IARE
INSTITUTE OF
AERONAUTICAL ENGINEERING

HIGH IMPACT PRACTICES (HIPS)

AI-POWERED DIGITAL TWIN FOR STRUCTURAL SYSTEM

INFORMATION PACKET

2025 - 2026

INSTITUTE OF AERONAUTICAL ENGINEERING

25 YEARS 2000 2025

I appreciate IARE students who are showing interest in **AI-Powered Digital Twin for Structural System** (AI-DTSS) Project Program at the Institute of Aeronautical Engineering!

A cornerstone project (CoP) is typically introduced during the early or middle stages of an academic program at the Institute of Aeronautical Engineering. It focuses on helping students build foundational skills and understand how to apply basic concepts to real-world scenarios. These projects are usually smaller in scope, moderately complex, and designed to strengthen practical understanding of core subjects.

The AI-DTSS Project team members work as part of a research group of students, research scholars, and faculty members to tackle novel research and design problems around a theme. The AI-DTSS project enables powerful capabilities that can significantly enhance the quality, efficiency, and adaptability of Structural project development. Intelligent Modelling and Simulation of Structural Systems Using AI significantly enhances project development by improving efficiency, accuracy, and adaptability across all phases**. A Digital Twin is a virtual replica of a physical system that simulates its real-time behaviour using data, physics, and machine learning. When applied to structural systems (like bridges, buildings, or towers), it enables predictive maintenance, performance optimization, and intelligent decision-making. Integrating Artificial Intelligence (AI) enhances this model with real-time analytics, anomaly detection, and adaptive learning.**

The goals of AI-DTSS projects are:

1. **Undergraduate Research in AI & CE:** Undergraduate research in AI & CE refers to student-led or supervised academic projects that explore how Artificial Intelligence can be integrated into the field of Civil Engineering to solve real-world problems, improve efficiency, and drive innovation in intelligent structural systems**.**
2. **Automation of Complex Simulations:** AI automates labour-intensive tasks such as finite element modelling, load application, and stress-strain analysis, reducing manual effort and saving engineering time.
3. **Capstone Design Projects:** Capstone Design Projects are culminating academic experiences undertaken by undergraduate students typically in their final year where they apply the knowledge, skills, and tools they've learned throughout their degree to design, build, and demonstrate a real-world engineering solution.
4. **Internships & Industry Engagement:** Internships and industry engagement refer to structured opportunities for students to gain practical experience in real-world work environments, typically within companies, research labs, or industrial organizations.
5. **Acceleration of Structural Analysis:** AI enables faster simulation runs by approximating complex calculations, making iterative design and real-time feedback feasible.
6. **Early Detection of Design Flaws:** By analysing structural models and historical failure data, AI helps identify potential failure points, stress concentrations, and unsafe design elements at early stages.
7. **Optimization of Structural Design:** AI algorithms optimize geometry, material usage, and load paths to achieve cost-effective, safe, and sustainable structures.
8. **Integration with BIM/CAD Platforms:** AI supports seamless integration with Building Information Modelling (BIM) and CAD tools by automating clash detection, design validation, and model updates.
9. **Enhanced Structural Health Monitoring:** AI processes sensor and IoT data from structures to predict damage, assess health conditions, and schedule maintenance proactively.
10. **Improved Decision-Making:** AI assists in complex decisions like material selection, cross-section sizing, and retrofit strategies by analysing multiple design scenarios and risk factors.

The research theme of this AI based projects also focuses on the challenges presented by the Sustainable Development Goals (SDGs).

Sustainability Development Goals (SDGs) for Department of CE	
SDG #8	Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all
SDG #9	Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation
SDG #11	Make cities and human settlements inclusive, safe, resilient and sustainable
SDG #12	Ensure sustainable consumption and production patterns
SDG #13	Take urgent action to combat climate change and its impacts

The following research domains are recommended for HIPs-AI- DTSS Projects, and selected students should find the research gap and frame the problem statements from any one of the themes below.

1. Development of AI Models for Lifecycle Structural Performance Prediction *(SDG #9, SDG #11)*
2. Hybrid AI-FEM Framework for Progressive Collapse Analysis *(SDG #12, SDG #13)*
3. Reinforcement Learning for Adaptive Structural Control Systems *(SDG #9, SDG #11)*
4. Integration of AI with BIM for Real-Time Structural Design Validation *(SDG #8, SDG #9, SDG #11)*
5. Development of AI Surrogate Models for Fast Structural Simulation *(SDG #9)*
6. AI-Powered Finite Element Model Generation for Complex Structural Systems *(SDG #8, SDG #9)*
7. Predictive Modelling of Structural Failures Using Machine Learning Techniques *(SDG #9, SDG #11)*
8. AI-Based Real-Time Structural Response Simulation under Dynamic Loading *(SDG #9, SDG #13)*
9. Deep Learning for Structural Damage Detection from Vibration and Strain Data *(SDG #9)*
10. AI-Based Multi-Objective Optimization for Sustainable Structural Design Loading *(SDG #9, SDG #12)*

In order to participate in **AI-DTSS** Projects, you must formally apply and be accepted by the project coordinator. To proceed, please mail to the project coordinator, **Dr. Venu Malagavelli**, Professor and Deputy Head, Department of CE, Email Id: venu@iare.ac.in. This will bring up all available open positions tagged as **AI-DTSS** projects. When submitting a project document and an updated résumé, include a statement regarding why you are interested in working with the team to which you are applying. Please note that participation by the **AI-DTSS** project team requires registration for the accompanying research statement from any of the specified domains. More information will be provided to all selected **AI-DTSS** project applicants who have been offered a position. If you have any questions about a particular team, please contact the team's faculty mentor(s). We encourage you to contemplate this fascinating new opportunity. We look forward to receiving your application submission.

Development of AI Models for Lifecycle Structural Performance Prediction

Dr. Venu Malagavelli, Professor, CE – Faculty Mentor

GOALS

The primary objective of this project is to develop AI models that can predict the long-term structural performance and degradation patterns of infrastructure throughout its entire lifecycle. This includes forecasting structural deterioration, identifying maintenance needs, and estimating remaining service life by analysing multi-source historical, environmental, and usage data.

- **Lifecycle Performance Prediction:** Predict long-term behaviour of structures (e.g., deflection, cracking, corrosion, fatigue) under varying operational and environmental conditions.
- **Data-Driven Deterioration Modelling:** Replace empirical deterioration models with AI-based predictive analytics trained on real-world condition monitoring data.
- **Remaining Useful Life (RUL) Estimation:** Use AI models to estimate the remaining service life of components or entire structures with confidence levels.
- **Maintenance Planning & Decision Support:** Enable predictive maintenance scheduling and prioritization of repair strategies based on AI forecasts.
- **Integration with Asset Management Systems:** Enhance BIM and digital twin platforms with intelligent lifecycle prediction tools for infrastructure asset management.
- **Support for Resilient and Sustainable Infrastructure:** Promote durable, cost-effective designs and timely interventions that reduce lifecycle costs and environmental impact.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

The development of this system involves several key methods:

- **Data Collection:** Historical performance records, inspection logs, environmental data (temperature, humidity), load histories, and SHM sensor outputs.
- **Data Preprocessing:** Data cleaning, outlier removal, interpolation, feature extraction (e.g., damage indices, strain profiles, corrosion rates).
- **Model Training & Evaluation:** Train AI/ML models using supervised learning on labelled structural performance data; use cross-validation and testing on unseen structures.
- **Performance Forecasting:** Use time-series and regression models to predict future degradation, crack propagation, stiffness loss, etc.
- **Lifecycle Modelling:** Simulate deterioration processes over time, incorporating uncertainty using probabilistic AI techniques.

Technologies Used

- **Python** (with Scikit-learn, TensorFlow, Keras, Pandas)
- **MATLAB** (for numerical modelling and time-series analysis)
- **ETABS / SAP2000 / OpenSees** for structural analysis simulations
- **Power BI / Tableau** for lifecycle visualization
- **IoT/Cloud Platforms** (e.g., AWS IoT, ThingSpeak) for real-time data

MAJORS & AREAS OF INTEREST

The Development of AI Models for Lifecycle Structural Performance Prediction is an interdisciplinary field that integrates concepts and skills from several academic majors and technical domains This project lies at the intersection of the following disciplines:

Structural and Civil Engineering

- Durability of materials (concrete, steel, composites)
- Lifecycle costing and service life estimation
- SHM and infrastructure deterioration mechanisms

Artificial Intelligence and Machine Learning

- Time-series forecasting
- Predictive modelling and supervised learning
- Uncertainty quantification and reliability analysis
-

Data Science and Analytics

- Data cleaning, mining, visualization
- Feature selection and model interpretability
- Degradation pattern recognition and clustering
-

Instrumentation and Communication Engineering

- Sensor technologies for structural condition monitoring
- Data acquisition systems and wireless sensor networks
- Integration with IoT and edge computing platforms

Infrastructure Asset Management

- Risk-based maintenance planning
- BIM and digital twin integration
- Policy and cost-driven decision frameworks

MENTOR CONTACT INFORMATION

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Hybrid AI-FEM Framework for Progressive Collapse Analysis

Dr. Venu Malagavelli, Professor, CE – Faculty Mentor

GOAL

The main objective of this research is to develop a Hybrid Artificial Intelligence–Finite Element Method (AI-FEM) framework that can effectively simulate and analyze progressive collapse in complex structures. Progressive collapse refers to a chain-reaction failure mechanism where local damage leads to the collapse of a larger portion—or the entire structure—disproportionately to the initiating cause. This project combines the accuracy of FEM with the speed and adaptability of AI to enable faster, data-driven assessment and prediction of collapse mechanisms under extreme loading.

- **Hybrid Modelling:** Integrate AI models with traditional FEM simulations to create a hybrid tool for faster and more scalable collapse analysis.
- **Collapse Pattern Prediction:** Use AI to identify and predict potential collapse mechanisms, such as pancake collapse, zipper failure, or instability-induced failures.
- **Dynamic Load Response Simulation:** Simulate progressive collapse scenarios under blast loads, impact, seismic excitations, and accidental column removals.
- **Real-Time Risk Assessment:** Enable near real-time simulation and decision-making in emergency or forensic scenarios using trained AI models.
- **Reduction of Computational Time:** Use AI surrogates to approximate expensive FEM subroutines (e.g., nonlinear material behaviour, damage propagation).
- **Validation with Case Studies:** Validate the framework using known real-world collapse events or experimental data (e.g., Ronan Point, World Trade Center, etc.)

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Finite Element Modelling (FEM):** Use software like ANSYS, ABAQUS, or OpenSees to model structural systems and simulate progressive collapse under various load scenarios.
- **AI Model Development:** Train machine learning models to learn collapse patterns, damage evolution, and stress redistribution from FEM simulation results.
- **Hybrid Integration:** Couple AI predictions with FEM subroutines to accelerate portions of the collapse analysis without sacrificing accuracy.
- **Data Generation:** Generate synthetic data from FEM simulations (e.g., load paths, element failure sequences, displacement histories) to train the AI models.
- **Validation and Testing:** Compare AI-FEM outputs against full FEM models, experimental data, and benchmark cases for accuracy and efficiency.

Technologies Used

- **FEM:** ABAQUS, OpenSees, ETABS, SAP2000
- **AI:** Python (TensorFlow, PyTorch, Scikit-learn)
- **Visualization:** Paraview, Power BI, MATLAB
- HPC or cloud computing platforms for large-scale simulations

MAJORS & AREAS OF INTEREST

This research draws from a wide range of technical and academic domains:

Structural and Civil Engineering

- Structural dynamics and nonlinear behaviour
- Collapse mechanics and failure modes
- Load path analysis and redistribution under sudden damage

Artificial Intelligence and Deep Learning

- Surrogate modelling and physics-informed AI
- Sequence modelling for collapse progression
- Spatial-temporal data learning from simulation outputs

Computational Mechanics & Simulation

- Hybrid modelling strategies
- FEM calibration, mesh refinement, and convergence
- Parametric modelling and uncertainty quantification

Instrumentation & Forensic Engineering

- Use of sensor data from test structures or real collapses
- Post-event structural analysis using AI-trained models

MENTOR CONTACT INFORMATION

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Reinforcement Learning for Adaptive Structural Control Systems

Dr. R Ramya Swetha, Associate Professor & Head, CE – Faculty Mentor

GOAL

The primary goal of this project is to develop an adaptive structural control system using Reinforcement Learning (RL) to mitigate structural vibrations and enhance stability under dynamic loads such as earthquakes, wind, traffic, or blasts. Unlike conventional control strategies that rely on fixed parameters, RL enables intelligent, real-time adaptation by learning optimal control policies through interaction with the environment, improving structural resilience and performance over time.

- **Adaptive Vibration Control:** Develop RL-based controllers to dynamically reduce structural vibrations using actuators such as Tuned Mass Dampers (TMDs), Magneto-Rheological Dampers (MRDs), or Active Mass Drivers (AMDs).
- **Learning-Based Control Policy Optimization:** Use RL algorithms to learn optimal control strategies from simulated or experimental structural response data.
- **Real-Time Decision Making:** Enable real-time control actions during dynamic events (e.g., earthquakes, strong winds) without prior tuning or rule-based logic.
- **Generalization Across Structural Systems:** Train RL models that adapt to a variety of structures (buildings, bridges, towers) and different types of dynamic excitations.
- **Integration with Smart Sensors & IoT Systems:** Use sensor feedback to allow the RL agent to update control actions continuously for active performance tuning.
- **Comparison with Classical Control Methods:** Evaluate the efficiency, stability, and robustness of RL-based control vs. traditional PID, LQR, or fuzzy logic controllers.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Simulation of Structural Dynamics:** Use finite element modelling (FEM) or simplified multi-degree-of-freedom (MDOF) models to simulate structural behaviour under dynamic loads.
- **Design of RL Framework:** Define state (e.g., displacement, velocity), action (e.g., damper force), and reward (e.g., minimized acceleration) for the control environment.
- **Training Algorithms:** Use Deep Reinforcement Learning algorithms like Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), or Deep Deterministic Policy Gradient (DDPG) to train control agents.
- **Validation:** Test RL controller on various dynamic scenarios (earthquake records, wind load profiles) and compare response metrics (e.g., inter-story drift, acceleration).
- **Hardware Integration (optional):** Implement trained control policy on a real-time platform with actuators and sensors for lab-scale experimental verification.

Technologies Used

- **Python + TensorFlow / PyTorch / Stable-Baselines3** – for RL model development
- **MATLAB / Simulink** – for structural system modelling and control simulation
- **OpenAI Gym or custom Gym environments** – for control environment creation
- **Simscape Multibody / ANSYS / OpenSees** – for detailed dynamic simulations

MAJORS & AREAS OF INTEREST

This project combines cutting-edge topics across several domains:

Structural and Earthquake Engineering

- Structural dynamics and control
- Vibration mitigation under dynamic loading
- Seismic and wind performance optimization

Artificial Intelligence & Reinforcement Learning

- Agent-environment interaction and control policy learning
- Deep reinforcement learning and neural control
- Model-free control under uncertainty

Control Systems and Automation

- Adaptive control theory and system identification
- Active and semi-active vibration control
- Feedback loop optimization and stability analysis

Instrumentation and Embedded Systems

- Sensor integration for real-time feedback
- Actuator interfacing and low-latency communication
- Edge deployment of RL models on embedded platforms

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Integration of AI with BIM for Real-Time Structural Design Validation

Mr. K Anand Goud, Assistant Professor, CE – Faculty Mentor

GOAL

The primary objective of this project is to integrate Artificial Intelligence (AI) with Building Information Modelling (BIM) systems to enable real-time structural design validation during the planning and construction phases. By embedding intelligent models into BIM workflows, this project aims to automatically detect design errors, code violations, and inefficiencies as the model is being developed—enhancing collaboration, reducing rework, and improving structural integrity from the earliest design stages.

- **Automated Structural Design Validation:** Implement AI algorithms that review structural components in BIM models for compliance with design codes, load paths, and best practices.
- **Real-Time Error Detection:** Detect clashes, over/under-designed elements, and unsupported loads dynamically as the model evolves in BIM.
- **Code Compliance Checks:** Use rule-based and machine learning models to validate structural elements against IS, ACI, Eurocode, or other relevant standards.
- **Design Optimization Suggestions:** Provide AI-driven recommendations to optimize material usage, structural member sizes, and layout based on historical project data.
- **AI-BIM Integration Framework:** Develop plug-ins or APIs to integrate AI tools with BIM platforms (e.g., Autodesk Revit, Tekla Structures).
- **Data-Driven Learning and Feedback:** Train AI models using past BIM project data, structural analysis results, and failure records to continuously improve validation accuracy.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **BIM Model Parsing:** Extract structural elements, geometry, loads, and metadata from BIM models (e.g., via Revit API or IFC files).
- **Data Preprocessing:** Clean, normalize, and classify data based on element type, load case, and material.
- **AI Model Development:** Use supervised and unsupervised learning for pattern recognition, anomaly detection, and rule learning from validated designs.
- **Rule-Based Validation:** Develop logical rules based on design standards and engineering judgment for code compliance checks.
- **Feedback Mechanism:** Embed continuous learning pipelines that refine AI validation based on new inputs and expert corrections.

Technologies Used

- **Autodesk Revit, Tekla Structures, ArchiCAD** – for BIM modeling
- **Dynamo, Forge API, Revit API** – for automation and integration
- **Python, TensorFlow, PyTorch, Scikit-learn** – for AI model development
- **Power BI / Tableau** – for design validation reporting and dashboards

MAJORS & AREAS OF INTEREST

This project combines knowledge across the following disciplines:

Structural and Civil Engineering

- Structural analysis and design principles
- Load paths, stability, and material behavior
- National and international design codes

Artificial Intelligence and Data Science

- Supervised and unsupervised learning for model validation
- Classification, clustering, and anomaly detection
- Feedback and continual learning systems

Building Information Modeling (BIM)

- 3D modeling, information exchange (IFC), BIM Level 2/3 practices
- Parametric modeling and data interoperability
- BIM-based coordination and error detection

Software Engineering and APIs

- Development of BIM plug-ins and AI-BIM interfacing
- Integration with cloud platforms or common data environments (CDEs)
- API-based data exchange and validation automation

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Development of AI Surrogate Models for Fast Structural Simulation

Dr. R Ramya Swetha, Associate Professor & Head, CE – Faculty Mentor

GOAL

The primary aim of this project is to develop AI-based surrogate models that can approximate complex structural simulations with high accuracy and significantly reduced computational cost. Traditional finite element method (FEM) simulations are time-consuming, especially for large or nonlinear structural systems. This project proposes the use of machine learning and deep learning models trained on high-fidelity simulation data to rapidly predict structural responses under various loading conditions—enabling real-time analysis, design optimization, and decision-making support in structural engineering.

- **Create AI Surrogates for FEM Outputs:** Replace computationally expensive FEM simulations with AI models that can predict displacements, stresses, or internal forces based on input parameters.
- **Reduce Simulation Time Without Sacrificing Accuracy:** Achieve near-FEM-level accuracy while reducing run times from hours/minutes to seconds or milliseconds.
- **Enable Real-Time Structural Analysis:** Facilitate fast what-if scenario analysis, design iterations, and control systems integration (e.g., digital twins, SHM systems).
- **Handle Nonlinear and Dynamic Problems:** Train models to approximate solutions for nonlinear material behaviour, large deformations, or dynamic loading (e.g., seismic or impact loads).
- **Develop Generalizable Models:** Create surrogate models that can adapt across different structural configurations, loading patterns, and boundary conditions.
- **Integrate with Design and Optimization Tools:** Use surrogate models in optimization loops for faster and automated design parameter tuning.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data Generation via FEM Simulations:**
  Use commercial tools (ANSYS, ABAQUS, OpenSees, SAP2000) to generate training datasets under varying loads, materials, and geometries.
- **Feature Engineering & Data Preprocessing:**
  Extract relevant input-output pairs: geometry, material, boundary conditions → response values (displacement, stress, reaction forces).
- **Surrogate Model Development:**
  Train AI models to map input parameters to simulation outputs using regression, time-series, or image-based learning techniques.
- **Model Evaluation & Validation:**
  Use metrics like RMSE, MAE, R^2, and response contour comparison to validate surrogate model accuracy against FEM ground truth.
- **Deployment:**
  Integrate models with GUI tools or cloud-based simulation platforms for practical use by engineers.

Technologies Used

- **FEM Tools:** ANSYS, ABAQUS, OpenSees, SAP2000
- **AI Libraries:** TensorFlow, PyTorch, Scikit-learn
- **Visualization:** Paraview, MATLAB, Plotly
- **Integration:** Python APIs, Jupyter Dashboards, cloud apps

MAJORS & AREAS OF INTEREST

This project intersects several key domains:

Structural and Civil Engineering

- Finite element modelling (linear/nonlinear)
- Dynamic and static structural behaviour
- Stress-strain relationships and structural responses

Artificial Intelligence and Deep Learning

- Surrogate modelling and regression
- Neural network training and hyperparameter tuning
- Physics-informed learning approaches

Computational Mechanics

- Simulation model generation
- Parametric analysis and sensitivity studies
- Data-driven approximation techniques

Data Science and Engineering

- Data curation and normalization
- Performance evaluation and model explainability
- Uncertainty quantification and robustness testing

MENTOR CONTACT INFORMATION

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PARTNERS & SPONSORS

None

AI-Powered Finite Element Model Generation for Complex Structural Systems

Dr. U Vamsi Mohan, Professor, CE – Faculty Mentor

GOAL

The core objective of this project is to automate and accelerate the generation of Finite Element Models (FEM) for complex structural systems using Artificial Intelligence techniques. Traditional FEM creation involves labour-intensive steps like geometry discretization, mesh generation, boundary condition assignment, and material specification—all requiring expert intervention. This project aims to develop AI-powered systems that learn from historical models and structural design rules to automatically generate, refine, and validate FEMs, especially for intricate geometries and real-world scenarios, thus enhancing modelling efficiency, reducing human error, and enabling rapid design iterations.

- **Automated Mesh Generation:** Train AI to generate high-quality meshes (structured/unstructured) adapted to geometry complexity and stress concentrations.
- **Geometry Recognition & Model Abstraction:** Use AI to identify structural components (beams, slabs, joints) from CAD/BIM inputs and convert them into FEM-ready domains.
- **Material & Boundary Condition Assignment:** Automatically assign appropriate materials and boundary conditions based on structural context, usage patterns, and historical data.
- **Model Validation and Correction:** Detect modelling errors such as disconnected elements, unrealistic boundary conditions, or poor mesh quality using intelligent algorithms.
- **Adaptive Modelling for Multi-scale Systems:** Generate FEMs that support hierarchical modelling—e.g., macro-models for global analysis and micro-models for detailed zones.
- **Reduce Time and Effort in Model Setup:** Drastically cut down the time required to prepare simulation-ready models, especially for large or complex infrastructure.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data-Driven Learning:** Train AI on existing databases of FEMs (including geometry, mesh, and simulation results) to identify patterns in model generation.
- **Shape and Topology Recognition:** Use image-based or point cloud-based deep learning models to interpret geometry from 2D/3D drawings or scans.
- **Mesh Prediction Models:** Predict element types (tetra, hexa), sizes, and distribution using reinforcement learning or graph neural networks (GNNs).
- **Knowledge-Based Systems:** Integrate domain-specific rules from structural mechanics to guide AI decision-making (e.g., stress-flow-based meshing).
- **Feedback Loop for Refinement:** Use simulation feedback (e.g., stress gradients, error estimates) to iteratively refine meshes using AI agents.

Technologies Used

- **CAD/BIM Integration:** Revit, AutoCAD, Rhino-Grasshopper
- **FEM Platforms:** ABAQUS, ANSYS, OpenSees, COMSOL
- **Programming & ML Frameworks:** Python, TensorFlow, PyTorch, Open3D, Gmsh API

MAJORS & AREAS OF INTEREST

This interdisciplinary project bridges the following technical domains:

Structural and Civil Engineering
- Structural element modelling (shells, beams, joints, etc.)
- Material behaviour and structural connectivity
- Meshing strategies for FEM convergence and stability

Artificial Intelligence
- Deep learning for spatial recognition and pattern detection
- Reinforcement learning for decision-based mesh creation
- Graph-based learning for mesh topology optimization

Computational Mechanics
- Finite element theory and stress-strain modelling
- Multi-scale modelling strategies and hierarchical FEM
- Simulation accuracy vs computational efficiency trade-offs

Geometric Computing & CAD/BIM
- Feature extraction from 3D models
- Rule-based abstraction of design intent
- Interoperability between AI tools and geometric models

MENTOR CONTACT INFORMATION

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PARTNERS & SPONSORS

None

Predictive Modelling of Structural Failures Using Machine Learning Techniques

Dr. Praveena Rao, Assistant Professor, CE – Faculty Mentor

GOAL

The main objective of this research is to develop robust machine learning (ML) models that can predict structural failures in buildings, bridges, and other civil infrastructure before they occur. These models will learn from historical data, sensor readings, inspection reports, and simulation outputs to identify failure-prone patterns. The goal is to anticipate critical damage, trigger preventive maintenance, and improve public safety by enabling data-driven decision-making in structural engineering and asset management.

- **Early Detection of Structural Deterioration:** Use historical inspection and sensor data to identify the early signs of fatigue, cracking, corrosion, or settlement.
- **Failure Classification and Severity Prediction:** Apply supervised ML models to classify potential failure modes (e.g., buckling, shear failure) and predict severity levels.
- **Real-Time Risk Assessment:** Integrate streaming sensor data (e.g., strain gauges, accelerometers) to assess failure risk in real-time under dynamic conditions.
- **Data Fusion from Multiple Sources:** Combine data from structural health monitoring (SHM) systems, maintenance logs, FEM simulations, and weather conditions for comprehensive modelling.
- **Predictive Maintenance Planning:** Recommend inspection or reinforcement schedules based on predicted deterioration trends to extend structure lifespan.
- **Model Explainability & Trustworthiness:** Incorporate interpretable ML methods to ensure model decisions are understandable and align with engineering knowledge.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data Collection & Cleaning:**
  Gather failure cases, maintenance logs, sensor data, and FEM results from real structures (bridges, buildings, etc.).
- **Feature Engineering:**
  Extract meaningful features (e.g., stress levels, vibration frequency, material age, loading cycles) from raw datasets.
- **Model Training & Validation:**
  Train models using classification and regression techniques, validate using cross-validation and test datasets.
- **Anomaly Detection:**
  Use unsupervised learning (e.g., Isolation Forest, DBSCAN) to detect abnormal structural behavior that precedes failure.
- **Time-Series Analysis:**
  Apply LSTM or Temporal CNNs for modeling degradation trends from continuous sensor streams.

Technologies Used

- **Programming & ML Frameworks:** Python, Scikit-learn, TensorFlow, PyTorch, Pandas, NumPy
- **FEM Tools:** OpenSees for simulations, SHAP for explainability
- **Mathematical Modelling:** MATLAB

MAJORS & AREAS OF INTEREST

This interdisciplinary project bridges the following technical domains:

Structural Engineering

- Structural mechanics, material degradation, fatigue, load path failure
- Failure case studies and safety analysis
- Maintenance and inspection strategies

Machine Learning & Data Science

- Supervised/unsupervised learning, ensemble models
- Feature selection, model evaluation, cross-validation
- Time-series prediction, anomaly detection

Structural Health Monitoring (SHM)

- Vibration analysis, strain measurement, displacement tracking
- Integration of IoT sensors and smart materials
- Real-time data acquisition systems

Risk and Reliability Engineering

- Probabilistic modelling of failure
- Fragility curves and reliability indices
- Risk-informed decision-making for infrastructure

MENTOR CONTACT INFORMATION

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AI-Based Real-Time Structural Response Simulation under Dynamic Loading

Dr. Praveena Rao, Assistant Professor, CE – Faculty Mentor

GOALS

The main objective of this project is to develop an AI-powered system capable of simulating and predicting the real-time structural response of buildings and infrastructure under dynamic loading conditions such as earthquakes, wind loads, traffic vibrations, or blasts. By leveraging AI techniques, the project aims to improve the speed, accuracy, and adaptability of structural simulations to support safer, smarter, and faster engineering decisions.

- **Real-Time Prediction of Structural Behaviour:** Simulate structural responses (displacement, acceleration, stress/strain) in real-time during dynamic events using AI models trained on past data and simulations.
- **Dynamic Load Identification:** Use AI to classify and interpret types of dynamic loading (e.g., seismic, wind, traffic) from sensor data.
- **Reduction of Computational Time:** Replace or support time-intensive Finite Element Method (FEM) simulations with AI surrogate models (e.g., neural networks, LSTMs).
- **Early Warning and Decision Support:** Enable fast decision-making by forecasting failure-prone components during extreme loading.
- **Model Generalization and Adaptability:** Train AI models to generalize across various structural types, materials, and boundary conditions.
- **Integration with Digital Twins and SHM Systems:** Enhance digital twin frameworks with real-time response simulations for continuous monitoring and proactive maintenance.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data Collection:** Dynamic response data from sensors (accelerometers, strain gauges), experimental shake tables, and FEM simulation results.
- **Data Processing:** Time-series filtering, noise reduction, normalization, and feature extraction (modal parameters, FFT, etc.)
- **Model Training:** Use supervised learning on labelled dynamic response datasets and time-series forecasting techniques.
- **Model Deployment:** Integrate trained models into real-time monitoring systems for live structural analysis.
- **Validation:** Compare AI predictions with FEM simulations and actual sensor responses under controlled dynamic loading.

Technologies & Tools

- **MATLAB/Simulink** – for simulation and control modelling
- **OpenSees / ABAQUS / SAP2000 / ANSYS** – for structural analysis modelling
- **TensorFlow / PyTorch / Scikit-learn** – for AI model training
- **LabVIEW or Python (with IoT libraries)** – for sensor interface and real-time integration

MAJORS & AREAS OF INTEREST

The relevant academic programs and technical domains that provide the foundational knowledge and skill sets needed to understand and develop AI-Based Real-Time Structural Response Simulation under Dynamic Loading.

This interdisciplinary project bridges the following technical domains:

Structural Engineering

- Structural dynamics, modal analysis, finite element modelling
- Seismic and wind response behaviour of buildings
- Structural health monitoring (SHM)

Artificial Intelligence and Computer Science

- Deep learning for time-series prediction
- Signal processing and sensor data fusion
- Real-time systems and data streaming architectures

Electronics and Communication Engineering

- Data acquisition systems and wireless sensor networks
- Real-time signal transmission and hardware-in-the-loop testing

Data Science and Analytics

- Feature engineering for structural data
- Anomaly detection and predictive modelling
- Time-series forecasting and model validation

MENTOR CONTACT INFORMATION

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Deep Learning for Structural Damage Detection from Vibration and Strain Data

Ms. B. Bhavani, Assistant Professor, CE – Faculty Mentor

GOALS

This project focuses on leveraging deep learning algorithms to detect and localize structural damage in real-time using vibration response and strain measurements. The goal is to create a smart, non-invasive system capable of identifying early signs of fatigue, cracking, or deformation in civil infrastructure, enabling timely maintenance, reducing failure risks, and extending structural life.

- **Real-Time Damage Detection:** Use vibration and strain sensor data to detect structural anomalies instantly without manual inspection.
- **Localization of Damage:** Identify the exact location of damage within the structure (e.g., beam, joint, slab) through deep learning interpretation of response patterns.
- **Feature Extraction from Sensor Data:** Automate the extraction of relevant features (e.g., frequency shifts, mode shape changes, strain spikes) using CNNs and RNNs.
- **Handling Noise and Uncertainty:** Improve robustness of detection models under environmental noise, sensor drift, and operational variability.
- **Damage Classification:** Classify damage types—crack, delamination, corrosion, fatigue—based on learned patterns from time-series signals.
- **Scalable Framework:** Develop a model adaptable to various structural types (bridges, buildings, towers) and materials (concrete, steel, composites).
- **Integration with SHM Systems:** Link the deep learning model with Structural Health Monitoring systems for continuous assessment and alert generation.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data Collection:** Gather high-frequency vibration and strain data using accelerometers, strain gauges, and fiber optic sensors during ambient and forced excitations.
- **Signal Processing:** Apply FFT, wavelet transforms, and time-frequency analysis to preprocess raw sensor signals.
- **Model Development:** Use deep learning models such as 1D CNNs, LSTMs, and autoencoders trained on labeled datasets to detect and classify damage.
- **Synthetic Data Generation:** Employ FEM tools to simulate damage scenarios and generate training data where real data is scarce.
- **Validation:** Test the trained models on laboratory or field-scale structures and compare with ground-truth or visual inspections.

Technologies & Tools

- **MATLAB Deep Learning Toolbox**– for simulation and control modelling
- **OpenSees -** for simulation and structural analysis modelling
- **TensorFlow / PyTorch / Scikit-learn** – for AI model training
- **LabVIEW or Python (with IoT libraries)** – for sensor interface and real-time integration

MAJORS & AREAS OF INTEREST

The relevant academic programs and technical domains that provide the foundational knowledge and skill sets needed to understand and develop AI-Based Real-Time Structural Response Simulation under Dynamic Loading.

This interdisciplinary project bridges the following technical domains:

Structural Engineering & Health Monitoring
- Modal analysis, damage mechanics
- Vibration-based assessment techniques
- Strain response under service and extreme loads

Deep Learning & Signal Intelligence
- Time-series modelling with neural networks
- Feature learning and dimensionality reduction
- Noise-resilient signal classification

Data Science & Sensing Technology
- Sensor calibration and fault tolerance
- Anomaly detection in real-world datasets
- Multi-sensor data fusion and interpretation

Simulation & Experimental Validation
- Damage modelling using FEM (ABAQUS, ANSYS)
- Laboratory-scale testing for model accuracy
- Ground-truth comparison with physical inspection

MENTOR CONTACT INFORMATION

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PARTNERS & SPONSORS

None

AI-Based Multi-Objective Optimization for Sustainable Structural Design

Mr. K.Anand Goud, Assistant Professor, CE – Faculty Mentor

GOALS

This project aims to leverage Artificial Intelligence (AI) for performing multi-objective optimization in structural engineering, focusing on achieving sustainability alongside structural performance. By integrating machine learning and optimization algorithms, the project seeks to find optimal design solutions that minimize material usage, cost, and carbon footprint while ensuring safety, durability, and compliance with design codes.

- **Multi-Criteria Design Optimization:** Simultaneously optimize for performance, cost, environmental impact, and structural efficiency.
- **Material and Energy Efficiency:** Select structural configurations and materials that reduce embodied energy and CO_2 emissions.
- **AI-Driven Design Exploration:** Use machine learning to explore a wide range of design alternatives beyond traditional trial-and-error.
- **Code-Compliant Sustainable Designs:** Ensure optimized solutions satisfy structural design codes and green building standards (e.g., LEED, GRIHA).
- **Performance-Based Design:** Include serviceability, durability, and life-cycle performance in the optimization process.
- **Integration with Simulation Tools:** Automate the feedback loop between structural analysis tools (e.g., FEM software) and AI optimizers.
- **Scalable Framework:** Develop a generalized tool applicable to various structures—buildings, bridges, towers—using different materials (steel, concrete, timber).

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Data Preparation:** Gather datasets of previous structural designs with performance, cost, and environmental metrics.
- **Objective Function Definition:** Define performance indicators: structural safety, weight, cost, CO_2 emissions, and material usage.
- **Optimization Algorithms:** Use AI-based multi-objective algorithms like Genetic Algorithms (GA), Particle Swarm Optimization (PSO), NSGA-II, and Bayesian Optimization.
- **Surrogate Modelling (Meta-Modelling):** Employ ML models (e.g., ANN, Gaussian Processes) to approximate expensive FEM simulations for faster optimization.
- **Sensitivity Analysis:** Identify key design parameters influencing sustainability and structural performance.
- **Decision-Making Framework:** Use Pareto Fronts and trade-off analysis to help designers choose optimal solutions.

Technologies & Tools

- **MATLAB/Simulink** – for simulation and control modelling
- **OpenSees / ABAQUS / SAP2000 / ANSYS** – for structural analysis modelling
- **Python (SciPy, DEAP, PyGMO, TensorFlow)**– for AI model training

MAJORS & AREAS OF INTEREST

The relevant academic programs and technical domains that provide the foundational knowledge and skill sets needed to understand and develop model for AI-Based Multi-Objective Optimization for Sustainable Structural Design.

This interdisciplinary project bridges the following technical domains:

Structural Engineering & Design

- Load-resisting systems, structural safety
- Limit state and performance-based design
- Material behaviour under multiple load combinations

Sustainability & Green Engineering

- Embodied carbon and energy metrics
- Life-cycle assessment (LCA)
- Eco-efficient structural materials

AI & Computational Optimization

- Multi-objective search algorithms
- Surrogate-assisted optimization
- High-dimensional design space exploration

Decision Support & Visualization

- Pareto optimization plots
- Trade-off analysis dashboards
- AI-assisted design feedback

MENTOR CONTACT INFORMATION

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