IARE
INSTITUTE OF
AERONAUTICAL ENGINEERING

HIGH IMPACT PRACTICES (HIPS)
CORNERSTONE PROJECTS: SMART MANUFACTURING SYSTEMS
INFORMATION PACKET

2025 - 2026

INSTITUTE OF AERONAUTICAL ENGINEERING

25 YEARS 2000 2025

I appreciate IARE students who are showing interest in AI-Driven Smart Manufacturing Systems (AI-DSMS) Project Program at the Institute of Aeronautical Engineering!

Cornerstone Projects are comprehensive, application-based projects typically undertaken by students in the second or third year of their academic programs. These projects serve experience that integrates the knowledge, skills, and competencies acquired throughout the curriculum. They are designed for a single semester with a small team upto two students to solve real-world problems through innovative, interdisciplinary.

The **AI-Driven Smart Manufacturing Systems (AI-DSMS)** 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 in Manufacturing Engineering Project Program at IARE fosters collaborative research to address key challenges in modern manufacturing using Artificial Intelligence. This initiative aims to revolutionize manufacturing processes by enhancing efficiency, sustainability, and product quality, while contributing to the Sustainable Development Goals (SDGs). To develop intelligent, adaptive, and sustainable manufacturing systems by integrating AI technologies across the product lifecycle from design to production to quality assurance.

Core Goals of **AI-Driven Smart Manufacturing Systems** are:

1. **Smart Process Optimization**
   Use AI to monitor and optimize machining, forming, casting, welding, and additive manufacturing for better quality and reduced waste.
2. **Predictive Maintenance & Fault Diagnosis**
   Implement AI models to predict equipment failures, reduce downtime, and schedule maintenance proactively.
3. **Quality Control through Computer Vision**
   Automate defect detection using AI-driven image processing and machine learning algorithms for real-time quality assurance.
4. **Energy-Efficient Manufacturing**
   Integrate AI to monitor energy consumption and optimize resource usage, supporting green manufacturing goals.
5. **Digital Twins in Manufacturing**
   Create AI-powered digital replicas of manufacturing systems for simulation, monitoring, and optimization.
6. **Intelligent Supply Chain and Inventory Management**
   Use AI to forecast demand, optimize inventory levels, and reduce lead times and logistics inefficiencies.
7. **AI-Based Robotics and Automation**
   Enable intelligent robotic systems for adaptive assembly lines, collaborative tasks, and autonomous material handling.
8. **Human-Centric AI in Industry 5.0**
   Develop AI systems that work in harmony with human workers, improving ergonomics, safety, and productivity.

9. **Sustainable Product Design and Lifecycle Management**
   Apply AI to support design-for-sustainability, lifecycle assessment, and eco-friendly production.
10. **Resilient and Smart Manufacturing Systems**
    Build adaptive systems capable of handling disruptions, demand variability, and real-time decision-making.

Cornerstone Projects (CoPs) focuses on the challenges presented by the Sustainable Development Goals (SDGs).

Sustainability Development Goals (SDGs) for the Dept. of ME, IARE	
SDG #4	Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all
SDG #7	Ensure access to affordable, reliable, sustainable and modern energy for all
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

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

1. Data-Driven Decision Making in Smart Manufacturing using Explainable AI **(SDG #4, SDG #12)**
2. Digital Twin of Smart Manufacturing Cells **(SDG #4, SDG #7)**
3. Ethical and Explainable AI in Manufacturing Decision Systems **(SDG #7, SDG #8)**
4. Adaptive AI-Based Process Planning and Scheduling **(SDG #4, SDG #12)**
5. Intelligent Scheduling System for Multi-Product Assembly Lines **(SDG #9, SDG #11)**
6. AI-Based Failure Prediction in Rotating Machinery using Vibration Signals **(SDG #4, SDG #12)**
7. Sustainable Product Design using AI and ML Techniques **(SDG #4, SDG #7)**
8. AI-Based Optimization of Welding Parameters for Defect-Free Welds **(SDG #8, SDG #9)**
9. Machine Learning for Real-Time Tool Wear Monitoring in CNC Machines **(SDG #11, SDG #12)**
10. Predictive Maintenance of Hydraulic Systems using Time-Series Forecasting **(SDG #7, SDG #9)**

In order to participate in **AI-DSMS** Projects, you must formally apply and be accepted by the project coordinator. To proceed, please mail to the project coordinator, Dr. Ch Sandeep, Associate Professor and Head of Mechanical Engineering, Email Id: ch.sandeep@iare.ac.in. This will bring up all available open positions tagged as **AI-DSMS** 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-DSMS** project team requires registration for the accompanying research statement from any of the specified domains. More information will be provided to all selected **AI-DSMS** 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.

Data-Driven Decision Making in Smart Manufacturing using Explainable AI

Dr. Ch Sandeep, Associate Professor & Head, Dept. of ME - Faculty Mentor

GOALS

This project focuses on harnessing Explainable Artificial Intelligence (XAI) to enhance data-driven decision-making in smart manufacturing environments. Traditional manufacturing decision processes rely heavily on expert intuition, rule-based heuristics, and limited data visibility often resulting in inefficiencies, bottlenecks, or delayed responses to changing conditions. With the advent of Industry 4.0, manufacturing systems now generate vast amounts of operational, sensor, and quality data. However, leveraging this data effectively requires more than just automation it demands transparency, interpretability, and trust in AI-based decisions.

The primary goal of this research is to design explainable AI systems that not only make accurate, real-time predictions and recommendations for manufacturing decisions but also provide clear, interpretable justifications for those decisions. This includes optimization of production schedules, defect diagnosis, predictive maintenance alerts, quality assurance, and energy/resource consumption decisions. By making AI-driven insights understandable to engineers, operators, and managers. The project aims to foster human-in-the-loop decision-making and drive sustainable, efficient, and adaptive manufacturing operations. Enable real-time, data-driven decision-making across manufacturing processes. Apply Explainable AI models to ensure transparency and user trust in AI-driven insights. Improve production efficiency, predictive maintenance, and quality control by leveraging data analytics. Bridge the gap between black-box AI models and human operators through interpretable systems.

METHODS & TECHNOLOGIES

The core technology enabler is Explainable AI (XAI) a set of methods that make the predictions of machine learning models transparent and understandable. Common XAI techniques such as SHAP (SHapley Additive Explanations)**,** LIME (Local Interpretable Model-Agnostic Explanations)**,** and counterfactual explanations will be applied to interpret decisions made by AI models in real-time manufacturing contexts.

Methods (Process & Approach)

The development of this system involves several key methods:

- **Data Collection & Preprocessing:**
  Gather data from IoT sensors, SCADA systems, and ERP logs. Clean, normalize, and structure the data for analysis.
- **Feature Engineering & Analytics:**
  Identify key performance indicators (KPIs) and relevant features. Apply statistical and machine learning techniques to extract patterns.
- **Model Development using Explainable AI:**
  Train models (e.g., decision trees, SHAP-enabled XGBoost, LIME-explained neural networks). Focus on interpretable algorithms for use in high-stakes production environments.
- **Dashboard & Visualization Tools:**
  Develop intuitive visual dashboards to display predictions and their explanations. Use visual tools (e.g., SHAP plots, decision rules) to interpret AI outputs.
- **Integration with Smart Manufacturing Systems:**
  Connect insights with MES (Manufacturing Execution Systems) and automation controls. Implement feedback loops for adaptive process control.
- **Testing & Deployment:**
  Validate model accuracy, robustness, and explainability. Monitor model drift and update based on new data.

Technologies Used:

- **Data Platforms & Tools:** SQL, Pandas, NumPy for data manipulation
- **AI & Machine Learning:** Scikit-learn, XGBoost, TensorFlow
- **Visualization & Interfaces:** Matplotlib / Plotly for XAI visualizations
- **Programming Languages:** Python (main AI & analytics logic), R (statistical modeling)

MAJORS & AREAS OF INTEREST

Cornerstone Project (CoP) team interested in from the following majors or areas of interest: Relevant Fields and Skills Development Through Project Execution

- **Predictive Maintenance & Anomaly Detection** – Equipment failure prediction, real-time monitoring using XAI models.

- **Process Optimization with Supervised Learning** – Improving yield, energy efficiency, and throughput using labelled sensor data**.**
- **Human-in-the-Loop Systems** – Incorporating operator feedback into explainable decision models for adaptive control.
- **Digital Twin & Simulation Modelling** – Creating interpretable virtual replicas of physical systems for optimization and forecasting**.**
- **Explainable Defect Detection in Quality Control** – Image-based inspection with model interpretability (e.g., Grad-CAM, SHAP).
- **Edge-AI for Smart Factories** – Deploying lightweight, explainable models on edge devices for real-time decision support**.**
- **Geospatial Integration in Plant Layout & Logistics** – Using GIS data for factory planning, routing, and environmental mapping.
- **Full-Stack Manufacturing Intelligence Systems** – Developing dashboards and web apps that integrate XAI insights for operators and managers**.**
- **Sustainable Manufacturing Analytics** – Modelling energy, water, and waste footprints using interpretable AI.
- **Data Engineering Pipelines for Manufacturing** – ETL workflows, sensor data fusion, and preprocessing for explainable model training

MENTOR CONTACT INFORMATION
Dr. Ch Sandeep
Email: ch.sandeep@iare.ac.in

Digital Twin of Smart Manufacturing Cells

Dr. G Hima Bindu, Assistant Professor, Dept. of ME - Faculty Mentor

GOAL

This project focuses on developing a Digital Twin a virtual replica of smart manufacturing cells to simulate, monitor, and optimize industrial operations in real time. In modern Industry 4.0 environments, digital twins are transformative tools that bridge the physical and digital worlds, enabling manufacturers to understand, predict, and enhance performance. Traditional monitoring and control systems often lack real-time adaptability and integration, resulting in inefficiencies, reactive maintenance, and suboptimal planning.

The main goal of this research is to build a comprehensive digital twin framework for individual or interconnected manufacturing cells, incorporating real-time data acquisition, AI-based analytics, and visual simulation to drive informed decision-making. This includes capturing machine states, operational metrics, process flows, and quality data to mirror the physical manufacturing process in a digital space. With the integration of AI and IoT, the digital twin will not only reflect the current status but also predict equipment failures, optimize process parameters, and simulate production scenarios. Ultimately, the project aims to enhance flexibility, adaptability, and sustainability in manufacturing systems aligning with SDG 9 and SDG 11 by promoting innovation, resilience, and smarter industrial infrastructure.

- Create a virtual representation of physical manufacturing cells that updates in real time.
- Enable real-time monitoring, predictive maintenance, and process optimization using sensor data and simulations.
- Facilitate what-if analysis, fault prediction, and performance improvement without disrupting actual operations.
- Integrate AI/ML models with the digital twin for intelligent decision-making and optimization.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

The development of this system involves several key methods:

- **Physical System Instrumentation:**
  Equip machines with IoT sensors (vibration, temperature, current, etc.) for real-time data collection.

- **3D Modelling & Simulation:**
  Use CAD software and simulation tools to build a virtual model of the manufacturing cell. Integrate physics-based simulation for mechanical processes.
- **Data Acquisition & Communication:**
  Stream real-time data using protocols like OPC UA, MQTT, or Modbus. Ensure bidirectional communication between the digital twin and physical systems.
- **Integration of AI & Analytics:**
  Use machine learning for anomaly detection, predictive maintenance, and optimization. Apply edge computing for real-time analytics close to the physical system.
- **Digital Twin Platform Development:**
  Develop a unified dashboard that visualizes key metrics, alerts, and simulation outputs. Enable scenario-based simulations to test various operating conditions.
- **Validation & Testing:**
  Calibrate the digital twin against actual performance data. Validate accuracy of predictions and simulation fidelity.

Technologies Used:

- **Hardware & Edge Devices:** IoT Sensors: Vibration, temperature, proximity, load cells
- **Modelling & Simulation Tools:** SolidWorks, MATLAB Simulink
- **Programming & Scripting:** Python (data processing, ML), C/C++, JavaScript
- **AI/ML Libraries:** Scikit-learn, TensorFlow, PyTorch for predictive modelling

MAJORS & AREAS OF INTEREST

Creating a digital twin for smart manufacturing cells involves multiple domains of engineering and computing, highlighting its interdisciplinary nature.

- **Digital Twin Modelling** – Creating real-time, virtual replicas of manufacturing cells to simulate, monitor, and optimize operations
- **Sensor Integration & IoT Connectivity** – Capturing live data from CNC machines, robots, and conveyors for digital synchronization
- **Explainable AI for Operational Insights** – Interpretable ML models for cycle time prediction, bottleneck identification, and downtime analysis
- **Data Visualization & Control Dashboards** – Interactive interfaces showing real-time KPIs, alerts, and model explanations

- **What-If Simulation & Optimization** – Testing different production scenarios and configurations in the digital space
- **Cloud & Edge Deployment** – Scalable architecture for digital twin services integrated with factory networks
- **Sustainable Operations Analysis** – Evaluating energy use, waste, and efficiency with interpretable models in the twin environment

MENTOR CONTACT INFORMATION

Dr. G Hima Bindu
Email: dr.ghimabindu@iare.ac.in

Explainable AI in Manufacturing Decision Systems

Dr. GVR Seshagiri Rao, Professor, Dept. of ME - Faculty Mentor

GOAL

The phrase "Explainable AI in Manufacturing Decision Systems" refers to the implementation of artificial intelligence models in manufacturing operations that not only deliver high-performance predictions and insights but also offer clear, human-understandable explanations for their outputs. In modern manufacturing, AI is widely used for tasks such as defect detection, process optimization, maintenance prediction, and supply chain decisions. However, when these AI models operate as “black boxes,” they can lead to distrust, misinterpretation, or poor decision-making.

Explainable AI (XAI) ensures that the reasoning behind AI-driven decisions is transparent, interpretable, and accessible to all stakeholders including engineers, managers, and operators leading to greater trust, accountability, and adoption in industrial environments.

The key objectives are:

- Implement interpretable and transparent AI models for key manufacturing decision processes.
- Enable real-time explanations of AI predictions to assist human decision-makers.
- Build trustworthy and auditable AI systems that can be validated by technical and non-technical users.
- Support data-driven decisions in areas like predictive maintenance, quality control, and production planning through interpretable models.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Use Case Selection:**
  Identify decision-making scenarios (e.g., tool wear prediction, production scheduling, defect classification). Define objectives, constraints, and stakeholders involved in each decision.
- **Data Acquisition & Preprocessing:**
  Collect data from sensors, control systems, and historical logs. Clean, transform, and label data for supervised learning tasks.

- **Model Development with Focus on Interpretability:**
  Use transparent models like decision trees, rule-based systems, or linear models. For complex models (e.g., neural networks, ensembles), apply post-hoc explainability tools.
- **Integration of Explainability Techniques:**
  Use tools like SHAP, LIME, and Anchors to generate explanations for model outputs. Visualize feature importance, decision paths, and what-if scenarios.
- **User Interface & Visualization:**
  Build dashboards that allow operators to interact with models and view explanations. Include tools for comparative analysis and confidence-level visualization.
- **Testing, Validation & Feedback Loop:**
  Evaluate model accuracy and clarity of explanations with domain experts. Incorporate user feedback to improve model and explanation quality.

Technologies Used

- **Machine Learning & AI Frameworks:** Scikit-learn, XGBoost, LightGBM, TensorFlow / PyTorch
- **Data Management & Processing:** Pandas, SQL, NumPy for structured data
- **Visualization & Dashboards:** Plotly, Matplotlib for explanation plots and feature visualizations
- **Programming Languages:** Python, JavaScript

MAJORS & AREAS OF INTEREST

This project lies at the intersection of artificial intelligence, manufacturing, and human-centered computing, drawing on a broad range of academic disciplines.

- **Model Transparency for Production Decisions** – Applying interpretable ML models (e.g., decision trees, SHAP, LIME) to aid decision-making in production planning and control.
- **Root Cause Analysis of Process Failures** – Using XAI techniques to identify contributing factors behind defects, delays, or quality issues.
- **Operator Trust and Human-in-the-Loop AI** – Designing decision systems where human operators can understand, validate, or override AI recommendations.
- **Intelligent Scheduling and Resource Allocation** – Explainable optimization of job-shop scheduling, machine assignment, and shift planning.

- **Visual Explanations in Quality Control** – Using techniques like Grad-CAM or saliency maps to explain AI-based image inspection systems.
- **Auditable AI for Compliance and Safety** – Ensuring regulatory transparency in automated decisions, especially in critical sectors like aerospace or pharma manufacturing**.**
- **Real-Time Decision Dashboards** – Integrating interpretable model outputs into dashboards for supervisors and plant managers.
- **Failure Prediction and Maintenance Decisions** – Explainable models that justify maintenance recommendations to engineers**.**
- **Bias and Fairness Assessment** – Identifying and mitigating biases in AI-driven decision systems affecting manufacturing operations or workforce management.
- **Integration with Digital Twins** – Embedding XAI within digital twin systems for explainable simulation and decision support

MENTOR CONTACT INFORMATION
Dr. GVR Seshagiri Rao
Email: gvr.seshagirirao@iare.ac.in

Adaptive AI-Based Process Planning and Scheduling

Dr. GVR Seshagiri Rao, Professor, Dept. of ME - Faculty Mentor

GOAL

Adaptive AI-Based Process Planning and Scheduling refers to the use of artificial intelligence (AI) to dynamically plan, optimize, and adapt production workflows in manufacturing environments based on real-time data, system constraints, and operational priorities. Traditional scheduling approaches are static and unable to respond quickly to disturbances such as machine breakdowns, urgent orders, or supply chain delays.

This project focuses on the design and deployment of intelligent, flexible, and self-adjusting planning systems that use AI/ML techniques to learn from production data and continuously adapt schedules and process plans. The aim is to maximize efficiency, utilization, and on-time delivery, while minimizing downtime and resource waste.

- Develop an AI-driven system for dynamic and adaptive manufacturing scheduling and process planning.
- Enable real-time response to disruptions and changes in production requirements.
- Use machine learning to learn optimal planning strategies from historical data and ongoing operations.
- Optimize resource allocation, machine utilization, and workflow efficiency.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Problem Definition & Modelling:**
  Define production goals, constraints (e.g., machine capacity, job priority), and variables (e.g., processing time, setup time). Model the scheduling problem using mathematical and AI-based approaches.
- **Data Collection & Analysis:**
  Collect historical and real-time production data (machine logs, job times, failure records). Preprocess and analyse data for pattern extraction.

- **AI/ML Model Development:**
  Use supervised learning (for time prediction, failure risk) and reinforcement learning (for decision-making in dynamic environments). Implement metaheuristics (e.g., Genetic Algorithms, Ant Colony Optimization) for complex scheduling scenarios.
- **Adaptive Scheduling Logic:**
  Develop algorithms that reschedule dynamically based on events like delays, machine faults, or urgent job arrivals. Incorporate feedback loops for continuous learning and improvement.
- **Simulation & Evaluation:**
  Simulate real-world factory scenarios using digital models. Evaluate performance using metrics like throughput, tardiness, machine utilization.
- **User Interface & Visualization:**
  Create dashboards for monitoring schedules, updating job queues, and visualizing adaptive decisions.

Technologies Used
AI & Optimization Frameworks: Scikit-learn, PyTorch, TensorFlow (for ML models)
Data Handling Tools: Pandas, NumPy, SQL for data processing
Scheduling & Planning Models: Job-Shop Scheduling, Flow-Shop Scheduling, Dynamic Scheduling
Visualization Tools: Streamlit, Dash, Plotly, Grafana for real-time visualization
Programming Languages: Python (core logic and AI), JavaScript / HTML

MAJORS & AREAS OF INTEREST

The project integrates concepts from artificial intelligence, industrial engineering, operations research, and systems automation, offering a multidisciplinary foundation.

- **Dynamic Job-Shop Scheduling with AI** – Real-time adjustment of task sequences based on machine availability, priority, and workload.
- **Reinforcement Learning for Adaptive Planning** – Training agents to learn optimal planning strategies in changing manufacturing environments.
- **Explainable Scheduling Decisions** – Using interpretable models (e.g., rule-based systems, SHAP) to justify task assignments and resource utilization.

- **Multi-Objective Optimization** – Balancing competing goals such as cost, time, and energy using evolutionary algorithms and explainable trade-offs.
- **Predictive Modelling for Bottleneck Identification** – Forecasting congestion points and re-routing workflows accordingly.
- **AI-Driven Resource Allocation** – Adaptive assignment of machines, tools, and personnel based on live production data.
- **Integration with ERP/MES Systems** – Seamless synchronization of AI scheduling with enterprise systems for execution**.**
- **Resilience Against Disruptions** – AI-based re-planning in case of machine breakdowns, supply delays, or urgent orders.
- **Human-AI Collaboration in Planning** – Tools that allow planners to interactively modify AI-generated schedules with feedback loops.
- **Visualization of Planning Outcomes** – Dashboards and Gantt charts with explainable AI annotations for decision support

MENTOR CONTACT INFORMATION
Dr. GVR Seshagiri Rao
Email: gvr.seshagirirao@iare.ac.in

Intelligent Scheduling System for Multi-Product Assembly Lines

Dr. V V S Harnadh Prasad, Professor, Dept. of ME - Faculty Mentor

GOAL

The project **"Intelligent Scheduling System for Multi-Product Assembly Lines"** refers to the development of a smart, AI-enabled system capable of planning, sequencing, and optimizing the scheduling of various products across shared assembly lines. In traditional manufacturing environments, fixed scheduling methods often struggle to handle variability in product types, demand changes, and resource constraints.

This system aims to bring intelligence and flexibility to multi-product production lines, ensuring better throughput, reduced changeover times, and high resource utilization. Grounded in operations research, artificial intelligence, and real-time control systems, the project leverages data from production environments to make adaptive scheduling decisions. The goal is to handle complex assembly constraints (like part availability, tool setup times, workforce skill levels) and dynamically adjust schedules to maintain productivity and on-time delivery.

- Automate and optimize the scheduling of diverse products across a shared assembly line.
- Minimize idle time, changeover delays, and bottlenecks while maximizing throughput.
- Adapt to real-time disruptions like machine breakdowns, urgent job insertions, or missing components.
- Ensure efficient resource utilization and delivery performance in multi-product manufacturing.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **System Analysis & Workflow Modelling:**
  Study product mix, assembly steps, changeover requirements, and production constraints. Model the workflow as a multi-product job-shop or flow-shop scheduling problem.
- **Data Collection & Feature Engineering:**
  Capture data related to product specifications, process durations, workstation capabilities, and real-time status updates. Identify key performance indicators (KPIs) such as makespan, throughput, and lead time.

- **AI-Based Scheduling Logic:**
  Apply AI/ML techniques such as reinforcement learning for dynamic decision-making. Use combinatorial optimization (e.g., genetic algorithms, simulated annealing) to generate and evolve schedules. Build predictive models to estimate delays and reschedule proactively.
- **Real-Time Adaptation:**
  Integrate edge computing or IoT systems to track machine and material status. Develop rescheduling algorithms to handle real-time disruptions like line stoppages or urgent jobs.
- **Simulation & Scenario Testing:**
  Use discrete-event simulation to test the scheduling logic under multiple demand and disruption scenarios.
- **Visualization & User Interface:**
  Design a control dashboard for supervisors to monitor schedules, job queues, and alerts. Enable manual overrides and "what-if" scenario testing.

Technologies Used

- **AI & Optimization Frameworks:** PyTorch, TensorFlow (for model training)
- **Data Handling:** Pandas, SQL, MQTT/OPC-UA for real-time and historical data
- **Visualization Tools:** Dash, Plotly, Grafana for dashboards
- **Programming Languages:** Python (core logic, AI), JavaScript/HTML

MAJORS & AREAS OF INTEREST

The project draws from a blend of disciplines to create a robust, intelligent scheduling system suited for the complexity of multi-product manufacturing environments.

- **AI-Powered Production Line Balancing** – Optimizing task allocation across stations for varied product types with minimal idle time.
- **Multi-Product Sequencing Algorithms** – Intelligent algorithms to determine the optimal order of products based on setup time, priority, and resource availability.
- **Constraint-Aware Scheduling** – Handling constraints like part availability, labor shifts, machine downtime, and delivery deadlines**.**
- **Real-Time Rescheduling with AI** – Dynamic adjustment of schedules in response to disruptions, such as equipment failure or urgent orders.

- **Explainable AI for Operator Trust** – Transparent decision logic using SHAP/LIME to explain why certain products or tasks are prioritized**.**
- **Integration with Assembly Line Sensors** – Real-time data acquisition from line sensors to enable responsive and adaptive scheduling.
- **Visualization Tools for Supervisors** – Interactive dashboards showing schedule status, bottlenecks, and upcoming transitions**.**
- **Reinforcement Learning for Continuous Improvement** – Learning-based systems that adapt scheduling strategies based on past performance data.
- **Multi-Criteria Optimization** – Balancing throughput, energy consumption, and setup changeover time using AI**.**
- **Interfacing with ERP and MES** – Seamless integration with enterprise resource and execution planning systems for synchronized operations

MENTOR CONTACT INFORMATION
Dr. V V S Harnadh Prasad
Email: vvshprasad@iare.ac.in

AI-Based Failure Prediction in Rotating Machinery using Vibration Signals

Dr. C Labesh Kumar, Assistant Professor, Dept. of ME - Faculty Mentor

GOAL

The project **"AI-Based Failure Prediction in Rotating Machinery Using Vibration Signals"** focuses on using artificial intelligence and signal processing techniques to monitor and predict potential faults in rotating equipment such as motors, pumps, turbines, and gearboxes. Rotating machinery is critical to industrial operations, and unexpected failures can lead to significant downtime, maintenance costs, and safety risks.

This project aims to develop an intelligent condition monitoring system that analyzes vibration data in real-time, detects early signs of wear, imbalance, misalignment, or bearing faults, and forecasts possible failures. The objective is to move from reactive or scheduled maintenance to predictive maintenance strategies, enhancing reliability, uptime, and equipment life.

- Develop AI/ML models to analyze vibration signals for early failure detection.
- Enable predictive maintenance by forecasting time-to-failure using real-time data.
- Reduce unplanned downtime and optimize equipment maintenance schedules.
- Classify fault types and severity using advanced signal features and machine learning.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Problem Definition & System Characterization:**
  Define machine types, failure modes, and vibration sources (e.g., bearing faults, unbalance, looseness). Understand frequency ranges, sensor types, and placement strategies.
- **Data Acquisition & Signal Processing:**
  Collect high-resolution time-series vibration data using accelerometers. Apply signal processing techniques such as Fast Fourier Transform (FFT), Wavelet Transform, and Envelope Analysis to extract time-domain and frequency-domain features.
- **Feature Engineering:**
  Extract statistical, spectral, and nonlinear features (e.g., RMS, kurtosis, crest factor). Use time-frequency techniques to capture transient behaviors.

- **AI/ML Model Development:**
  Train supervised learning models (e.g., Random Forest, SVM, XGBoost) for fault classification. Use deep learning (e.g., 1D-CNN, LSTM) for feature learning and failure prediction. Apply unsupervised learning (e.g., Autoencoders, Clustering) for anomaly detection in unlabeled data.
- **Prediction & Health Indexing:**
  Develop regression models for Remaining Useful Life (RUL) estimation. Create health indices to visualize and track equipment degradation over time.
- **System Deployment & Visualization:**
  Integrate with edge devices or IoT gateways for real-time monitoring. Design dashboards for visualization, alerts, and predictive maintenance scheduling.

Technologies Used

AI & ML Frameworks: Scikit-learn, TensorFlow, Keras, PyTorch (for model training)

Signal Processing Tools: MATLAB (optional) for signal analysis

Data Handling & Acquisition: Pandas, NumPy for data processing

- **Visualization Tools:** Plotly for signal visualization
- **Programming Languages:** Python (core ML, signal processing), MATLAB / C

MAJORS & AREAS OF INTEREST

This project is inherently multidisciplinary, drawing from mechanical systems, data science, instrumentation, and artificial intelligence.

- **Signal Processing for Feature Extraction** – Time-domain and frequency-domain analysis of vibration data to extract key indicators (RMS, kurtosis, FFT, etc.)
- **Supervised Learning for Fault Classification** – Using labelled datasets to train models (e.g., SVM, Random Forest, CNN) to classify bearing or rotor faults.
- **Anomaly Detection with Unsupervised Learning** – Identifying deviations from normal behaviour using clustering or autoencoders when labelled data is limited.
- **Explainable AI for Diagnostic Transparency** – Applying techniques like SHAP or LIME to interpret model predictions and pinpoint contributing features.
- **Edge AI for Onboard Monitoring** – Deploying lightweight AI models on embedded systems for real-time fault detection at the machine level.

- **Sensor Fusion and Data Acquisition** – Integrating accelerometers, tachometers, and temperature sensors to improve diagnostic accuracy.
- **Predictive Maintenance Scheduling** – Forecasting remaining useful life (RUL) to plan optimal maintenance intervals**.**
- **Visualization Dashboards for Plant Engineers** – Interactive dashboards displaying health indices, prediction confidence, and failure modes.
- **Digital Twin Integration** – Simulating machine behavior using AI-inferred degradation trends for proactive planning**.**
- **Industry Use Cases and Validation** – Application to pumps, motors, turbines, and compressors with field data validation

MENTOR CONTACT INFORMATION
Dr. C Labesh Kumar
Email: c.labeshkumar@iare.ac.in

Sustainable Product Design using AI and ML Techniques

Dr. K China Apparao, Associate Professor - Faculty Mentor

GOAL

"Sustainable Product Design Using AI and ML Techniques" refers to leveraging artificial intelligence and machine learning to create products that are environmentally responsible, resource-efficient, and aligned with circular economy principles. Traditional product design methods often overlook lifecycle impacts, energy usage, material recyclability, and carbon footprint.

This project aims to integrate data-driven intelligence into the product design process to enable sustainability-aware decisions. AI and ML models will be used to optimize material choices, manufacturing processes, energy consumption, and product lifecycle impacts. The focus is on developing smart tools that assist designers and engineers in evaluating and improving the environmental performance of products from concept to end-of-life.

- Develop AI/ML models to support sustainable material and process selection.
- Optimize product designs for minimal environmental footprint and maximum reusability.
- Enable lifecycle assessment (LCA) and predictive environmental impact evaluation.
- Support circular design by integrating end-of-life recovery and reuse strategies.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Problem Definition & Sustainability Metrics:**
  Define sustainability criteria: energy consumption, emissions, recyclability, durability, etc. Establish quantitative design goals and constraints.
- **Data Collection & Preprocessing:**
  Collect datasets on materials, energy profiles, emission factors, environmental impact indicators. Use external LCA databases (e.g., Ecoinvent, GaBi) and company-specific sustainability reports.
- **Feature Engineering & Impact Modeling:**
  Extract features like material composition, processing energy, transport modes, and use-phase energy. Model environmental impacts using ML-driven surrogate models of LCA tools.

- **AI/ML Model Development:**
  Apply supervised learning for predicting sustainability scores of design alternatives. Use optimization algorithms (e.g., Genetic Algorithms, Bayesian Optimization) to find sustainable configurations. Implement recommender systems for eco-friendly material/process alternatives.
- **Design Decision Support System:**
  Build interactive tools that suggest design modifications based on AI insights. Include "green scorecards" to visualize environmental trade-offs.
- **Simulation & Evaluation:**
  Simulate product usage scenarios to estimate lifecycle energy usage and emissions. Evaluate designs using metrics like carbon footprint, recyclability index, and cost-benefit ratio.

Technologies Used

- **AI & ML Libraries:** Scikit-learn, TensorFlow, XGBoost (for predictive models)
- **Sustainability Analysis Tools:** Python-based surrogate LCA models
- **Visualization & UI Tools:** Plotly, Seaborn for sustainability metric visualization
- **Programming Languages:** Python (AI modeling and data processing)

MAJORS & AREAS OF INTEREST

This project draws from a rich intersection of engineering, environmental science, and data analytics to drive sustainability in product development.

- **Material Selection Optimization** – AI-based recommendations for eco-friendly, recyclable, or bio-degradable materials based on mechanical and environmental properties.
- **Life Cycle Assessment (LCA) with ML Models** – Predicting environmental impact across a product's lifecycle using machine learning for faster, data-driven analysis.
- **Design for Disassembly and Reuse** – ML-assisted design tools that suggest modular, easily dismantlable structures to support circular economy.
- **Topology Optimization with Sustainability Constraints** – Generative design techniques that reduce material usage while maintaining structural performance.
- **AI-Powered Cost-Impact Trade-off Analysis** – Balancing cost, performance, and environmental footprint using multi-objective optimization models.
- **Intelligent CAD Systems** – Integration of AI within CAD environments to provide real-time design feedback for sustainability.

- **ML-Based Consumer Usage Pattern Prediction** – Forecasting user behavior to inform sustainable feature design and product lifespan.
- **Explainable AI in Design Decision-Making** – Transparent insights into why certain sustainable design choices are preferred by the model**.**
- **Data-Driven Benchmarking of Eco-Designs** – Comparing design alternatives against sustainability metrics using curated data and ML insights.
- **Integration with Digital Product Twins** – Simulating and validating sustainable performance before physical prototyping.

MENTOR CONTACT INFORMATION
Dr. K China Apparao
Email: k.chinnaapparao@iare.ac.in

AI-Based Optimization of Welding Parameters for Defect-Free Welds

Dr. Ch Sandeep, Associate Professor & Head, Dept. of ME - Faculty Mentor

GOALS

"AI-Based Optimization of Welding Parameters for Defect-Free Welds" focuses on utilizing artificial intelligence (AI) and machine learning (ML) to optimize welding process parameters—such as current, voltage, welding speed, gas flow rate, and electrode angle—to achieve high-quality, defect-free welds. Traditional welding relies heavily on trial-and-error methods, manual tuning, and expert intuition, which can lead to inconsistent results and production inefficiencies.

This project aims to develop intelligent models that can learn from welding data and recommend optimal parameters that reduce common weld defects such as porosity, cracks, lack of fusion, and undercuts. The goal is to improve weld quality, reduce waste and rework, and increase productivity in automated and manual welding operations.

- Develop AI/ML models to predict and minimize welding defects based on parameter settings.
- Create a decision-support system for parameter selection tailored to material and joint type.
- Integrate real-time monitoring and feedback systems for adaptive welding control.
- Enhance consistency, quality, and efficiency in welding operations.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Problem Formulation & Parameter Identification:**
  Identify key welding parameters influencing quality (current, voltage, speed, etc.). Define quality indicators (defect type, weld strength, bead shape).
- **Data Acquisition:**
  Collect welding datasets including process parameters, images/videos of welds, and non-destructive testing (NDT) results. Use sensors (IR, acoustic, thermocouples) for real-time process monitoring.
- **Data Preprocessing & Feature Engineering:**
  Clean and normalize data; extract key features like heat input, energy density, and arc stability indicators. Label weld quality using NDT reports or expert ratings.

- **AI/ML Model Development:**
  Use regression models (e.g., Random Forest, XGBoost) to predict defect probabilities. Apply classification models (e.g., SVM, Neural Networks) for defect type identification. Use optimization algorithms (Genetic Algorithms, Bayesian Optimization) to recommend parameter sets that minimize defects.
- **Welding Optimization Framework:**
  Implement inverse modeling to suggest parameter values for target weld properties. Build an adaptive loop that learns from ongoing welding outcomes to refine recommendations.
- **Interface & Integration:**
  Develop dashboards for visualizing welding parameters and predicted defect risks. Integrate with welding robots or CNC-based welding systems for real-time adjustments.

Technologies & Tools

- **AI & ML Frameworks:** Scikit-learn, TensorFlow, PyTorch (for predictive and classification models)
- **Welding Monitoring Tools:** Thermal cameras, acoustic sensors, arc sensors, Data acquisition systems (DAQ) and PLC integration
- **Simulation & Modeling Software:** ANSYS WeldSim, Simufact Welding (for thermal and mechanical simulation), MATLAB/Simulink (for process modeling)
- **Data Handling & Visualization:** Pandas, NumPy for data processing
- **Programming Languages:** Python (AI/ML), C++ / LabVIEW

MAJORS & AREAS OF INTEREST

This project draws on a blend of mechanical, materials, and AI disciplines to modernize and optimize welding processes using smart data-driven methods.

- **Process Parameter Prediction with Supervised Learning** – Training ML models (e.g., Random Forest, ANN, SVR) to predict optimal welding current, voltage, speed, and gas flow
- **Defect Detection and Classification** – Using AI on sensor data or weld images to identify and classify defects such as porosity, cracks, or undercuts
- **Multi-Objective Optimization Algorithms** – Applying genetic algorithms, PSO, or Bayesian optimization to balance weld strength, bead geometry, and heat input

- **Sensor-Based Data Acquisition** – Real-time collection of arc voltage, temperature, vibration, and acoustic signals to feed into AI models
- **Image Processing for Weld Quality Assessment** – Computer vision techniques (e.g., CNNs) for analyzing weld bead profiles and surface finish
- **Explainable AI for Process Insight** – Understanding the influence of each parameter using XAI tools (e.g., SHAP, LIME) to build trust in model recommendations
- **Closed-Loop Control Systems** – AI-driven adaptive control to fine-tune parameters in real-time during robotic or automated welding
- **Simulation and Digital Twin of Welding Process** – Modeling heat flow and weld pool dynamics virtually with feedback from AI predictions
- **Integration with Industry 4.0 Platforms** – Real-time weld quality monitoring and parameter tuning in smart manufacturing environments
- **Sustainable Welding Practices** – Reducing rework, energy consumption, and material wastage by achieving first-pass quality through AI optimization

MENTOR CONTACT INFORMATION

Dr. Ch Sandeep
Email: ch.sandeep@iare.ac.in

Machine Learning for Real-Time Tool Wear Monitoring in CNC Machines

Dr. V V S Harnadh Prasad, Professor, Dept. of ME - Faculty Mentor

GOALS

"Machine Learning for Real-Time Tool Wear Monitoring in CNC Machines" aims to develop intelligent systems that detect and predict tool wear during machining operations using real-time data such as vibration, acoustic emission, spindle load, and temperature. Tool wear directly affects surface finish, dimensional accuracy, machine health, and productivity. Conventional wear detection is reactive and inspection-based, often leading to tool failure and downtime.

This project proposes a machine learning (ML)-based predictive monitoring system that analyzes sensor data to determine tool condition and remaining useful life (RUL). The goal is to prevent tool failure, reduce downtime, and optimize tool replacement schedules by enabling proactive and intelligent decision-making.

- Develop ML models that can classify tool wear stages and predict tool life using sensor data.
- Enable real-time monitoring and early detection of abnormal tool behavior.
- Reduce unplanned stoppages and improve product quality through intelligent maintenance.
- Create a feedback system that integrates with CNC controls to issue alerts or adjust machining parameters.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **Tool Wear Characterization & Problem Definition:**
  Define tool wear types (flank wear, crater wear, chipping) and failure thresholds. Establish performance metrics (wear rate, RUL, surface finish correlation).
- **Sensor Integration & Data Acquisition:**
  Integrate sensors like accelerometers, acoustic emission sensors, dynamometers, and IR thermometers. Acquire multivariate time-series data from live CNC operations.
- **Data Preprocessing & Feature Extraction:**
  Clean noisy signals, perform segmentation, and normalize readings. Extract statistical, frequency-domain, and time-frequency features (FFT, RMS, kurtosis, wavelets).
- **Machine Learning Model Development:**

Apply classification models (Random Forest, SVM, CNN) to determine wear states (e.g., normal, moderate, critical). Use regression or RUL models (XGBoost, LSTM) to predict tool life. Implement anomaly detection models (Autoencoders, Isolation Forest) for real-time deviation detection.

- **Real-Time Monitoring System:**
  Develop a streaming pipeline to process sensor data and update tool condition status continuously. Integrate model predictions with CNC interface for visualization or adaptive control.
- **Validation & Deployment:**
  Validate ML models with experimental or simulated machining datasets. Deploy the system on industrial CNCs with feedback loops for corrective action.

Technologies & Tools

- **AI & ML Libraries:** Scikit-learn, PyTorch, TensorFlow (model training and evaluation)
- **Sensor & Hardware Integration:** Vibration sensors, acoustic emission sensors, load cells, thermocouples
- **Visualization & Monitoring:** Grafana, Streamlit, Dash for real-time dashboards
- **Programming Languages:** Python, C++ / Ladder logic for CNC control interface

MAJORS & AREAS OF INTEREST

This project spans across mechanical engineering, data science, instrumentation, and AI, supporting the shift toward predictive maintenance in Industry 4.0-enabled smart factories.

- **Sensor-Based Data Acquisition** – Collecting real-time data such as vibration, acoustic emission, spindle load, and temperature from CNC machines.
- **Feature Extraction and Signal Processing** – Time-domain, frequency-domain, and time-frequency analysis to extract relevant features (RMS, kurtosis, FFT, wavelets)**.**
- **Supervised Learning Models for Wear Prediction** – Training ML models (e.g., Random Forest, SVM, ANN) to estimate tool wear based on labeled datasets.
- **Unsupervised Learning for Anomaly Detection** – Clustering and autoencoder-based methods to detect unusual wear patterns in unlabeled conditions**.**
- **Real-Time Decision Support Systems** – AI-based monitoring systems that alert operators before critical tool failure.

- **Explainable AI for Maintenance Decisions** – Using XAI tools (e.g., SHAP, LIME) to interpret model predictions and guide tool replacement timing**.**
- **Edge Computing for Local Processing** – Deploying lightweight ML models on embedded devices for on-machine inference.
- **Digital Twin Integration** – Simulating tool wear behavior virtually and updating models based on live data streams**.**
- **Reduction of Downtime and Scrap Rates** – Enhancing productivity and sustainability by avoiding tool-induced defects through timely interventions.
- **Visualization Dashboards for Operators and Engineers** – Interactive interfaces showing tool condition, prediction confidence, and trends

MENTOR CONTACT INFORMATION
Dr. V V S Harnadh Prasad
Email: vvshprasad@iare.ac.in

Predictive Maintenance of Hydraulic Systems using Time-Series Forecasting

Dr. C Labesh Kumar, Assistant Professor, Dept. of ME - Faculty Mentor

GOALS

"Predictive Maintenance of Hydraulic Systems using Time-Series Forecasting" aims to develop an intelligent system that continuously monitors key parameters of hydraulic systems (pressure, temperature, flow rate, vibration, oil quality) to detect signs of degradation or impending failure. Instead of relying on periodic maintenance or post-failure repair, this approach uses time-series data and forecasting models to predict failures in advance, ensuring proactive maintenance and minimal downtime.

Hydraulic systems are critical in manufacturing, aerospace, automotive, and heavy equipment, where failure can cause major disruptions. The goal is to increase reliability, reduce maintenance costs, and extend system life through AI-based predictive analytics.

- Forecast critical system parameters using time-series models to predict anomalies or threshold violations.
- Detect degradation patterns and anticipate failures in pumps, valves, hoses, and seals.
- Minimize unplanned downtime and optimize maintenance schedules.
- Improve safety and extend the operational lifespan of hydraulic components.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

- **System Modeling & Failure Mode Analysis:**
  Identify key failure modes (e.g., pump leakage, valve sticking, seal wear). Define measurable indicators (e.g., pressure drops, temperature spikes, contamination levels).
- **Sensor Integration & Data Acquisition:**
  Install pressure, temperature, vibration, flow, and oil quality sensors on hydraulic components. Acquire high-frequency time-series data using DAQ or IoT platforms.
- **Data Preprocessing & Feature Engineering:**
  Clean and normalize time-series data, handle missing values. Extract features such as trends, moving averages, FFT, statistical moments, and frequency-domain signatures.
- **Time-Series Forecasting Model Development:**

Apply forecasting models (ARIMA, LSTM, GRU, Prophet) to predict future values of critical parameters. Use change detection and anomaly detection methods (Z-score, threshold rules, control charts) on forecasts.

- **Remaining Useful Life (RUL) Estimation:**
  Combine historical degradation data with forecasting trends to estimate RUL. Use models like survival analysis, regression, or deep learning (e.g., DeepAR) for prognostics.
- **Dashboard & Alert System:**
  Build a live dashboard for real-time monitoring of health indicators and forecast trends. Integrate threshold-based alarms and maintenance recommendations based on predicted failures.

Technologies & Tools

- **AI & Forecasting Frameworks:** Scikit-learn, PyTorch, TensorFlow (for RUL and ML models)
- **Data Acquisition & Handling:** Pandas, NumPy, SQL for data processing and time-series storage
- **Sensors & Edge Devices:** Pressure transducers, accelerometers, oil condition sensors, temperature probes
- **Visualization & Alerting Tools:** Grafana, Dash, Streamlit for real-time dashboards
- **Programming Languages:** Python (main ML, data processing), JavaScript / HTML

MAJORS & AREAS OF INTEREST

This project brings together mechanical systems understanding, data science, AI, and control engineering, supporting intelligent maintenance practices under Industry 4.0 frameworks.

- **Sensor Data Collection and Logging** – Monitoring key parameters such as pressure, temperature, flow rate, and fluid contamination in hydraulic circuits.
- **Time-Series Preprocessing Techniques** – Handling missing values, noise filtering, resampling, and normalization for reliable model input**.**
- **Statistical and Deep Learning Forecasting Models** – Applying ARIMA, LSTM, GRU, and Prophet to predict anomalies and degradation patterns.
- **Multivariate Time-Series Analysis** – Correlating multiple signals for accurate failure prediction and condition assessment**.**

- **Early Fault Detection and Remaining Useful Life (RUL) Estimation** – Forecasting component wear-out (e.g., valves, pumps, filters) to schedule proactive maintenance.
- **Edge-AI for Onboard Diagnostics** – Deploying lightweight forecasting models on embedded controllers for real-time prediction**.**
- **Explainable AI for Maintenance Decisions** – Interpreting model forecasts using SHAP or attention mechanisms to support human decision-making.
- **Anomaly Detection and Alerting** – Identifying deviations from normal operational baselines using residual analysis and thresholding**.**
- **Integration with CMMS & SCADA Systems** – Linking AI forecasts with maintenance management systems for automatic scheduling and reporting.
- **Reduction in Downtime and Maintenance Costs** – Enhancing hydraulic system availability and reliability through predictive insights

MENTOR CONTACT INFORMATION
Dr. C Labesh Kumar
Email: c.labeshkumar@iare.ac.in