responses and to calculate material fatigue in cracked or damaged components.

3.1.2. The Material's Fatigue Level

The fatigue level of a material refers to its progressive structural degradation under cyclic loading, leading to stiffness reduction and potential failure over time. This phenomenon is characterized by microcrack initiation, propagation, and eventual fracture, significantly affecting the material's load-bearing capacity. Understanding fatigue behavior is crucial for assessing structural integrity, predicting service life, and implementing effective maintenance strategies in engineering applications. The fatigue ΔK, was determined using Equation (1), [63].

$$\Delta K = \frac{\Delta P\ (2+\alpha)}{B\sqrt{W\ (1-\alpha)^{3/2}}}\ (0{,}886 + 4{,}64\ \alpha^2 + 14{,}72\ \alpha^2) \quad (1)$$

Annotations;

ΔK: The change in stress intensity factor used to measure the stress level around the crack tip (MPa√m), caused by the cyclic load/applied cyclic load on the specimen ΔP (Newtons); α: The ratio between the effective crack length (a) and the specimen width (W); B: Thickness of the specimen material (mm). W: Width of the specimen (mm); a: Crack length (mm).; 1−α: a geometry-based correction factor that represents the remaining width of the specimen after subtracting the crack length; Coefficients in the function (0.886, 4.64, -14.72).

Empirical correction factors to account for the influence of the specimen geometry on the stress distribution at the crack tip. The ratio a/W (the crack length to specimen width), calculated using a polynomial equation based on the value of ux, which is related to experimental parameters such as load or material conditions. This function implies a complex and non-linear relationship between these variables. If ux is a parameter influenced by test conditions, then by knowing the value of ux. the ratio a/W, determined value (a) computed using equation (2) corresponds to the following equation:

$$\frac{a}{W} = 1{,}0010 - 4{,}6695\ ux + 18{,}46u_x^2 - 236{,}82\ u_x^3 + 1214{,}9\ u_x^4 - 2143{,}6\ u_x^5 \quad (2)$$

The formula above calculates the ratio between the crack length (a) and the specimen width (W), which is used to assess the relative size of the crack in relation to the specimen dimensions. ux is a parameter associated with the specimen's behavior or experimental conditions (equations 3). The constant coefficients (1.0010, −4.6695, 18.46, −236.82, 1214.9, −2143.6) represent the contribution of each term in the polynomial to the final value of the ratio (a/W) for a given ux. The first coefficient (1.00101): Serves as the base constant, representing the value of the ratio when ux=0, The second coefficient (−4.6695), Represents the first-order effect of ux on the ratio (a/W). Subsequent coefficients (18.46, −236.82, 1214.9, −2143.6) Represent the sequential contributions of ux^2, ux^3, ux^4, and ux^5 to changes in the ratio (a/W). The terms (n=1, 2, 3, 4, 5) indicate higher-order contributions to account for the non-linear relationship between ux and the ratio (a/Wa). The *UX* value calculated by equation (3).

$$ux = \left(\left[\frac{EVgB}{P}\right]^{\frac{1}{2}} + 1\right)^{-1} \quad (3)$$

Annotations; Ux; The parameter derived from the test conditions, often used to normalize or scale the geometric or material properties in relation to the applied load. E**:** Modulus of elasticity (Young's modulus) of the material, representing the material's stiffness, Pa (Pascals) or GPa (Gigapascals). Vg: Geometric factor or a parameter associated with the geometry of the specimen, typically dimensionless**.** B**:** Thickness of the specimen material, (m (meters) or mm (millimeters). P**:** Applied load during the experiment. N (Newtons) or kN (kilonewtons). By assessing changes in steel ductility, the remaining deformation capacity of components and the structure can be predicted before a potential failure occurs. These measurements allow for a precise estimation of the maximum deformation that can be sustained prior to structural collapse. The following equation is utilized to evaluate ductility (μ):

$$\mu = \frac{\delta_u}{\delta_y} \quad (4)$$

The ductility ratio (μ) is calculated as the ratio of the ultimate displacement (δu) to the yield displacement (δ). It provides a quantitative measure of the material's or structure's capacity to deform plastically before failure. Ductility refers to a structure's ability to absorb energy before collapsing [64]. Stages of developing SML diagnostics, according to analysis capabilities shown in figure 3.

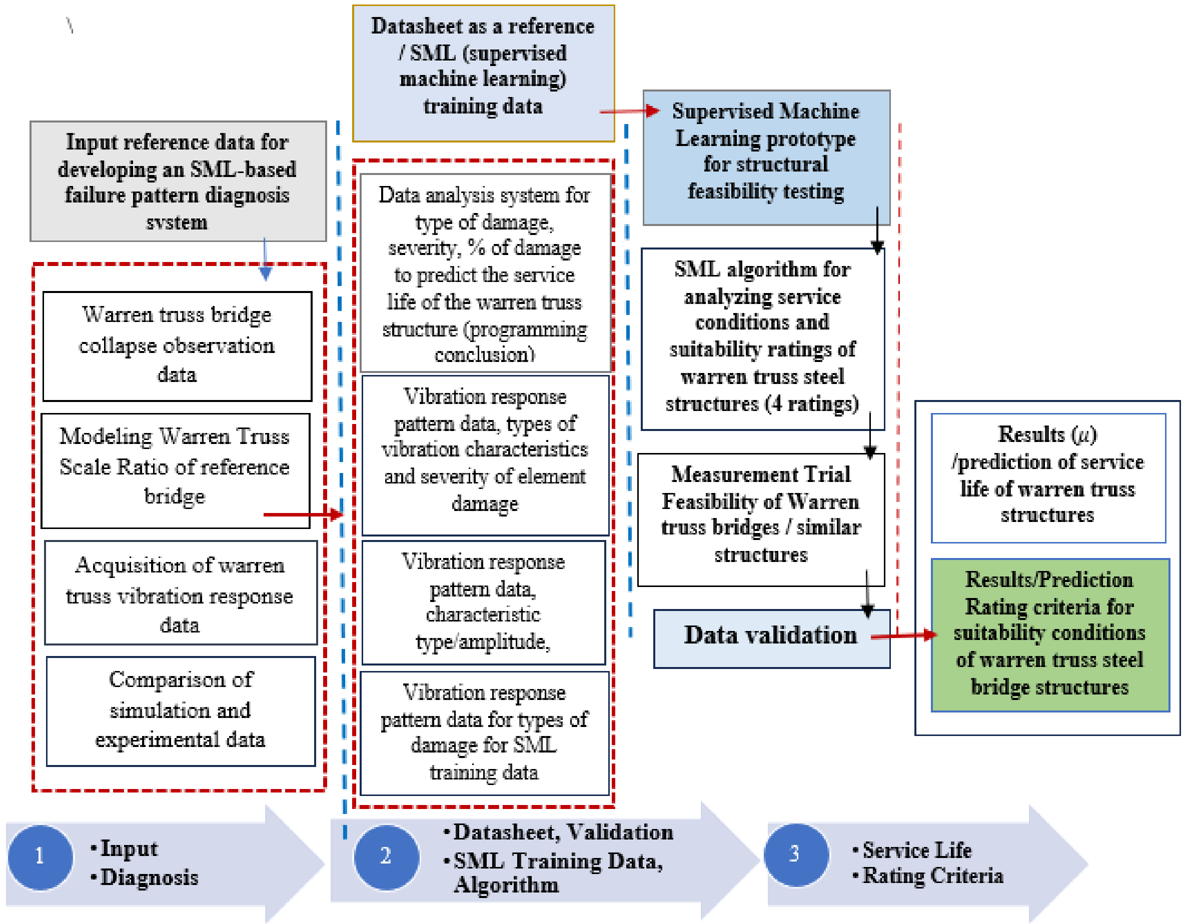


Figure 3. *Stages of developing SML machine learning diagnostics, according to analysis capabilities; (1). Observation data, sensor modeling, and data acquisition, (2). Validation, Fusion & algorithms, (3) validation, prediction of remaining service. [The author].*

Figure 3 illustrates the staged approach based on the diagnostic system's analytical capabilities, enabling classification, structural analysis, and evaluation. The system's capacity to analyze the structure, contingent on the extent of element damage, demonstrates the analytical potential of machine learning. The analysis was categorized into five diagnostic levels. Level I (damage detection) serve as the foundational level in the SHM/machine learning diagnostic framework. The continuous updating of SHM data facilitates the recognition of abnormal events, thus providing a more accurate temporal assessment. Level II (damage localization) identifies damage and determines its location within the structure. Level III (damage classification) allows the system to categorize the type, cause, and severity of damage based on the system's algorithm. Level IV (damage quantification) evaluates the extent of damage by determining the percentage of degradation. Level V (damage prognosis) evaluates the residual service life, assigns a damage classification, and determines the overall adequacy of the structure for ongoing operation.

3.2. Modeling of Fatigue Degradation in Warren Truss Bridge Elements

Modeling of Warren Truss bridge elements with fatigue treatments (30%, 50%, and 70%) to identify the impact of degradation on structural conditions. The simulation data will be used as a reference for determining the bridge's condition rating. The model refers to the dimensions of 56 meters in length, 7 meters in width, and 5 meters in height. Modelling and ANSYS Analysis shown figure 4.

Table 3. *Dimensional Data of the Warren Truss Bridge at Sendang Mulyo, Semarang, Central Java.*

Length (m)	Width (m)	Height (m)	Sidewalk (m)	Class
55,30	7,0	5,0	1,0	C

Figure 4. Depicted a model of the Sendang Mulyo Bridge in Semarang, Indonesia.

The geometry of the Warren Truss Bridge was modeled in ANSYS using the FEM. Each element, such as truss members, joints, and connecting elements, was accurately represented to capture the bridge's vibration response and load distribution. The material (S355) Steel used underwent stiffness degradation to simulate the effects of fatigue. The stiffness reduction was applied at 30%, 50%, and 70% levels to model the damage caused by fatigue. The static and dynamic load was applied, with vehicle loads based on standard truck weights, equivalent to 320 kN, to observe the bridge's response under normal conditions and during fatigue-induced degradation.

The ANSYS simulation was conducted to validate the damage rating of the bridge, serving as a reference for clustering in machine learning. The bridge model underwent fatigue degradation by gradually reducing material stiffness to compute the stress distribution and deformation based on the stiffness reduction, to predict the behavior of the bridge under static loading. The material properties presented in Table 4 pertain to ASTM A572 Grade 55. The variations in stiffness degradation levels shown in Table 5.

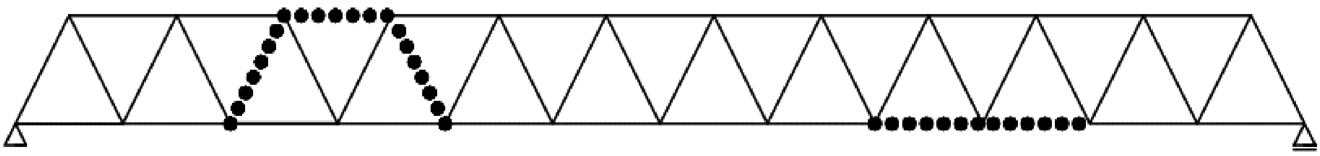
Table 4. Material Classification S355/ASTMA572 Grade55.

Parameters	Mechanical Properties
Density	7.8 g/cm^3
Modulus Young (Gpa)	200 GPa
Poission'sRatio	0,3
Bulk Modulus	166 GPa
Shear Modulus	76.9 GPa
Tensile Yield Strength	430
Tensile Ultimate Strength	550

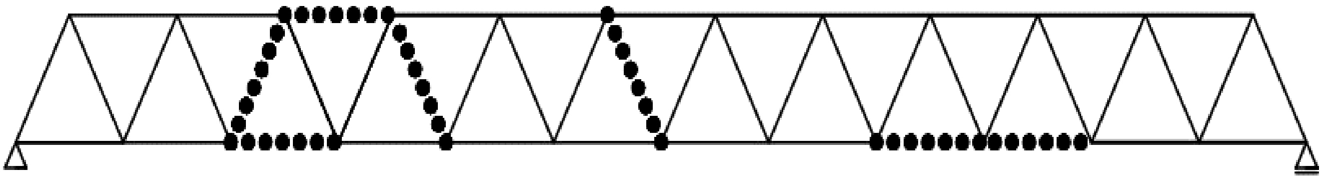
Table 5. Parameters and Level of stiffness degradation levels.

Parameters	No Fatik	30%	50%	70%
Modulus Young (Gpa)	200	140	100	60
Poission's Ratio	0,3	0,3	0,3	0,3
Tensile Yield Strength (Mpa)	430	301	215	129
Compressive Yield Strength (Mpa)	430	301	215	129
Tensile Ultimate Strength (Mpa)	550	385	275	165

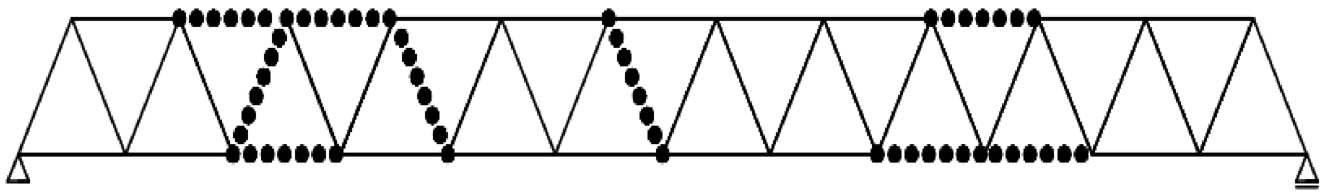
The fatigue treatment on the elements is simulated by defining several elements with bold lines, as illustrated in Figure 5.



(a). The elements marked with bold lines are subjected to 30% fatigue treatment.



(b). The elements marked with bold lines are subjected to 50% fatigue treatment.



(c). The elements marked with bold lines are subjected to 70% fatigue treatment.

Figure 5. *The treatment of fatigue on elements under varying static loads induced by vehicles.*

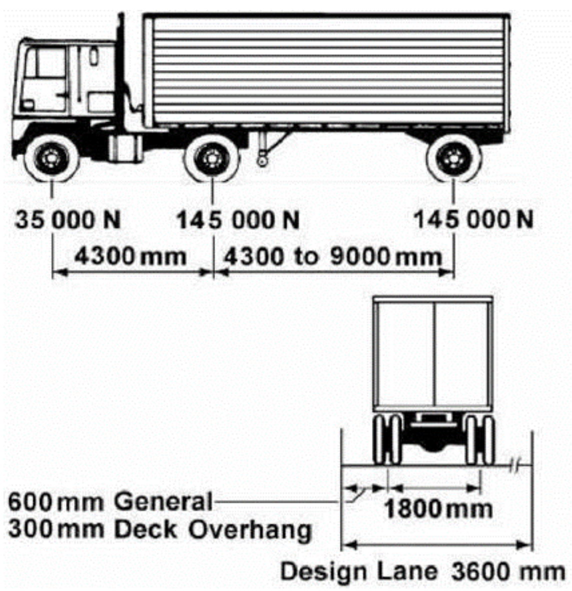
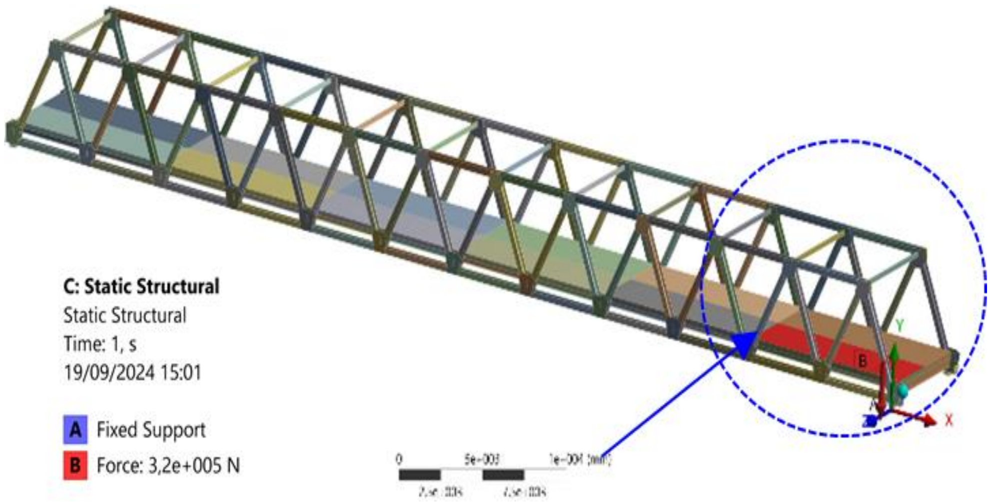


Figure 6. *Reference truck load for static vehicle load analysis.*

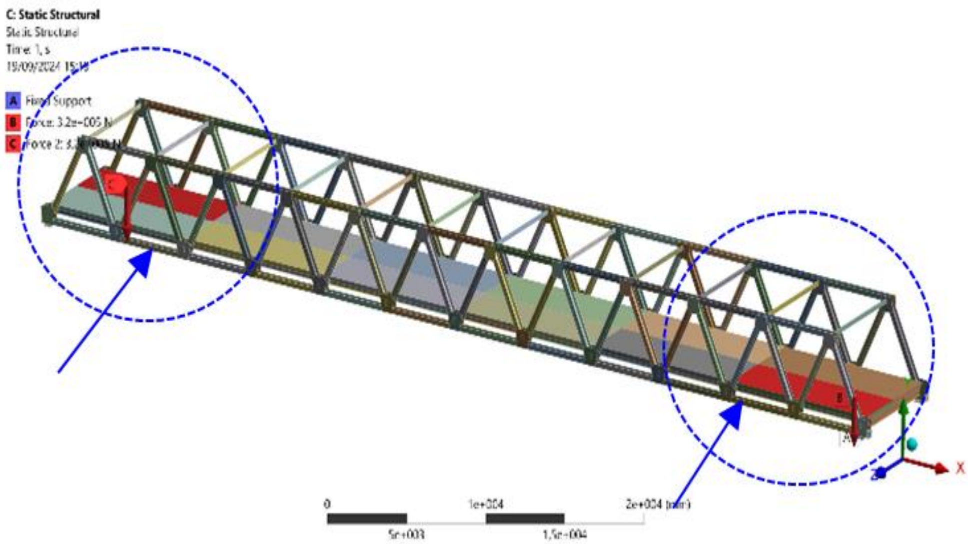
The steel bridge design, permissible deflection limits are often set to control excessive deformation that could compromise structural integrity and serviceability. According to standard guidelines, such as those outlined by the American Association of State Highway and Transportation The static load, corresponding to Truck HL 93 as specified in AASHTO LRFD, shown in Figure 6.

4. Results

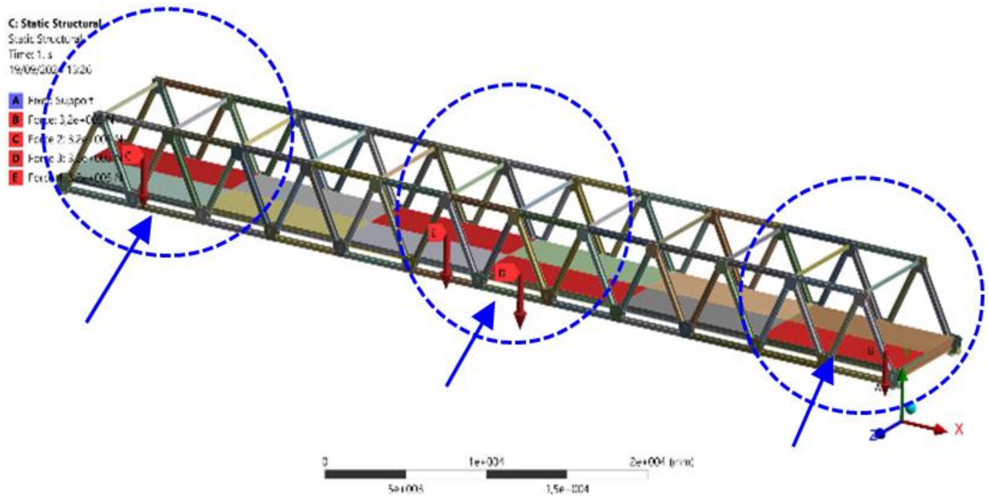
The permissible deflection for steel bridges subjected to live loads is typically limited to L/800. This limit is established to prevent uncomfortable vibrations and excessive bending, which could lead to long-term damage to the structure. The bridge model referenced in Figure 5, with a span length of 56 meters (L), a width of 7 meters, and a height of 5 meters, has an allowable deflection of approximately 70 mm when subjected to live loads (calculated as 56,000 mm/800). This deflection limit is widely recognized within the engineering field as a standard measure to ensure the structural integrity and durability of steel bridges under various static and dynamic load conditions. This standard plays a critical role in maintaining the safety and serviceability of such structures [65]. Shown in Figure 7.



(a). Static Load (1 unit of truck /320 kN)



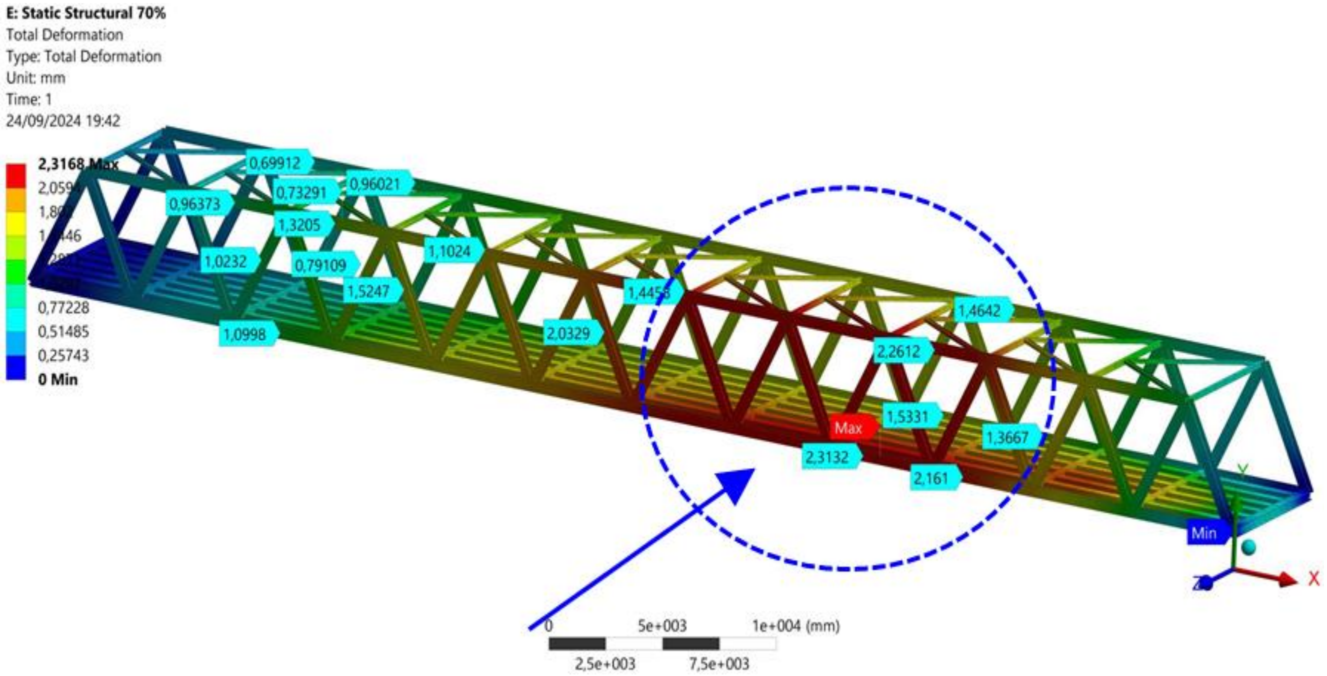
(b). Static Load (2 unit of truck /640 kN)



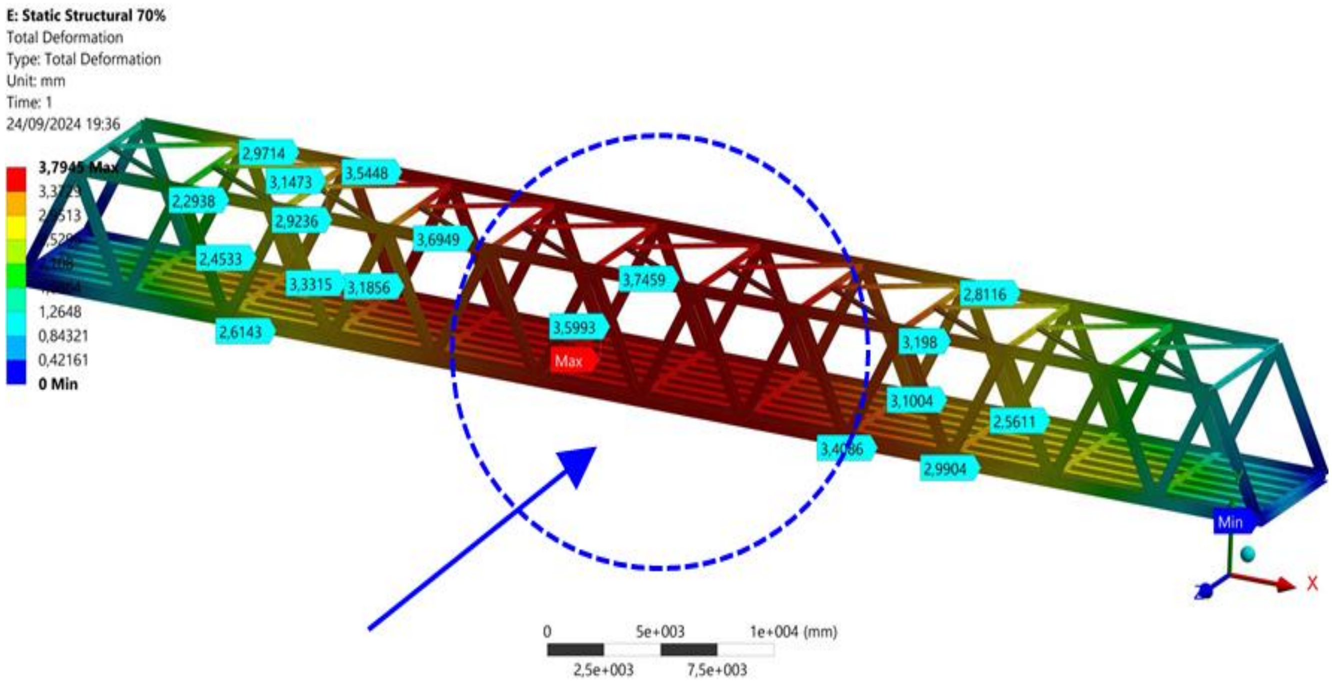
(c). Static Load (4 unit of truck /1280 kN)

Figure 7. *The static load distribution of a truck, with variations in the number of units, (1 unit, 2 units, and 4 units) and their positions (indicated by red markers).*

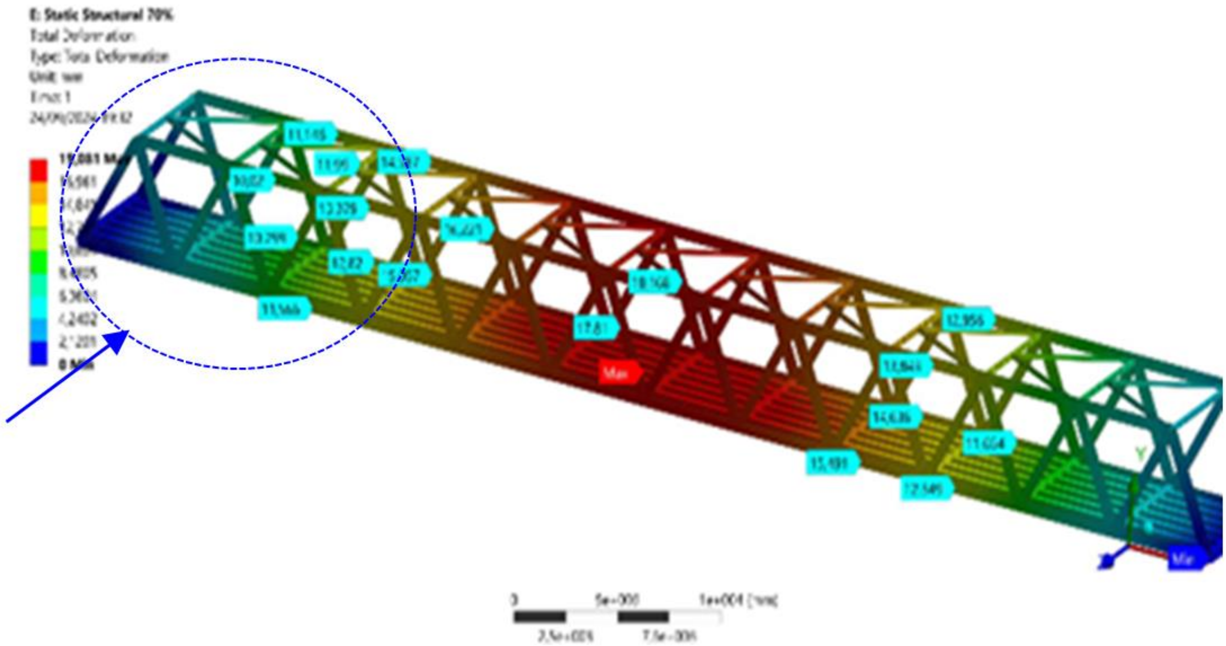
The analysis focuses on a 56-meter long, 7-meter wide, and 5-meter (high) of Warren Truss bridge model, using ANSYS simulation to assess deflection behavior under loading conditions and material degradation. The study incorporates findings from literature and compares the simulated deflection results with standard deflection limits for steel Warren Truss bridges to evaluate the bridge's condition, potential criticality, and maintenance at 70% degradation, the deflection is recorded at 2.3168 mm. shown in Figure 8.



(a). The deflection behavior of elements deteriorated by 70% within a bridge subjected to the load of a single HL-93 truck.



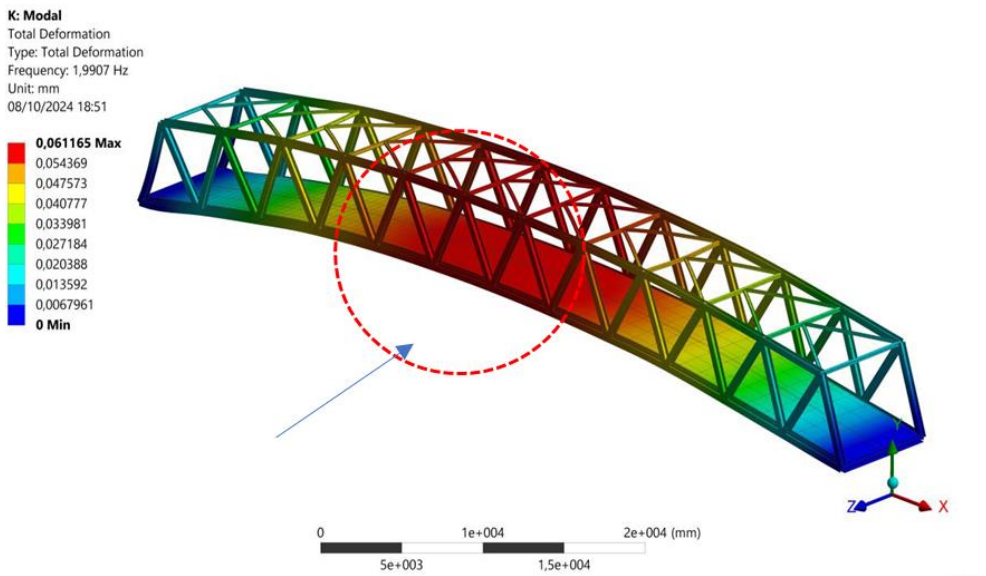
(b). The deflection state of elements experiencing 70% degradation in a bridge subjected to the loading of two HL-93 trucks.



(c). The deflection state of components subjected to 70% fatigue degradation in a bridge loaded with four HL-93 trucks

Figure 8. *The deflection under static load, condition of elements degraded by 70%.*

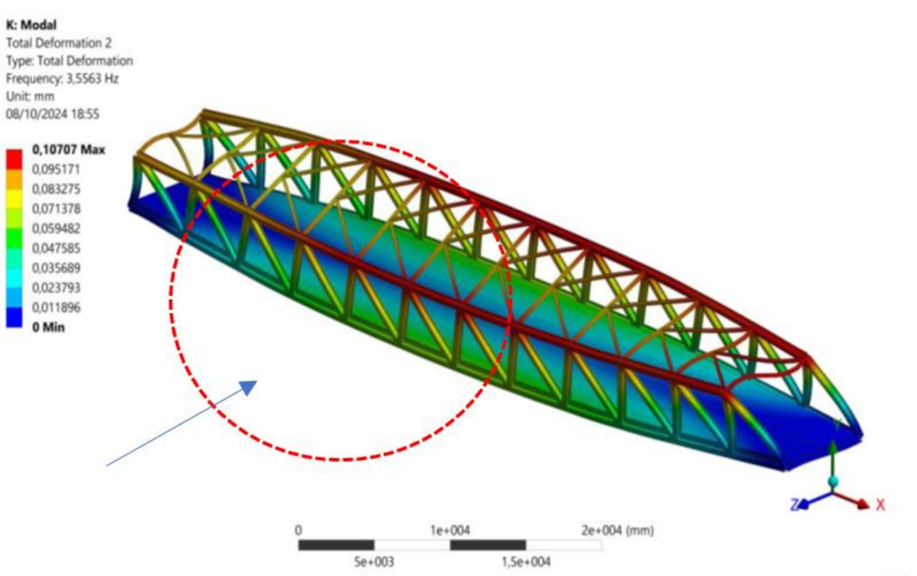
Under moderate loading conditions, the number of deflections indicates that even degraded components retain some degree of structural resilience. Figure 8 (b) shows that under the load of two HL-93 trucks (each with a nominal weight of 320 kN), the deflection increases to 3.7945 mm, indicating a higher stress concentration, particularly in areas with prior fatigue damage. Figure 8 (c) demonstrates that under the load of four HL-93 trucks (total load = 1280 kN), the maximum deflection reaches 19.081 mm. This value significantly exceeds the deflection observed under lower load scenarios, reinforcing the trend that fatigue degradation intensifies with increasing load, consistent with findings from other studies on midspan deflection under truck loading. The results of ANSYS simulations under dynamic loading, with primary elements degraded due to fatigue as shown in Figure 5(c), reveal a significant reduction in material stiffness, which directly affects the structure's natural frequency. Higher levels of degradation result in more severe material damage, rendering the structure incapable of vibrating at higher frequencies as observed in its original state. The alteration of natural frequency due to 70% degradation in structural elements is presented in Figure 9.



Tabular Data

	Mode	Frequency [Hz]
1	1,	1,9907
2	2,	3,5563
3	3,	4,9059
4	4,	5,4339
5	5,	7,9649
6	6,	8,1372
7	7,	9,3406
8	8,	9,8233
9	9,	10,982
10	10,	10,985
11	11,	11,008
12	12,	11,017
13	13,	11,026
14	14,	11,031
15	15,	11,037
16	16,	11,045
17	17,	11,048
18	18,	11,054
19	19,	11,058
20	20,	11,643
21	21,	12,836
22	22,	13,389
23	23,	13,391
24	24,	13,393
25	25,	13,393
26	26,	13,393
27	27,	13,397
28	28,	13,507
29	29,	13,601
30	30,	14,941

(a)



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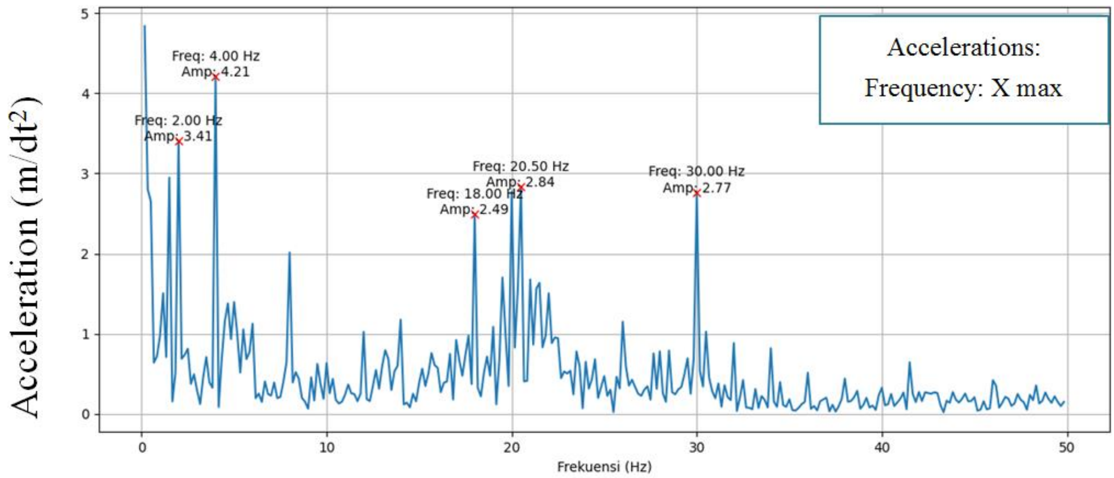
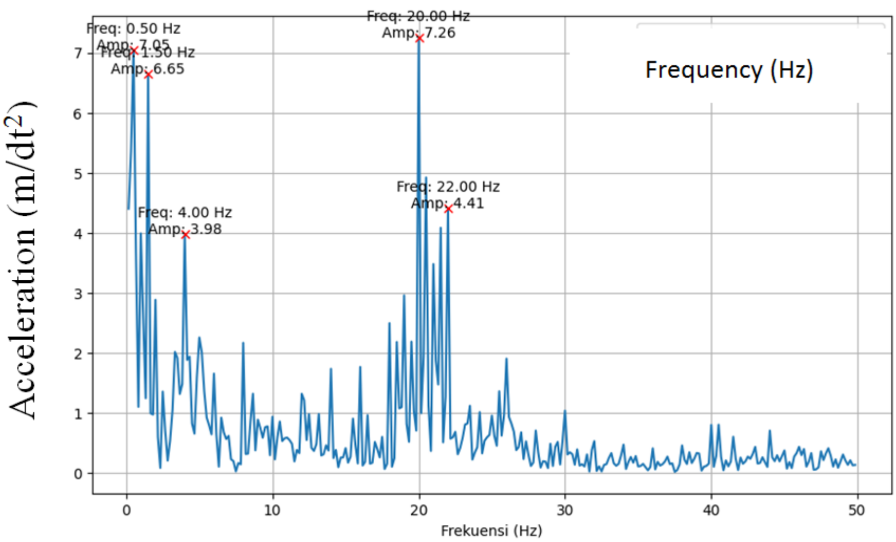
21	21,	12,836
22	22,	13,389
23	23,	13,391
24	24,	13,393
25	25,	13,393
26	26,	13,393
27	27,	13,397
28	28,	13,507
29	29,	13,601
30	30,	14,941

(b)

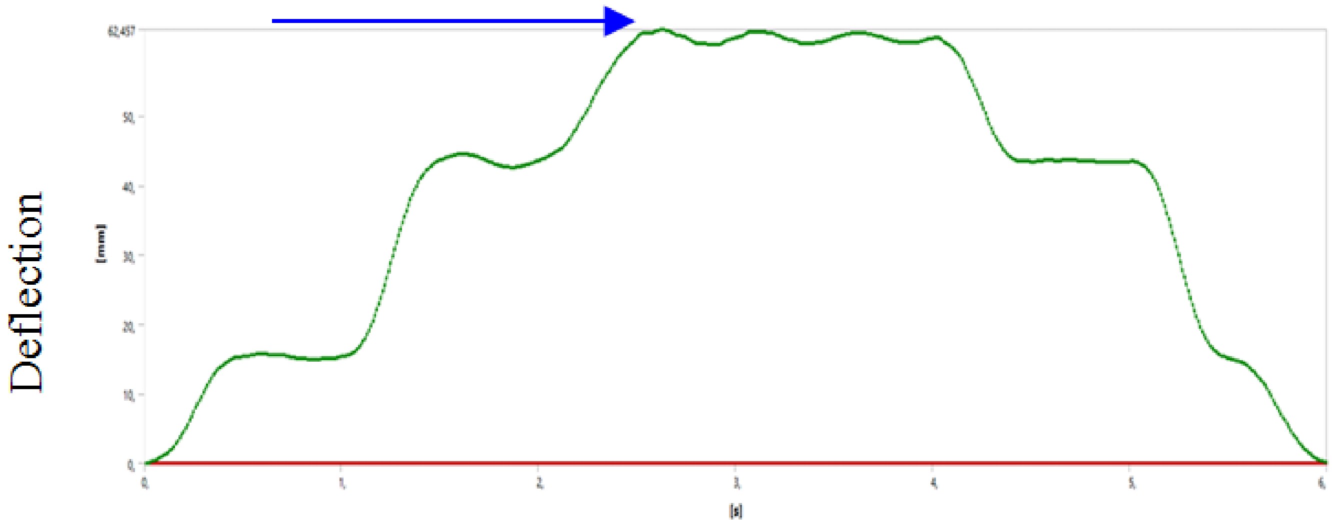
Figure 9. *ANSYS Simulation Results: Natural Frequency Variation Due to 70% Element Degradation.*



(a)



(b)



(c)

Figure 10. *Frequency and Amplitude for: (a) Load from a single truck (320 kN), (b) Load from two trucks (640 kN), and (c) Dynamic load under (2.560 kN), and critical deflection of 62.457 mm.*

Figure 9 demonstrates that a lower natural frequency indicates the structure is approaching its failure threshold. This implies that as fatigue degradation progresses, the structure becomes increasingly susceptible to resonant vibrations, which can accelerate structural failure. Dynamic load effects under critical conditions are illustrated in Figure 10.

Based on Figure 10, the structure was subjected to a single truck load (320 kN), revealing that frequencies of 2.00 Hz and 4.00 Hz generated relatively high acceleration amplitudes. Low frequencies contributed significantly to the structural response. In Figure 10.b, it is confirmed that the peak acceleration occurred at a frequency of 20.00 Hz with an amplitude of 7.26 m/s^2. This condition indicates that with the presence of two trucks, vibrations at higher frequencies have a more substantial impact, with dominant vibrations occurring at frequencies above 20 Hz. The additional load from the second truck increased the bridge's sensitivity to high-frequency vibrations. Low frequencies (1.50 Hz, 3.50 Hz, and 4.00 Hz) also exhibited notable amplitudes but were comparatively lower than those observed at higher frequencies. Maximum deformation, as shown in Figure 10.c, resulted from a dynamic load of 2,560 kN causing a deflection of 62.457 mm. This value approaches the critical threshold, with the peak deformation located at the mid of the bridge span.

5. Discussion

The deflection is consistently observed at the midpoint of the bridge, which is in line with numerous studies that indicate the midpoint of Warren Truss bridges as a critical region for deflection accumulation, [43-45, 49]. This is due to the symmetrical distribution of load and the inherent flexural behavior of trusses increases deflection under heavier loads. The critical load leading to potential failure, an extrapolation from the current deflection data suggests that an additional increase in load beyond the current 1280 kN (4 HL 93 trucks) would push the bridge toward its deflection limits. Based on the observed progression of deflection, a load of approximately 2.560 kN could result in deflections approaching the 70 mm limit, thus entering the critical phase for the bridge's structural integrity. The deflection data showing signs of fatigue degradation, remains structurally capable under significant loads. The bridge's midpoint, is crucial for early detection of potential failure points. Predictive maintenance strategies should focus on the elements most susceptible to fatigue degradation, ensuring the bridge operates safely within standard deflection limits.

5.1. Scenario of Critical Element Damage

Static loads, such as heavy trucks or equipment positioned on the bridge for extended periods, would induce continuous stress. Based on current data, the load of 4 HL 93 trucks (1280 kN) produced a maximum deflection of 19.081 mm. To reach 70 mm, an extrapolated static load of approximately (2560 kN) may be necessary. This load could represent a rare scenario, such as a construction overload or accidental overloading, but it would be worth simulating in ANSYS to observe the bridge's performance under extreme static conditions. Future research stemming from this review will aim to evaluate the excessive stress redistribution that can occur due to resonance, potentially amplifying the dynamic stress experienced by the main elements of a bridge model. Preliminary data from ANSYS simulations under dynamic loading show that elements with 70% material fatigue experience a maximum deflection of 62.457 mm, which approaches the design limit. Dynamic loads, such as wind-induced vibrations, seismic activity, or moving vehicle traffic, have a more severe impact due to their fluctuating nature.

Considering resonance and fatigue from ANSYS simulation data under static and dynamic loading, it is observed that a deflection of approximately 70 mm is generated at a load of around 2560 kN due to oscillations and stress concentrations, particularly when accounting for fatigue degradation at 70%. The application of 30%, 50%, and 70% levels represents an interpretation based on a factor-driven approach and levels to be tested in prototype and actual experiments on a bridge model. The resulting data, in the form of vibration patterns for each level, will serve as training data for SML.

Dynamic stress resulting from resonance may lead to uncontrolled stress redistribution, increasing the risk of stress concentration in specific areas such as welded joints or diagonal elements. This phenomenon facilitates the understanding of crack propagation due to material fatigue, especially when the material has undergone significant degradation. Excessive deflection and stiffness reduction can be identified by evaluating deflection magnitudes at each degradation level. These analyses are crucial for determining the extent of structural stiffness loss during resonance, which could reveal vibration patterns with high amplitudes that may cause permanent deformation in structural elements.

The various causes and types of damage, along with their impacts on structural stability, were assessed to obtain supporting data for the SML system, which was developed as a failure pattern diagnosis datasheet. The identified element damage was validated using scanning electron microscopy (SEM), X-ray fluorescence (XRF), and corrosion analysis. Material degradation and collapse were investigated through mechanical, microstructural, and compositional testing, followed by sampling. The elements' conditions were comprehensively evaluated to determine crystal orientation, corrosion mechanisms, and fatigue strength. The objective of these tests was to detect hidden or latent defects within the structure, often referred to as blind spots.

5.2. Resonance Measurement in Warren Truss Bridge Models

The Measuring resonance in Warren truss bridge models is crucial for assessing stress redistribution caused by dynamic loads. Resonance occurs when the excitation frequency of external forces, such as moving traffic or wind-induced vibrations, aligns with the structure's natural frequency, leading to amplified vibrations and stresses. Critical parameters include natural frequency, excitation frequency, vibration amplitude, damping ratio, and maximum deflection. Modal testing determines fn and vibration modes by exciting the structure using mechanical shakers or modal hammers, with responses recorded via accelerometers. Time and frequency domain's characteristics are extracted through data acquisition systems and Fourier analysis to provide a comprehensive evaluation of the structure's dynamic behavior. These analyses are especially important for structures with material fatigue. Preliminary studies indicate that elements with 70% material fatigue approach the design deflection limit of 62.457 mm under dynamic loading. The analysis includes evaluating the damping ratio and identifying resonance to assess structural resilience.

Dynamic response patterns in training datasets can be derived by simulating damage to specific elements, such as deactivating diagonal side members. Connection tests can also be performed by applying concentrated loads or removing connection elements to evaluate their contribution to overall structural performance. The diagnostic system analyzes the input data through sampling and compares it with the observed amplitude [19, 66]. Observations and simulations using FEM, alongside mathematical calculations, will generate a validation model for fatigue levels and their effects on bridge structures [67].

The correlation between vibrational data and structural damage was categorized into damage intensity levels to inform maintenance strategies. The SML models have been employed to analyze structural behavior based on vibration characteristics, with specific focus given to Warren Truss bridges. Damage levels ranging from moderate to critical were classified to guide repair and management plans. Extensively, data collected from various bridges were applied to train diagnostic systems, which forecast failure sequences and predict structural dysfunction based on vibrational response.

In recent research, vibration-based SHM techniques have been explored for their ability to ensure durability and safety in bridge structures. These methods use algorithms for anomaly detection to identify material degradation and connection failures, correlating vibration patterns with specific structural damage types. Moreover, the integration of SHM with Digital Twin models has been proposed to advance intelligent management practices through digital visualization of structural conditions. These approaches offer new avenues for improving safety and operational performance in steel bridges. The detailed breakdown of SML models tailored for vibrational analysis, explicitly addressing damage classifications (moderate, urgent, critical) and their implications for structural maintenance strategies. The vibrational patterns are tied directly to structural failure diagnostics, making it practical for real-world applications in repairs and performance improvement.

The deployment of periodic and real-time monitoring systems to assess vibration patterns in large structures and long spans presents challenges, particularly in the placement of vibration sensors. Manual sensor installation on high and complex structures is costly; therefore, an alternative approach involves using specially modified drones to install sensors on visually damaged elements. The sensor is equipped with a magnetic mechanism that enables simple attachment to the steel surface, transported by the drone's camera. Real-time monitoring technology incorporates camera systems, wireless remote sensors, interferometry systems based on wave amplitude and phase shifts, and 3D scanning to enable visual data acquisition and the measurement of dynamic response patterns. Drone systems equipped with optics and directional cameras are especially useful for identifying blind spots. Initial data collection includes measurements of other influencing factors, such as temperature and wind speed, within the steel bridge environment. Utilizing drone camera sensing to measure damaged areas, particularly those in difficult-to-reach or concealed locations, minimizes the need for personal protective equipment and reduces the risk of workplace accidents.

This study investigates the feasibility of detecting bridge deterioration through vibration patterns that indicate actual damage, as observed in published cases of bridge collapse and failure, combined with simulated damage treatment in FE modeling of steel bridge structural components. A smart diagnostic strategy, utilizing camera systems, remote wireless sensors, interferometry, 3D scanning, and drones, is expected to enhance the collection of visual data for more accurate, safe, and efficient assessments. Significant characteristics and damage clusters, quantified in percentages, are identified as key factors influencing the degradation of bridge structural performance. The challenges of developing the SML approach become increasingly apparent. The FE numerical method allows for the detection of potential damage in blind spots and fractures within structural elements.

5.3. Level Rating Clusters Damage Assessments Warren Truss Steel Bridges

The system focuses on providing sufficient data for analysis according to feasibility ratings, which are divided into three clusters: (1) moderate (30%), (2) urgent (50%), and (3) severe/critical (≥70%). Each rating cluster requires training data that reflects the dynamic response patterns of the bridge for types of damage such as fatigue, corrosion, and plastic buckling, as well as the location of the damage. Additionally, structural loads including weight, vehicle or train loads, and other complex factors are essential for establishing a precise diagnostic system. The analytical capacity of the SML system is restricted to structures with consistent dimensions, such as the span, width, and height of Warren truss bridges. Other critical aspects include cross-sectional type and maximum load capacity with each aspect requiring validation through reliable data.

Based on the constraints outlined above, a smart diagnostic system for efficient SML can be developed with the following capabilities: utilizing digital sensor devices and a drone system to detect structural damage and evaluate feasibility criteria, as illustrated in Figure 11.

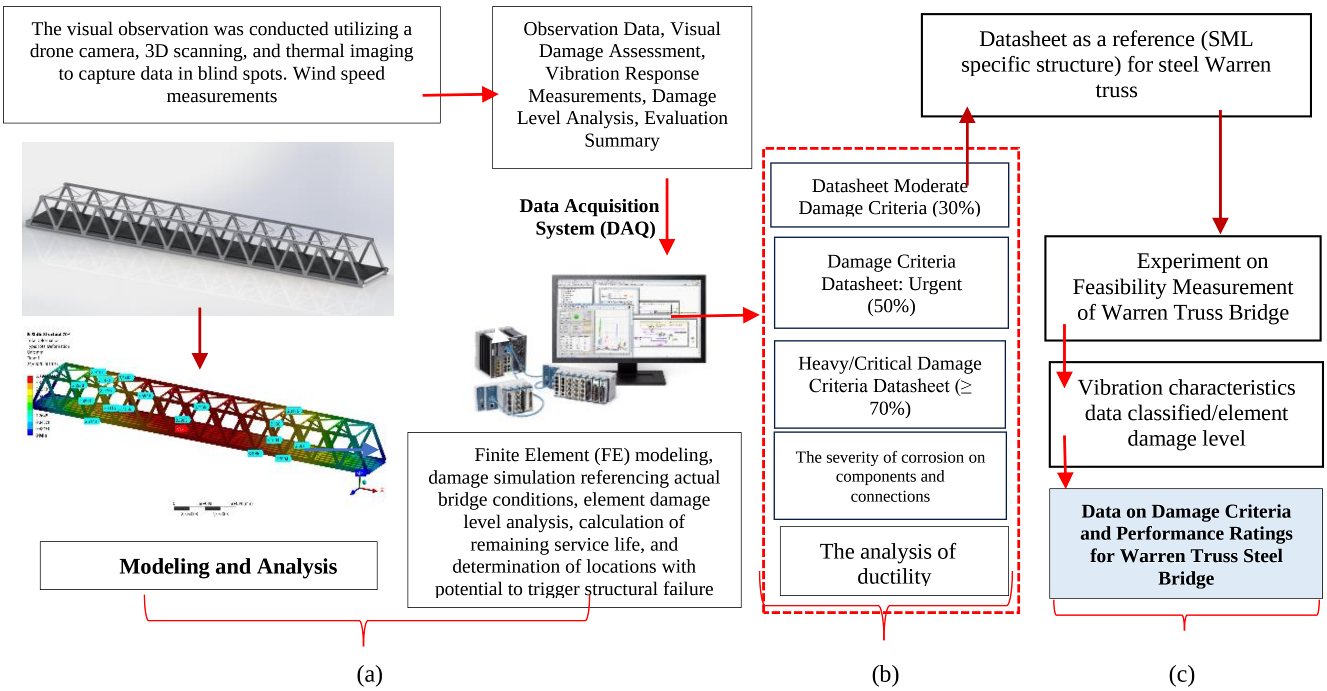


Figure 11. *The smart diagnostic system is illustrated in (a), where visual inspection and modeling are performed. In (b), training data are compiled, validated, (c), supervised machine learning (SML) [The Author].*

The subsequent phase of this research is focused on assessing the effectiveness of SML across complex environments and varied conditions, alongside determining the vibration response data required for different types of steel bridge constructions. Testing will be conducted on a range of bridge structures to evaluate SML's efficiency, accuracy, and to identify any potential limitations. Prioritizing the advancement of SML technology is a critical step toward achieving technological maturity, facilitating the development of a highly efficient and precise diagnostic system. The successful advancement of this technology will play a pivotal role in automating analysis processes, offering rapid, cost-efficient, and highly accurate monitoring solutions.

5.4. Assessments Actual Warren Truss Steel Bridges

Testing on actual bridges involves the installation of accelerometer sensors at critical points, such as main joints, diagonal elements, and mid-span locations, to capture vibration responses. A mechanical exciter (shaker) is employed to introduce structural excitation, and vibration data is recorded using a data acquisition system. Fourier analysis is then applied to identify vibration modes and natural frequencies. Dynamic load simulations are conducted to observe the structural response to moving loads or oscillatory forces. These simulations involve vehicles with varying speeds and weights to record acceleration, deflection, and stress distribution. Wind-induced vibrations are simulated using a wind tunnel, where wind speed is varied to study resonance effects. Additionally, seismic sensors measure responses to seismic loads, while load cycle data from the sensors are used to evaluate cracks or material degradation through Non-Destructive Testing (NDT) methods such as ultrasonic, radiographic, and thermal imaging. Material damage levels are categorized for labeling (Moderate, Urgent, or Critical).

The SML prototype model is validated to ensure its predictions can be generalized to actual bridges by comparing the predicted damage risks and maximum deflection with measurements from different bridges varying in geometry, material conditions, and load characteristics. Training data are utilized to assess bridge conditions and provide recommendations for maintenance and monitoring. This approach ensures a robust model capable of delivering actionable insights for effective bridge management.

5.5. Implications of the Study

This study provides recommendations and diagnostic approaches for identifying failure patterns in steel bridge structures, particularly for Warren truss systems. It also offers a reference framework for evaluating the safety and operational feasibility of such bridges. The data and validation systems generated aim to simplify maintenance assessments and strength predictions, ensuring the construction performs optimally, especially in analyzing structural behavior and material degradation.

5.6. State of the Art

The study will investigate fatigue degradation levels in the primary elements of a laboratory-scale Warren truss bridge prototype with a scale ratio of 1:20, referencing the actual Sendang Mulyo bridge in Semarang. Both static and dynamic load tests will be conducted on degraded elements, varying in both the number of elements affected and the degree of degradation, to determine the influence of each factor at critical thresholds. Degradation levels of 30%, 50%, and 70% are interpreted based on a factor-level approach to be tested on both the prototype and the actual bridge model. The resulting data will consist of vibration patterns corresponding to each fatigue level, combined with other factors such as corrosion levels and buckling. Numerical data in the form of vibration patterns will be utilized as training data for SML. In the initial stages, each factor will be tested and partially simulated to validate its effects.

The development of supervised machine learning models will analyze damage in Warren truss bridges, focusing on Fatigue levels and specific locations on elements subjected to tension or stress, measuring percentage degradation in structural equilibrium, crack-level modeling to assess structural impacts, corrosion levels, particularly in elements and connections critical to the overall structure and Structural analysis under critical loading conditions.

Validated experimental data will populate a database for further diffusion analysis, which will then be used to develop computational and statistical damage models. These models aim to analyze structural failure patterns in Warren truss steel bridges. The diagnostic system, leveraging machine learning techniques, evaluates structural stability and offers insights into the feasibility and safety of bridge construction. However, several critical factors continue to impede the development of a robust bridge failure pattern diagnosis model based on vibration responses, as outlined in previous studies. The SML diagnostic system still relies on visual data representing damage and the positional information of structural elements, due to the inherent limitations of visual recovery techniques in damaged areas, physical intervention remains essential. Furthermore, implementing SML requires testing on a structurally identical bridge model, to accurately assess the extent of damage, analytical modeling tools remain indispensable. Comparative testing is also necessary to evaluate the vibration response of the bridge model under varying visual damage scenarios.

The data collected is being used to develop an algorithm that employs computational and statistical damage modeling to analyze failure patterns in Warren truss steel bridge designs. The diagnostic system currently under development utilizes machine learning to investigate structural stability, providing critical information on the feasibility and safety of bridge construction. Structural degeneration has been categorized into three distinct levels: moderate (30%), urgent (50%), and severe/critical (≥70%). These classifications inform the planning of maintenance and technical operations related to Warren Truss Bridge upkeep, addressing the overall structural performance.

5.7. Scope and Limitations

The research focuses on developing a vibration-based validation system, emphasizing the specific modeling of Warren truss steel bridges. This includes incorporating measurable material degradation and dysfunction in structural elements while maintaining equilibrium in normal forces, dynamic load applications, and real-condition anomalies. Simulated damage scenarios are tailored to reflect common steel bridge failures, categorized as minor, moderate, or severe (critical), based on existing research. Certain actual parameters are excluded to streamline the vibration data scaling model.

6. Conclusion

The phenomena and simulations reveal a maximum deflection under a static load of 2,560 kN, with fatigue levels (30%, 50%, and 70%) significantly influencing structural deformation. The effects of low and high frequencies were also identified, although lower frequencies resulted in reduced amplitude fluctuations. Dynamic loading produced a complex structural response, creating significant stress variations and contributing to material fatigue. Compared to static loading, dynamic loading demonstrated a substantial increase in stress, with dynamic acceleration fluctuations due to structural resonance observed at critical points, particularly when a truck was positioned at the center of the bridge. At a fatigue level of 70%, the increased deflection of 62.457 mm highlights the cumulative effects of dynamic load cycles. High-frequency dynamic loads generated greater amplitude impacts, with a maximum acceleration of 1.333 m/s^2 recorded under 70% fatigue conditions, indicating a heightened risk of resonance. These findings underscore the importance of considering dynamic loading effects and fatigue levels in structural analysis to ensure safety and longevity.

These findings provide a foundation for developing training datasets in Supervised Machine Learning (SML) models. Experimental data from static and dynamic testing, extending to tests on actual bridge models, include key parameters such as natural frequency, maximum acceleration, deflection, and material fatigue levels. Data labeling is based on structural damage levels and performance, categorized into clusters of Moderate, Urgent, and Critical. The resulting dataset is used to train supervised learning algorithms for predicting damage risk and maximum deflection under dynamic loads and varying fatigue levels. Resonance analysis is integrated as a critical risk indicator. Model validation is conducted to ensure generalization across bridges with diverse geometries, material conditions, and load scenarios. This approach enhances the robustness and reliability of predictions in assessing structural performance and safety.

Abbreviations

SML	Supervised Machine Learning
IoT	Internet of Things
GPS	Global Positioning System
GNSS	Global Navigations Satellite System
FE	Finite Element
FEM	Finite Element Method
NDT	Non-Destructive Testing
UT	Ultrasonic Testing
CWT	Continuous Wavelet
HHT	Huang-Hilbert
AI	Artificial Intelligence
SEM	Scanning Electron Microscopy
XRF	X-Ray Fluorescence
ΔK	Fatigue Level of the Material
W	The Element Specimen's Dimensions/Width
a	Material Thickness
B	Specimen Length
α	The Typical Crack Length
Vg	The Width of the Crack Opening
P	Applied Load
μ	Ductility
δu	Crucial Deformation Near Collapse
δy	Deformation at the Initial Melt

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Author Contributions

Susilo Adi Widyanto: Formal Analysis, Methodology, Visualization, Writing – original draft

Achmad Widodo: Formal Analysis, Funding acquisition, Methodology, Validation, Writing – original draft

Sukamta Sukamta: Data curation, Formal Analysis, Investigation, Supervision, Validation, Visualization, Writing – original draft

Bambang Sugiantoro: Conceptualization, Project administration, Resources, Software, Writing – original draft

Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Biography

Bambang Sugiantoro is a lecturer specializing in Mechanical Engineering and currently a doctoral candidate in the Mechanical Engineering Department, Faculty of Engineering, Diponegoro University. He holds a master's degree in Engineering and focuses his dissertation research on the design of structural damage diagnostics for steel constructions, particularly steel bridges, utilizing vibration-based methodologies. His research aims to develop diagnostic systems that generate data for supervised machine learning, focusing on material characteristics under varying levels of damage. He is actively involved in various research initiatives and technological implementations, including mitigation strategies and the environmental impact of industrial operations. Bambang has secured several patents and industrial designs, with some of his machinery successfully commercialized. He has contributed to the deployment of industrial-scale technologies in several locations, including Banyumas, Purbalingga, and Banjarnegara. His work also includes developing IoT-based control systems for production machinery and intelligent applications that enable real-time performance monitoring and process analysis.

Susilo Adi Widyanto is a senior lecturer at Mechanical Engineering Department the Faculty of Engineering, Diponegoro University, as a postgraduate (doctoral-level). He had completed both his Master's and Ph.D. degrees at Universitas Gadjah Mada, Yogyakarta. With a strong academic foundation, he actively teaches various subjects, including manufacturing, robotics, and structural design. Renowned for his significant contributions, he has designed innovative machinery ranging from prototype to industrial-scale applications. His achievements include developing continuous tube annealing machines and conducting environmental impact analyses. Additionally, he has worked extensively on structural mitigation projects, particularly in steel construction. His expertise lies in vibration system analysis and material treatment to evaluate fatigue limits and fatigue life. Over the years, he has actively participated in collaborative research projects, contributing to advancements in structural diagnostics and material properties. One notable project involved determining the modulus of elasticity, Poisson's ratio, and strain hardening coefficients of metals through discontinuous uniaxial tensile testing, which has direct applications in vibration-based diagnostic systems for steel structures.

Achmad Widodo is a senior lecturer at the Department of Mechanical Engineering, Faculty of Engineering, Diponegoro University, where he teaches postgraduate (doctoral-level) courses. He earned his Master of Engineering (M.Eng.) degree from the Department of Mechanical Engineering, Bandung Institute of Technology (ITB) in 2000. He pursued his doctoral studies and received a Doctor of Engineering (Dr.Eng.) degree from Pukyong National University, South Korea, in 2007. Currently, he is actively teaching courses in mechanical engineering, focusing on areas such as Engineering Mathematics, Engineering Analysis, Mechanical Vibrations, Kinematics and Dynamics, and Principles of Optimization. His research is centered on developing machine learning systems for machine fault diagnosis and prognosis, with a particular interest in intelligent fault diagnostics and prognostics. His expertise includes applications of support vector machines (SVMs) for machine condition monitoring and fault diagnosis, as well as integrating thermal imaging and vibration signal analysis for intelligent diagnostics. Additionally, he investigates machine health prognostics using survival probability models and SVM techniques. His work reflects a strong commitment to advancing predictive maintenance technologies and enhancing machine reliability through intelligent diagnostics and prognostics systems.

Sukamta Sukamta is a senior lecturer in Civil Engineering at the Faculty of Engineering, Diponegoro University, Semarang, Indonesia. He earned his Ph.D. in Civil Engineering from Tokushima University, Japan, in 2008 and Master of Engineering in Civil Engineering from Gadjah Mada University, Indonesia, in 2001. He is widely recognized for his exceptional contributions to civil engineering research and practice. He has made significant advancements in structural and aerodynamics engineering. Notably, he contributed to the aerodynamic analysis of the Musi III Cable-Stayed Bridge (2013) in collaboration with PT. Wiratman Jakarta and the Aero-Gas Dynamics and Vibration Laboratory under the Ministry of Public Works. His innovative work includes a patented method for anchoring reinforced concrete beams using Fiber-Reinforced Polymer (FRP) sheets, titled “Method of Anchoring (Anchor) with Recesses in the External Strengthening of Reinforced Concrete Beams Using Fiber-Reinforced Polymer Sheets.”. His also committed to community outreach and engineering applications. He has been involved in capacity-building initiatives, such as assisting with the design and construction of retaining walls in Jembrak Village, Semarang in 2017. In recent years, he has actively participated in international research collaborations, contributing to advancing civil engineering knowledge and practices globally.

Research Field

Sukamta Sukamta: Improvement of structural performance of RC Beams with external reinforcement method: An experimental investigation, Method Assessment of Bridge Conditions Using Vibration Mode Patterns, Development Experimental Investigations of Truss Bridge Model for Vibration-Based Structural Health Monitoring, Optimization Analysis of Size and Distance of Hexagonal Hole in Castellated Steel Beams, Development Experimental Investigations of Truss Bridge Model for Vibration-Based Structural Health Monitoring.

Achmad Widodo: Support vector machine in machine condition monitoring and fault diagnosis, Combination of independent component analysis and support vector machines for intelligent faults diagnosis, Wavelet support vector machine for induction machine fault diagnosis based on transient current signal, Machine health prognostics using survival probability and support vector machine, Intelligent fault diagnosis system of induction motor based on transient current signal.

Susilo Adi Widyanto: Method Assessment of Bridge Conditions Using Vibration Mode Patterns, Analyzing the Homogeneity In The Reduction Of Water Content During The Drying Process Of Grains Using A Flatbed Dryer Machine Equipped With A Stirring Mechanization System, Stress analysis of waveguide with two layers of material polyester - Chitosan using finite element method, Development Experimental Investigations of Truss Bridge Model for Vibration-Based Structural Health Monitoring,

Bambang Sugiantoro: Experimental Investigation of Hot Alkaline Treatment on Strength Characteristics of Cantala Fiber Reinforced Composites and Microcrystalline Cellulose, Investigation Interfacial Shear Strength And Mechanical Propertis Of Alkali Treated Honey Pineapple Fiber/Microcrystalline Cellulose Composite, The Effect of Alkali and Fumigation Treatments on King Pineapple Fiber Properties and Interfacial Bonding of King Pineapple Fiber/Unsaturated Polyester on Microcrystalline. Analysis of the Morphology and Mechanical Properties of Polymer Composite Materials (PCM) from Silicon Dioxide (SiO2) and Multiwalled Carbon Nanotubes.