IARE
INSTITUTE OF
AERONAUTICAL ENGINEERING

HIGH IMPACT PRACTICES (HIPS)
CORNERSTONE PROJECTS: INDUSTRIAL ENGINEERING
INFORMATION PACKET

2025 - 2026

INSTITUTE OF AERONAUTICAL ENGINEERING

25 YEARS 2000 2025

I appreciate IARE students who are showing interest in **AI-Driven Industrial Engineering Innovation (AI-DIEI)** 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

We extend our appreciation to the students at IARE who are actively participating in the **AI-Driven Industrial Engineering Innovation (AI-DIEI)** Project Program. This initiative brings together undergraduate students, research scholars, and faculty members to form interdisciplinary research teams that address key challenges in modern industrial engineering using Artificial Intelligence and Machine Learning.

The AI-EIE program is designed to revolutionize traditional industrial engineering practices by integrating intelligent algorithms and data-driven methods into systems optimization, operations research, logistics, quality control, and sustainable manufacturing. It aims to bridge theoretical knowledge with practical applications, enabling agile, smart, and efficient industrial operations.

Core Goals of AI-Driven Industrial Engineering Innovation (AI-DIEI) Project Program:

- **Integrate AI into Core Industrial Engineering Practices**
  Embed AI and machine learning techniques into traditional industrial domains such as operations research, manufacturing systems, logistics, quality control, and supply chain management.
- **Foster Undergraduate Research Culture**
  Promote hands-on, interdisciplinary research experiences for students, enabling them to apply AI in solving complex industrial engineering problems through data-driven experimentation.
- **Encourage Innovation in Smart Manufacturing**
  Drive innovation in production and operations through AI-powered solutions such as predictive analytics, intelligent automation, digital twins, and cyber-physical systems.
- **Bridge Academia and Industry**
  Establish strong linkages with industrial partners to provide students exposure to real-world challenges, tools, and workflows involving AI in industrial settings.
- **Promote Sustainable and Lean Industrial Practices**
  Use AI for optimizing energy, material, and time efficiency, aligning with lean manufacturing principles and global sustainability standards.
- **Enable Intelligent Decision-Making**
  Develop AI-powered decision support systems to improve planning, scheduling, risk management, and resource allocation in industrial systems.
- **Empower Human-Centered Industrial Design**
  Design systems that incorporate AI while considering ergonomics, worker safety, and ethical implications, fostering inclusive and responsible industrial engineering.
- **Enhance Career Readiness and Global Competence**

Prepare students for careers in Industry 4.0 and 5.0 environments, equipping them with skills in AI technologies, smart systems integration, and collaborative international project work.

- **Support Community-Centric Engineering Solutions**
  Encourage students to develop low-cost, scalable AI-based industrial solutions for local businesses, MSMEs, and public sector services.

The research theme of this AI based AI-DIEI projects also 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 #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-DIEI** Projects, and selected students should find the research gap and frame the problem statements from any one of the themes below.

1. AI-Driven Process Optimization in Manufacturing Systems ***(SDG #8, SDG #9, SDG #12)***
2. Intelligent Inventory Management and Forecasting **Systems** ***(SDG #8, SDG #9, SDG #12)***
3. Digital Twins for Industrial System Monitoring and Control ***(SDG #12, SDG #13)***
4. AI-Based Quality Control using Computer Vision ***(SDG #8, SDG #9, SDG #12)***
5. Smart Supply Chain Optimization using AI and IoT Integration ***(SDG #9, SDG #11)***
6. AI for Lean Waste Detection and Elimination in Production Lines ***(SDG #8, SDG #9, SDG #12)***
7. Energy-Efficient Plant Operations using AI-Based Control Systems ***(SDG #9, SDG #13)***
8. AI-Driven Simulation for Complex Industrial Systems ***(SDG #9, SDG #12)***
9. Sustainable Packaging and Logistics Optimization using AI Models ***(SDG #9, SDG #12, SDG #13)***
10. AI in Safety and Risk Assessment for Industrial Workspaces ***(SDG #4, SDG #9)***

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

AI-Driven Process Optimization in Manufacturing Systems

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

GOALS

This project focuses on leveraging Artificial Intelligence (AI) and Machine Learning (ML) to optimize critical manufacturing processes, improve operational efficiency, and enable data-driven decision-making. Traditional process optimization in manufacturing often depends on manual analysis, trial-and-error methods, or static models that cannot adapt to real-time changes on the shop floor. AI-Driven Process Optimization leverages machine learning, deep learning, and real-time data analytics to make manufacturing systems more intelligent, adaptive, and efficient. By continuously learning from process data and responding dynamically to changing conditions, AI enables predictive decision-making and real-time optimization that significantly improves throughput, reduces waste, and enhances product quality.

The primary objective of this project is to build an intelligent process optimization framework that continuously learns from operational data to enhance productivity, minimize waste, reduce cycle times, and improve quality. The framework will integrate predictive analytics, reinforcement learning, and digital twin simulations to adaptively control processes in dynamic manufacturing environments.

Key Goals:

- Optimize manufacturing workflows using predictive and prescriptive analytics.
- Improve production efficiency by minimizing downtime, bottlenecks, and cycle time.
- Use AI to enhance decision-making in scheduling, dispatching, and resource planning.
- Implement real-time monitoring and anomaly detection to ensure process stability and quality.
- Enable adaptive control systems that learn and evolve with process data.
- Support sustainable manufacturing by minimizing energy usage, material waste, and rework.

METHODS & TECHNOLOGIES

This project employs a data-centric approach, integrating AI/ML algorithms with digital manufacturing environments. It involves historical and real-time data collection, data preprocessing, model training, deployment, and feedback loop integration.

Methods (Process & Approach):

- **Data Collection & Preprocessing**
  Collect historical and real-time data from sensors, SCADA systems, MES, and ERP platforms. Clean, normalize, and structure data for machine learning pipelines.
- **Process Modelling & Learning**
  Use supervised learning for quality prediction, time-series models for demand forecasting, and unsupervised learning for anomaly detection. Employ reinforcement learning for real-time adaptive decision-making in dynamic production systems.
- **Optimization & Simulation**
  Integrate AI models with discrete event simulation (DES) and digital twin platforms. Apply optimization algorithms (e.g., genetic algorithms, swarm intelligence) for scheduling and workflow improvement.
- **Deployment & Integration**
  Integrate AI models into existing manufacturing execution systems (MES) or control platforms. Use dashboards and visual interfaces for human-in-the-loop decision support.

- **Feedback & Continuous Improvement**
  Monitor KPIs (key performance indicators) such as cycle time, OEE, defect rate, and energy consumption. Continuously retrain models with new data for performance improvement.

Technologies Used:

- **AI/ML Frameworks:** Scikit-learn, TensorFlow, PyTorch, XGBoost
- **Data Platforms:** SQL/NoSQL Databases, Apache Kafka, OPC-UA
- **Simulation Tools:** AnyLogic, FlexSim, Plant Simulation, Simio
- **Manufacturing Systems Integration:** MES, PLCs, IoT Gateways
- **Programming Languages:** Python, R, MATLAB, JavaScript (for dashboards)

MAJORS & AREAS OF INTEREST

This project is suited for students from Mechanical Engineering, Industrial Engineering, Computer Science, Electrical Engineering, and Data Science who are interested in smart manufacturing, real-time optimization, and AI-driven process **control**. Key focus areas include:

- **Predictive & Prescriptive Analytics for Manufacturing** – Using machine learning models to forecast equipment performance, production demand, and process deviations for proactive optimization.
- **Reinforcement Learning for Process Control** – Applying RL algorithms to dynamically adjust process parameters (e.g., temperature, pressure, speed) for optimal efficiency.
- **Digital Twin & Real-Time Simulation** – Developing AI-enhanced digital replicas of manufacturing systems for virtual testing and adaptive optimization.
- **Anomaly Detection & Fault Diagnosis** – Leveraging deep learning models for real-time detection of bottlenecks, equipment failures, and quality issues.
- **AI-Enhanced Scheduling & Resource Planning** – Optimizing job sequencing, dispatching, and workforce allocation using predictive and prescriptive AI models.
- **Energy & Resource Efficiency** – Using AI to minimize energy consumption, raw material usage, and production waste to support sustainable manufacturing.
- **IoT & Edge AI for Smart Factories** – Integrating AI models with IoT sensor networks and edge devices for real-time process monitoring and control.
- **Data Engineering for Manufacturing Analytics** – Building ETL pipelines, sensor data fusion, and high-quality datasets for training and deploying AI models.
- **Adaptive Quality Control Systems** – Applying AI to detect and correct quality deviations during production to reduce rework and improve yield.
- **Human-in-the-Loop AI Systems** – Designing AI tools that complement human expertise, enabling collaborative and transparent process optimization.

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Intelligent Inventory Management and Forecasting Systems

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

GOAL

This project aims to develop an AI-powered inventory management and forecasting system that transforms how industries plan, stock, and replenish inventory. Traditional inventory systems often rely on static models and historical averages, which are inadequate in handling modern challenges like demand volatility, lead time variability, and supply chain disruptions.

Using machine learning, time-series analysis, and reinforcement learning, this project builds intelligent systems that can predict inventory needs, optimize reorder points, and adapt dynamically to changes in customer demand and supplier behavior. These systems reduce stockouts, minimize excess inventory, and improve supply chain resilience and cost-efficiency.

Key Goals:

- Predict inventory demand accurately using AI and data-driven forecasting models.
- Minimize stockouts and excess inventory through smart reorder policies.
- Enable real-time visibility and decision support across the supply chain.
- Use reinforcement learning and optimization to create adaptive inventory control strategies.
- Enhance sustainability by reducing waste, overproduction, and storage costs.

METHODS & TECHNOLOGIES

Methods (Process & Approach):

This project combines data analytics, machine learning, and systems integration to create a complete forecasting and inventory control solution.

Methods (Process & Approach):

- **Data Collection & Preprocessing**
  Gather historical sales data, lead times, supplier performance metrics, and seasonality factors. Clean, structure, and analyze data for insights and feature selection.
- **Demand Forecasting Models**
  Apply time-series models (ARIMA, Prophet, LSTM) for short- and long-term forecasting. Use ensemble models and hybrid approaches for greater accuracy.
- **Inventory Optimization**
  Use EOQ (Economic Order Quantity), ABC analysis, and service level targets. Implement AI-based optimization techniques (genetic algorithms, particle swarm optimization) to determine optimal reorder levels and quantities.
- **Reinforcement Learning for Adaptive Policies**
  Develop agents that learn optimal inventory decisions under uncertainty. Use Q-learning or deep reinforcement learning for dynamic policy generation.
- **System Integration & Real-Time Monitoring**
  Integrate AI models into ERP and inventory management systems. Use dashboards for KPI tracking (e.g., fill rate, inventory turnover, carrying cost).

Technologies Used:

- **AI/ML Frameworks:** TensorFlow, PyTorch, Scikit-learn
- **Time-Series Libraries:** statsmodels, Darts, GluonTS
- **Optimization Tools:** Gurobi, DEAP, OR-Tools
- **Programming Languages:** Python, R, SQL

MAJORS & AREAS OF INTEREST

This project is ideal for students from Mechanical Engineering, Industrial Engineering, Computer Science, Data Science, and Operations Research who are interested in AI-powered supply chain optimization, predictive modeling, and smart inventory control. Key focus areas include:

- **AI & Machine Learning for Inventory Forecasting** – Using advanced ML models (e.g., ARIMA, LSTM, Prophet) to predict demand trends and optimize stock levels.
- **Reinforcement Learning for Inventory Control** – Developing adaptive reorder policies that dynamically respond to demand fluctuations, supplier delays, and lead times.
- **Data-Driven Demand Forecasting** – Leveraging historical sales, seasonality, and external factors (e.g., market trends, weather) for accurate predictions.
- **Optimization Algorithms for Stock Management** – Using AI to determine optimal reorder points, lot sizes, and safety stock levels.
- **Real-Time Inventory Visibility** – Integrating IoT sensors, RFID, and real-time analytics to track inventory health across warehouses and supply chains.
- **Supply Chain Resilience & Risk Management** – Applying predictive analytics to anticipate disruptions (e.g., delays, shortages) and maintain operational continuity.
- **Sustainability in Inventory Systems** – Reducing overproduction, storage costs, and wastage through AI-optimized inventory planning.
- **Integration with ERP & MES Systems** – Creating AI modules that enhance existing enterprise systems for smarter inventory decisions.
- **Simulation & Digital Twins of Supply Chains** – Developing virtual models of inventory systems to test various demand and supply scenarios.
- **Dashboard & Decision Support Tools** – Designing user-friendly AI-driven interfaces for inventory planners, managers, and supply chain operators.

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Digital Twins for Industrial System Monitoring and Control

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

GOAL

This project focuses on the development and deployment of Digital Twin technology integrated with AI to enhance real-time monitoring, control, and predictive analysis in industrial systems. A Digital Twin is a dynamic, virtual replica of a physical system that continuously updates using real-time data and simulates behavior, performance, and potential failures.

By leveraging IoT, AI/ML, and simulation modeling, this project aims to create intelligent digital replicas of machines, production lines, and industrial environments. These twins enable real-time diagnostics, predictive maintenance, process optimization, and decision support, thereby increasing operational efficiency, reliability, and sustainability.

Key Goals:

- Develop real-time digital replicas of industrial systems for monitoring and control.
- Enable predictive maintenance and fault detection using AI-based insights.
- Optimize operational efficiency through virtual experimentation and control strategies.
- Provide a decision support platform for operators and engineers via simulation and data analytics.
- Reduce downtime, energy consumption, and material wastage through real-time interventions.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

This project integrates physical sensor data with virtual models using cyber-physical systems and cloud-based AI frameworks. It emphasizes the closed-loop interaction between physical and digital environments.

Methods (Process & Approach):

- **System Modeling & Data Integration**
  Create 3D and physics-based models of industrial assets. Integrate sensor data using IoT protocols (MQTT, OPC-UA) to enable live updates.
- **Real-Time Data Acquisition**
  Use PLCs, edge devices, and IoT platforms to collect data on temperature, pressure, vibration, flow, etc. Store and stream data securely to cloud or local servers for processing.
- **AI-Enhanced Predictive Analytics**
  Train ML models (e.g., regression, neural networks) to predict equipment health and performance. Use anomaly detection models for early fault warnings.
- **Simulation & Control Feedback Loop**
  Use digital twin simulations to test process changes or control strategies. Implement feedback loops where the digital twin adjusts control parameters in the physical system based on AI insights.

- **Visualization & User Interface**
  Develop interactive dashboards and 3D environments for real-time monitoring. Allow operators to test "what-if" scenarios virtually before implementation.

Technologies Used

- **AI/ML Frameworks:** TensorFlow, Scikit-learn, PyCaret
- **Simulation Tools:** AnyLogic, MATLAB Simulink
- **IoT Platforms:** AWS IoT, Azure
- **Programming Languages:** Python, C++, JavaScript

MAJORS & AREAS OF INTEREST

This project is ideal for real-time system modeling, AI-driven monitoring, and digital twin applications in smart manufacturing. Key focus areas include:

- **Digital Twin Development & System Modeling** – Creating virtual replicas of machines, production lines, or entire industrial systems with real-time synchronization.
- **AI for Predictive Maintenance** – Using machine learning and deep learning models to forecast equipment failures, detect anomalies, and reduce downtime.
- **IoT Integration & Data Acquisition** – Connecting sensors, PLCs, and SCADA systems to gather real-time data for twin updates and process monitoring.
- **Process Optimization & Virtual Experimentation** – Simulating and testing control strategies in the twin environment before applying them to the physical system.
- **Real-Time Monitoring & Visualization** – Developing dashboards and visualization tools to display system health, performance KPIs, and predictive analytics.
- **Simulation-Driven Decision Support** – Using AI-enhanced simulations to provide actionable insights for operators and engineers.
- **Industrial Control & Automation** – Integrating digital twins with control systems (e.g., MES, PLCs) for adaptive and autonomous operations.
- **Energy & Resource Efficiency** – Applying digital twin insights to optimize energy consumption, material flow, and process sustainability.

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AI-Based Quality Control using Computer Vision

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

GOAL

This project aims to develop an intelligent AI-based quality control system that leverages computer vision to inspect, detect, and classify manufacturing defects in real time. Traditional manual inspection methods are prone to human error, are time-consuming, and often fail to maintain consistent quality across high-volume production.

By using deep learning models and image processing algorithms, this project seeks to automate visual inspection processes to ensure high product quality, reduce waste, and increase manufacturing efficiency. It is applicable to various sectors including automotive, electronics, textile, food processing, and precision manufacturing.

Key Goals:

- Automate defect detection and classification using image-based AI models.
- Improve consistency and accuracy of quality inspection processes.
- Enable real-time quality control with edge deployment on the shop floor.
- Reduce dependence on manual inspection, minimizing human fatigue and subjectivity.
- Support zero-defect manufacturing through early fault identification and process feedback.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

This project follows a vision-based AI pipeline that combines hardware (cameras, lighting, edge devices) with software (machine learning, computer vision, and integration with manufacturing systems).

Methods (Process & Approach):

- **Data Acquisition & Annotation**
  Capture images or video of products on the production line using high-resolution cameras. Label datasets for training AI models with various defect types (scratches, cracks, misalignments, discoloration, etc.).
- **Image Preprocessing**
  Apply filters, edge detection, normalization, and ROI extraction to prepare input for training.
- **Model Development**
  Train Convolutional Neural Networks (CNNs) or YOLO/SSD/Mask R-CNN models for real-time defect classification and localization. Use traditional techniques (HOG, SIFT) in hybrid systems for simpler features.
- **Model Deployment**
  Deploy trained models on edge devices or cloud-connected systems for real-time inference. Integrate with PLCs or MES for triggering alarms or diverting defective products.
- **Monitoring, Feedback & Retraining**

Continuously monitor model performance, collect false positives/negatives. Use retraining pipelines to adapt models to new defect types or changing visual conditions.

Technologies Used

- **Computer Vision Libraries:** OpenCV, scikit-image
- **Deep Learning Frameworks:** TensorFlow, Keras, PyTorch
- **Model Architectures:** CNN, ResNet,
- **Visualization Tools:** Streamlit, Dash, Grafana
- **Programming Languages:** Python, C++,
- **Industrial Integration:** SCADA, MES platforms

MAJORS & AREAS OF INTEREST

This project is ideal for AI-driven inspection systems, computer vision, and smart manufacturing quality control. Key focus areas include:

- **Computer Vision for Defect Detection** – Applying image processing and deep learning (CNNs, YOLO, Faster R-CNN) to detect and classify surface defects, shape deviations, or assembly errors.
- **Real-Time Quality Control on Edge Devices** – Deploying lightweight AI models on embedded systems (e.g., NVIDIA Jetson, Raspberry Pi) for on-site inspections.
- **Image Preprocessing & Feature Extraction** – Using algorithms for noise reduction, edge detection, and texture analysis to enhance defect visibility.
- **AI for Zero-Defect Manufacturing** – Leveraging predictive and prescriptive analytics to identify root causes of defects and prevent recurrence.
- **Integration with Manufacturing Lines** – Designing automated inspection pipelines that integrate with robotic arms, conveyor systems, or PLC-controlled environments.
- **Data Augmentation & Synthetic Image Generation** – Using generative models (e.g., GANs) to create diverse training datasets for rare defect scenarios.
- **Industrial Applications of Vision-Based AI** – Adapting the system for various industries like automotive paint inspection, PCB solder quality, textile weaving patterns, or food contamination detection.
- **Real-Time Feedback & Process Optimization** – Providing actionable feedback to adjust machine parameters and eliminate defects early in the production cycle.
- **Explainable AI in Quality Inspection** – Using interpretable models and visualizations (Grad-CAM, SHAP) to explain AI-based defect classifications.
- **Dashboard & Analytics for Quality Monitoring** – Building interfaces that display defect statistics, quality KPIs, and historical trends for continuous improvement.

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Smart Supply Chain Optimization using AI and IoT Integration

Dr. V Mahider Reddy, Assistant Professor, Dept. of ME - Faculty Mentor

GOAL

This project aims to develop an intelligent and responsive Smart Supply Chain Management (SCM) system by integrating Artificial Intelligence (AI) with Internet of Things (IoT) technologies. Traditional supply chains often suffer from inefficiencies such as demand uncertainty, poor visibility, delayed logistics, and siloed data systems.

By combining real-time IoT data (e.g., from RFID, GPS, sensors) with AI-powered analytics (e.g., machine learning, optimization, and forecasting models), the project seeks to create data-driven, automated, and resilient supply chain systems that are agile, efficient, and adaptive to disruptions.

Key Goals:

- **Improve supply chain visibility** through real-time IoT data streams from inventory, transportation, and warehousing systems.
- **Optimize logistics and operations** using AI-driven routing, scheduling, and inventory control models.
- **Enhance demand forecasting and procurement planning** with predictive analytics.
- **Enable end-to-end traceability and transparency** across the supply chain.
- **Reduce operational costs, delays, and carbon footprint** through intelligent automation and resource optimization.
- **Increase responsiveness and resilience** to supply chain disruptions (e.g., raw material shortages, transport delays).

METHODS & TECHNOLOGIES

Methods (Process & Approach)

This project integrates IoT infrastructure for real-time data collection and AI models for intelligent decision-making across the supply chain network.

Methods (Process & Approach):

- **IoT Data Acquisition & Connectivity**
  Use sensors, RFID tags, GPS modules, and barcode scanners to track goods, monitor storage conditions, and detect delays or anomalies. Connect data sources using IoT protocols (MQTT, CoAP, OPC-UA) to cloud platforms.
- **Data Processing & Integration**
  Aggregate real-time and historical data from ERP, WMS, TMS, and CRM systems. Preprocess and normalize data for AI model input.
- **AI-Powered Forecasting & Optimization**
  Use time-series forecasting models (LSTM, Prophet) for demand prediction. Apply optimization algorithms (genetic algorithms, linear programming, ant colony optimization)

for routing, inventory levels, and delivery schedules. Use reinforcement learning for adaptive policy generation in dynamic supply networks.

- **Digital Twin & Simulation for Decision Support**
  Develop digital twins of supply chains for scenario analysis and proactive planning. Simulate disruption impacts and test mitigation strategies virtually.
- **Monitoring, Dashboards, and Alerts**
  Build dashboards to track KPIs like order fill rate, lead time, inventory turnover, and shipment status. Implement real-time alert systems for deviation detection and decision support.

Technologies Used

- **AI/ML Frameworks:** TensorFlow, PyTorch, Scikit-learn, Prophet, XGBoost
- **IoT Platforms & Protocols:** AWS IoT Core, Azure IoT Hub, ThingsBoard,
- **Simulation Tools:** AnyLogic, Simio, NetLogo
- **Programming Languages:** Python, JavaScript,
- **Visualization & Dashboards:** Grafana, Power BI, Streamlit, Dash

MAJORS & AREAS OF INTEREST

This project is ideal for AI-powered logistics, IoT-enabled supply chain visibility, and real-time operational optimization. Key focus areas include:

- **AI-Powered Supply Chain Forecasting** – Using machine learning and time-series models (ARIMA, LSTM) for demand prediction, procurement planning, and supplier risk analysis.
- **IoT Integration & Real-Time Data Collection** – Leveraging IoT devices such as RFID tags, GPS trackers, and warehouse sensors for end-to-end visibility of goods and resources.
- **AI-Driven Logistics & Route Optimization** – Applying reinforcement learning and optimization algorithms to minimize transportation costs, delivery times, and fuel consumption.
- **End-to-End Supply Chain Transparency** – Developing traceability systems to monitor goods from production to delivery using blockchain or distributed ledger technologies (DLT).
- **Inventory & Warehouse Optimization** – Integrating AI with real-time inventory data for efficient storage, replenishment, and order fulfillment.
- **Supply Chain Risk & Disruption Management** – Predicting and mitigating delays, shortages, and disruptions through AI-driven risk models.
- **Sustainable & Green Supply Chains** – Optimizing transportation, energy usage, and logistics to reduce carbon footprint and environmental impact.
- **Digital Twins for Supply Chain Simulation** – Building virtual models of supply chains for scenario analysis, "what-if" simulations, and resilience testing.

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AI for Lean Waste Detection and Elimination in Production Lines

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

GOAL

This project focuses on the integration of Artificial Intelligence (AI) with Lean Manufacturing Principles to detect, quantify, and eliminate the Seven Wastes (Muda) in production lines—namely overproduction, waiting, transport, overprocessing, inventory, motion, and defects.

Conventional lean tools rely heavily on manual observation and retrospective data analysis, which may be slow and subjective. This project aims to build AI-powered systems that leverage sensor data, video analytics, and production metrics to automatically identify inefficiencies in real-time, allowing for proactive intervention, continuous improvement, and enhanced process efficiency.

Key Goals:

- Detect and categorize waste types using AI algorithms and real-time data analytics.
- Quantify losses and inefficiencies in terms of time, material, energy, and motion.
- Enhance productivity and throughput by recommending corrective actions based on root cause analysis.
- Support continuous improvement (Kaizen) with automated feedback loops and lean dashboards.
- Improve sustainability by minimizing resource waste and maximizing value-added activities.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

This project combines video/image processing, IoT sensors, process mining, and AI/ML models to detect and eliminate non-value-adding activities across the shop floor.

- **Data Acquisition and Digital Observation**
  Use **IoT sensors**, **CCTV cameras**, and **PLC logs** to monitor production activities in real time. Capture data on cycle time, idle time, WIP movement, and operator behavior.
- **AI-Based Waste Detection Models**
  Apply **computer vision** to detect motion waste, waiting periods, bottlenecks, and defects. Use **unsupervised learning** (e.g., clustering) to identify abnormal patterns. Apply **process mining** to analyze workflow deviations and detect redundant steps.
- **Root Cause Analysis and Classification**
  Use **decision trees** and **classification models** to identify causes of waste. Perform **correlation analysis** between process KPIs and operational variables.
- **Action Recommendation and Visualization**
  Generate lean recommendations such as layout redesign, takt time adjustment, or operator reallocation. Provide **real-time dashboards** and **alerts** to operators and process engineers.
- **Kaizen Loop and Continuous Learning**
  Continuously retrain AI models with new data for adaptive improvement. Enable shop-floor personnel to annotate and validate AI findings for system refinement. Assess accuracy, time savings, and mesh quality using standard benchmarks.

- **Integration with CAE Tools:**
  Interface the AI module with commercial or open-source FEM solvers (e.g., ANSYS, Abaqus, FEniCS). Automate the end-to-end pipeline from pre-processing to result visualization.

Technologies Used

- **I/ML Frameworks:** PyTorch, TensorFlow, Scikit-learn
- **IoT & Data Collection:** Arduino, Raspberry Pi, OPC-UA, MQTT
- **Simulation & Analytics:** SimPy, AnyLogic, Excel VBA
- **Programming Languages:** Python, MATLAB, C++

MAJORS & AREAS OF INTEREST

This project is ideal for AI-enhanced lean manufacturing, process optimization, and real-time waste detection. Key focus areas include:

- **AI for Lean Manufacturing** – Leveraging machine learning, video analytics, and sensor data to detect and eliminate the seven wastes (Muda) in production lines.
- **Computer Vision for Process Monitoring** – Using deep learning models (e.g., YOLO, Faster R-CNN) to track operator movements, material flow, and equipment utilization to identify inefficiencies.
- **Real-Time Waste Quantification** – Applying data analytics to measure time, energy, and material losses in the production process.
- **Root Cause Analysis with AI** – Utilizing predictive models and anomaly detection techniques to determine the sources of waste and inefficiencies.
- **Kaizen & Continuous Improvement Automation** – Developing AI-powered dashboards to monitor lean KPIs and provide actionable recommendations for improvement.
- **Digital Twin of Production Lines** – Simulating production workflows to evaluate the impact of proposed improvements before implementation.
- **Predictive Maintenance & Downtime Reduction** – Identifying and addressing equipment-related waste (waiting and motion) through AI-driven maintenance strategies.
- **Sustainable Manufacturing Practices** – Minimizing energy consumption, material waste, and overproduction using AI-optimized lean frameworks.
- **Integration with MES & ERP Systems** – Enhancing existing manufacturing systems with AI-based lean waste detection modules.

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Energy-Efficient Plant Operations using AI-Based Control Systems

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

GOAL

This project aims to optimize energy consumption across industrial plants by deploying AI-based control systems for dynamic monitoring, prediction, and regulation of energy-intensive operations. In traditional manufacturing environments, energy optimization often relies on static control logic and delayed human intervention, which can lead to significant inefficiencies and carbon emissions.

By integrating machine learning, control theory, and real-time plant data, this project focuses on enabling self-optimizing energy management systems that reduce power usage while maintaining productivity, quality, and operational stability. These systems adapt continuously to fluctuations in production demand, environmental conditions, and equipment behavior.

Key Goals:

- Reduce energy consumption in industrial operations through intelligent, adaptive control.
- Predict and mitigate energy spikes and inefficiencies in real time.
- Enhance process efficiency by tuning control parameters based on predictive models.
- Enable energy-aware decision-making at both machine and system levels.
- Align operations with sustainable manufacturing goals by reducing carbon footprint and improving energy intensity metrics.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

The project implements **AI-based predictive and prescriptive control frameworks** to regulate HVAC systems, pumps, compressors, lighting, and other energy-intensive components in industrial settings.

- **Energy Data Acquisition & Preprocessing**
  Collect historical and real-time energy usage data from smart meters, SCADA systems, and IoT sensors. Clean, normalize, and segment the data into control-relevant intervals.
- **AI-Powered Energy Modeling**
  Use regression, neural networks, and time-series models (e.g., LSTM) to forecast short-term energy demand. Train classification models to identify anomalous or wasteful energy patterns.
- **Smart Control System Design**
  Apply **Model Predictive Control (MPC)** enhanced with AI for optimal scheduling and load balancing. Use reinforcement learning agents to learn optimal control strategies over time.
- **System Integration and Automation**
  Interface with programmable logic controllers (PLCs), variable frequency drives (VFDs), and plant automation systems. Implement feedback mechanisms to continuously adapt setpoints and schedules.
- **Monitoring, Visualization, and Optimization**
  Develop energy dashboards and alerts using real-time visualization tools. Enable operators to simulate “what-if” energy scenarios using AI-powered decision support. Develop mobile apps or dashboards for clinicians to adjust fit/functionality post-delivery.

Technologies Used

- **AI/ML Frameworks:** TensorFlow, PyTorch, Scikit-learn
- **Time Series & Forecasting:** Prophet, ARIMA, LSTM Networks
- **Control Systems:** Model Predictive Control (MPC), Reinforcement Learning,
- **Simulation & Modeling:** MATLAB/Simulink
- **Programming Languages:** Python, C++, MATLAB

MAJORS & AREAS OF INTEREST

This project is ideal for students from Mechanical Engineering, Industrial Engineering, Electrical Engineering, Computer Science, and Energy Engineering who are interested in AI-powered energy optimization, control systems, and sustainable manufacturing practices. Key focus areas include:

- **AI for Energy Optimization** – Using machine learning and deep reinforcement learning to optimize energy usage across industrial processes and equipment.
- **Predictive Energy Analytics** – Forecasting energy spikes, inefficiencies, and load demands using AI-based predictive models.
- **Adaptive Control Systems** – Designing self-learning control systems that automatically tune parameters to minimize energy consumption without sacrificing performance.
- **Real-Time Monitoring & IoT Integration** – Leveraging IoT sensors, smart meters, and SCADA systems for dynamic energy data acquisition and analysis.
- **Process Efficiency Enhancement** – Applying AI-driven control logic to reduce downtime, idle energy consumption, and process bottlenecks.
- **Digital Twins for Energy Management** – Simulating plant operations to test and validate energy-saving strategies in a virtual environment.
- **Sustainable Manufacturing Practices** – Reducing carbon footprint and optimizing energy intensity metrics to align with global sustainability standards.
- **Integration with Industrial Automation Systems** – Enhancing existing PLCs, DCS, and MES systems with AI-based energy control modules.
- **Data Engineering & ETL for Energy Data** – Developing pipelines to preprocess and analyze real-time energy consumption data for actionable insights.

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AI-Driven Simulation for Complex Industrial Systems

Dr. G Sarat Raju, Assistant Professor, Dept. of ME - Faculty Mentor

GOALS

This project aims to transform how complex industrial systems are modeled, simulated, and optimized by integrating Artificial Intelligence with traditional simulation techniques. In industries such as manufacturing, logistics, energy, and process engineering, simulation models are essential for predicting system performance, identifying bottlenecks, and evaluating decision alternatives. However, building accurate models of large-scale systems with dynamic interactions is time-consuming and often requires domain expertise.

AI-driven simulation addresses these challenges by enabling data-driven model generation, real-time scenario analysis, and adaptive learning from operational data. This project seeks to build hybrid simulation platforms that combine discrete-event, agent-based, and system dynamics modeling with AI tools to provide fast, scalable, and interpretable simulations.

Key Goals:

- Develop intelligent simulators that can learn from real-world data and adapt to system changes.
- Enable real-time predictive simulation for decision-making in complex environments.
- Reduce the time and effort required for simulation model creation and validation.
- Incorporate AI-based optimization for scenario planning and system tuning.
- Support strategic planning and operational control across manufacturing and logistics domains.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

This project uses AI-enhanced simulation models built through a combination of historical data analysis, automated system identification, and hybrid simulation approaches. It integrates machine learning to create surrogate models that approximate high-fidelity simulations in real time.

- **System Modeling & Data Collection**
  Identify system components (machines, processes, agents, queues, resources). Collect operational data through IoT, ERP, MES, and SCADA systems.
- **AI-Based System Identification**
  Use clustering and classification to segment operational modes. Apply neural networks or symbolic regression to approximate system dynamics.
- **Simulation Development**
  Build base models using discrete-event simulation (DES), agent-based simulation (ABS), or system dynamics (SD). Integrate AI models for intelligent agents or decision nodes.
- **Scenario Generation & Optimization**
  Simulate different configurations, policies, or events (e.g., demand surges, machine failures). Use reinforcement learning or genetic algorithms to optimize system parameters.

- **Validation, Visualization & Decision Support**
  Compare simulation outcomes with actual performance metrics. Provide dashboards for interactive scenario testing and strategic planning.

Technologies & Tools

- **Simulation Tools:** MATLAB/Simulink
- **AI Frameworks:** PyTorch, TensorFlow, Scikit-learn
- **Optimization Engines:** Simulated Annealing, Genetic Algorithms
- **Visualization:** Streamlit, Dash, 3D simulation viewers
- **Programming Languages:** Python, Java, MATLAB, C++

MAJORS & AREAS OF INTEREST

This project is ideal for AI-driven modeling, hybrid simulation techniques, and optimization of large-scale industrial processes. Key focus areas include:

- **AI-Enhanced Simulation Modeling** – Using machine learning and deep learning to create data-driven simulation models that complement traditional approaches (discrete-event, agent-based, and system dynamics).
- **Predictive Simulation for Real-Time Decision-Making** – Leveraging AI algorithms to run "what-if" scenarios and predict outcomes under changing operational conditions.
- **Hybrid Simulation Platforms** – Integrating multiple modeling paradigms (e.g., discrete-event + AI-based surrogate models) to simulate complex, dynamic systems.
- **Optimization and Scenario Planning** – Applying AI-based optimization techniques (e.g., genetic algorithms, reinforcement learning) to identify best-case operational strategies.
- **Digital Twin Integration** – Using real-world operational data to create intelligent virtual representations of industrial systems.
- **System Bottleneck Analysis** – Automating detection of inefficiencies and constraints within complex workflows using AI-based analytics.
- **Scalable Simulation Frameworks** – Developing cloud-based or distributed simulation solutions for large-scale industrial environments.
- **Explainable AI in Simulation** – Ensuring transparency in AI-generated simulation outputs to enhance trust and usability for engineers and managers.
- **Applications in Manufacturing and Logistics** – Simulating factory layouts, supply chain networks, transportation systems, and energy systems with AI-driven intelligence.
- **Visualization and Decision Support** – Designing interactive dashboards and simulation interfaces for monitoring KPIs and analyzing outcomes in real time.

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Sustainable Packaging and Logistics Optimization using AI Models

Dr. V Mahider Reddy, Assistant Professor, Dept. of ME - Faculty Mentor

GOALS

This project aims to advance the sustainability and efficiency of packaging and logistics systems by leveraging artificial intelligence (AI) models for intelligent decision-making. Traditional logistics and packaging workflows often lead to excessive material usage, increased carbon emissions, and suboptimal load configurations. Through AI-based optimization, this project targets reduced environmental footprint, improved packaging design, and more efficient transportation routes and warehouse utilization.

By integrating machine learning, operations research, and environmental impact modeling, the project promotes a data-driven, eco-conscious supply chain approach. It enables industries to automate the selection of eco-friendly packaging materials, optimize packaging geometry, reduce empty space in shipments, and minimize energy consumption across the logistics network.

Key Goals:

- Develop AI models for optimizing package design based on volume, weight, cost, and sustainability criteria.
- Improve logistics routing and load planning to reduce fuel usage and CO_2 emissions.
- Enable real-time demand forecasting and inventory alignment for smarter shipping decisions.
- Promote material efficiency through intelligent packaging material selection.
- Support closed-loop logistics and reverse logistics planning for circular supply chains.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

The project follows a layered approach—starting from packaging design, extending to logistics network modeling, and integrating sustainability metrics. It uses AI and ML for prediction, optimization, and simulation of end-to-end packaging and transport systems.

- **Sustainable Packaging Design**
  Use computer vision and ML models to analyze existing package formats. Optimize shape, material, and structural integrity using generative design algorithms.
- **AI-Driven Logistics Optimization**
  Implement AI-based **vehicle routing**, **bin packing**, and **fleet scheduling** algorithms. Integrate route prediction with real-time data (e.g., traffic, weather, delivery time windows).
- **Forecasting & Inventory Synchronization**
  Apply time series and regression models to forecast demand. Align packaging and dispatch schedules with real-time inventory levels.
- **Sustainability Assessment & Optimization**
  Use life cycle assessment (LCA) tools to evaluate packaging and logistics impact. Employ multi-objective optimization to balance cost, carbon emissions, and delivery efficiency.
- **System Integration & Simulation**
  Simulate packaging and shipping scenarios under different constraints and demand patterns. Integrate with ERP and WMS platforms for real-time control.

Technologies & Tools

- **AI/ML Frameworks:** Scikit-learn, TensorFlow, XGBoost, PyTorch
- **Sustainability Tools:** OpenLCA, SimaPro
- **CAD/CAE Tools:** SolidWorks, Autodesk for packaging simulation
- **Logistics & Routing:** ArcGIS, Google Maps API
- **Programming Languages:** Python, R, JavaScript

MAJORS & AREAS OF INTEREST

This project is ideal for sustainable packaging, AI-driven logistics, and eco-friendly supply chain optimization. Key areas include:

- **AI for Sustainable Packaging Design** – Leveraging machine learning and generative design to minimize packaging material usage while ensuring durability and cost efficiency.
- **Logistics Route & Load Optimization** – Applying algorithms (e.g., vehicle routing problem, heuristic optimization, reinforcement learning) to minimize transportation distance, fuel consumption, and emissions.
- **Eco-Friendly Material Selection** – Using AI models to evaluate recyclable and biodegradable packaging materials based on performance and environmental impact.
- **Carbon Footprint Analysis** – Incorporating lifecycle assessment (LCA) techniques to quantify and reduce environmental impact across packaging and logistics operations.
- **Predictive Demand & Inventory Forecasting** – Using AI and time-series models to optimize production and shipment schedules, reducing waste and overstocking.
- **Warehouse Space Utilization** – Designing efficient package stacking and load arrangements to minimize unused space and transportation costs.
- **Reverse & Circular Logistics** – Implementing AI strategies for closed-loop packaging, material recovery, and reuse in supply chain cycles.
- **Operations Research & Optimization Models** – Applying linear programming, metaheuristics, and AI-driven optimization to achieve cost-effective and sustainable logistics operations.
- **IoT-Enabled Smart Logistics** – Integrating IoT sensors (RFID, GPS, temperature sensors) for real-time tracking and condition monitoring of packages.

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AI in Safety and Risk Assessment for Industrial Workspaces

Dr. G Sarat Raju, Assistant Professor - Faculty Mentor

GOALS

This project focuses on utilizing Artificial Intelligence (AI) for proactive safety management and risk assessment in industrial environments such as factories, processing plants, and assembly lines. Conventional safety protocols often rely on manual audits, incident reporting, and reactive measures, which may fail to prevent accidents or adapt to dynamic work conditions.
By integrating computer vision, machine learning, and sensor analytics, this project aims to create an intelligent safety monitoring and predictive risk management system. The system will help identify hazardous behaviors, non-compliance with safety protocols (e.g., PPE usage), equipment malfunctions, and environmental risks in real time—thereby reducing workplace accidents, improving compliance, and ensuring worker well-being.

Key Goals:

- Develop AI systems for real-time detection of safety violations and hazardous events using vision and sensor data.
- Predict potential risks and near-miss incidents through historical data analysis.
- Automate incident reporting and root cause analysis using natural language processing (NLP) and expert systems.
- Ensure compliance with occupational health and safety (OHS) standards via intelligent monitoring.
- Promote a culture of proactive safety using AI-driven alerts, reports, and interventions.

METHODS & TECHNOLOGIES

Methods (Process & Approach)

The project blends data science, vision-based analytics, and industrial safety engineering to design a multi-layered intelligent safety system.

- **Data Collection & Hazard Mapping**
  Use CCTV footage, IoT sensors, and wearable data (smart helmets, safety vests). Tag and classify historical incident reports, near-miss events, and unsafe zones.
- **Computer Vision for Real-Time Detection**
  Use deep learning (CNNs, YOLO, EfficientDet) to detect: PPE compliance (helmets, gloves, goggles), Unsafe postures or hazardous machine proximity, Fire, smoke, leaks, or spills
- **Predictive Risk Modeling**
  Apply ML models to identify patterns leading to frequent safety violations. Use time series models and anomaly detection to forecast potential risks.
- **NLP-Based Incident Analysis**
  Extract insights from textual safety logs, maintenance reports, and audits using NLP. Classify causes of accidents and recommend mitigations.

- **Safety Dashboard & Alert System**
  Build a centralized dashboard for safety status, alerts, and risk heatmaps. Integrate with SMS/email/PA systems for instant warnings and response coordination.

Technologies & Tools

- **AI/ML Frameworks:** TensorFlow, PyTorch, OpenCV, Scikit-learn
- **Computer Vision Tools:** YOLOv8, Detectron2, Mediapipe
- **IoT Platforms:** Arduino, Raspberry Pi, ESP32, AWS IoT Core
- **Programming Languages:** Python, JavaScript, C++

MAJORS & AREAS OF INTEREST

This project is ideal for AI-powered workplace safety, predictive risk assessment, and industrial monitoring systems. Key areas include:

- **Computer Vision for Safety Monitoring** – Developing AI models (e.g., YOLO, Faster R-CNN) to detect unsafe behaviors, PPE compliance, and hazardous conditions.
- **Predictive Risk Analysis** – Using machine learning to identify potential accidents or failures based on historical safety and sensor data.
- **Real-Time Hazard Detection** – Leveraging IoT sensors, thermal cameras, and vision systems to monitor equipment health and environmental risks.
- **Natural Language Processing for Incident Reports** – Automating analysis of safety logs, incident reports, and worker feedback for root cause detection.
- **Expert Systems for OHS Compliance** – Designing AI tools that monitor adherence to occupational health and safety (OHS) regulations and generate automated alerts.
- **Worker Behavior Analytics** – Applying AI-based motion tracking to assess ergonomics, unsafe movements, or fatigue-related risks.
- **Digital Twins for Risk Scenarios** – Simulating hazardous events and safety interventions in a virtual environment for proactive risk mitigation.
- **Anomaly Detection in Equipment & Processes** – Identifying early signs of malfunction or unsafe conditions using AI-driven predictive maintenance.
- **Decision Support Dashboards** – Building interactive dashboards for safety KPIs, risk scores, and real-time alerts to supervisors.
- **Sustainable & Safe Industrial Practices** – Ensuring a balance between productivity and worker well-being through AI-optimized safety protocols.

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