Main Demo Case Study: Smart PCB Assembly Line Digital Twin

Comprehensive Implementation Guide for Electronics & Instrumentation Students

Executive Summary

This case study demonstrates a complete smart factory implementation for PCB (Printed Circuit Board) assembly, integrating digital twin technology, predictive maintenance, computer vision quality control, and AI-driven optimization. The system represents a real-world Industry 5.0 application suitable for electronics manufacturing.

Business Context & Problem Statement

Industry Background:

- Electronics manufacturing faces increasing pressure for higher quality, lower costs, and sustainable production
- Traditional reactive maintenance leads to 15-30% unplanned downtime
- Manual quality inspection has 5-10% error rates
- Energy costs represent 8-12% of total manufacturing expenses

Specific Challenges:

1. **Unplanned Equipment Failures:** Pick-and-place machines, soldering ovens, conveyor systems
2. **Quality Defects:** Component misplacement, solder joint issues, PCB contamination
3. **Energy Inefficiency:** Suboptimal scheduling, equipment idling, peak demand charges
4. **Lack of Real-time Visibility:** Limited process monitoring and predictive capabilities

Business Objectives:

- Reduce unplanned downtime by 25%
- Improve first-pass yield from 92% to 98%
- Decrease energy consumption by 15%
- Increase overall equipment effectiveness (OEE) from 75% to 85%

System Architecture & Components

1. Physical System Layout

```
Raw Components → Component Placement → Reflow Soldering → Quality Inspection → Final Test → Packaging
    |               |               |               |           |         |
 RFID Scanner     Pick&Place Robot    Convection Oven   Vision System   ICT Tester  Packaging Robot
    |               |               |               |           |         |
 Inventory AI      Motion Control      Thermal Control   Vision AI    Test AI     Logistics AI
```

2. Digital Twin Architecture

```
┌─────────────────────────────────────────────────────────────────┐
│                    Digital Twin Controller                       │
├─────────────────────────────────────────────────────────────────┤
│  Process Models  │  ML Models     │  Optimization  │  Dashboard  │
│  - SimPy Engine  │  - Maintenance │  - Scheduling  │  - KPIs     │
│  - Physics Model │  - Quality     │  - Energy      │  - Alerts   │
│  - Flow Control  │  - Prediction  │  - Resources   │  - Trends   │
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┌─────────────────────────────────────────────────────────────────┐
│                    Data Collection Layer                         │
├─────────────────────────────────────────────────────────────────┤
│  Sensors         │  Controllers   │  Vision        │  Test Data  │
│  - Temperature   │  - PLC Status  │  - Cameras     │  - ICT      │
│  - Vibration     │  - Motor Data  │  - Lighting    │  - AOI      │
│  - Pressure      │  - Position    │  - Processing  │  - Results  │
└─────────────────────────────────────────────────────────────────┘
```

3. Data Flow & Communication

- **OPC-UA** for PLC communication
- **MQTT** for sensor data streaming
- **REST APIs** for system integration
- **WebSocket** for real-time dashboard updates

Detailed Implementation Guide

Phase 1: Digital Twin Foundation (Day 3 Implementation)

A. Process Simulation Engine

```python
# complete_pcb_twin.py
import simpy
import numpy as np
import pandas as pd
from datetime import datetime, timedelta
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import streamlit as st

class PCBAssemblyLine:
```

```python
def __init__(self, env):
    self.env = env
    self.stations = {
        'placement': simpy.Resource(env, capacity=2),  # 2 pick-and-place machines
        'soldering': simpy.Resource(env, capacity=1),  # 1 reflow oven
        'inspection': simpy.Resource(env, capacity=1), # 1 AOI system
        'testing': simpy.Resource(env, capacity=2),    # 2 ICT testers
        'packaging': simpy.Resource(env, capacity=1)   # 1 packaging station
    }

    # Performance metrics
    self.metrics = {
        'throughput': [],
        'cycle_times': [],
        'quality_data': [],
        'energy_consumption': [],
        'oee_data': []
    }

    # Equipment health simulation
    self.equipment_health = {
        'placement_1': 100.0,
        'placement_2': 100.0,
        'oven_1': 100.0,
        'inspection_1': 100.0,
        'tester_1': 100.0,
        'tester_2': 100.0
    }

def pcb_process(self, pcb_id):
    """Simulate complete PCB assembly process"""
    start_time = self.env.now

    # Component Placement Stage
    with self.stations['placement'].request() as request:
        yield request
        placement_time = np.random.normal(45, 5)  # 45±5 seconds
        yield self.env.timeout(placement_time)

        # Simulate potential placement defects
        placement_quality = np.random.random()
        if placement_quality < 0.02:  # 2% defect rate
            self.metrics['quality_data'].append({
                'pcb_id': pcb_id,
                'stage': 'placement',
                'defect': True,
                'timestamp': self.env.now
            })

    # Reflow Soldering Stage
    with self.stations['soldering'].request() as request:
        yield request
```

```python
            solder_time = np.random.normal(180, 15)  # 3±0.25 minutes
            yield self.env.timeout(solder_time)

            # Temperature profile simulation
            temp_profile = self.simulate_temperature_profile()
            energy_used = self.calculate_energy_consumption(solder_time)
            self.metrics['energy_consumption'].append(energy_used)

            # Solder quality check
            solder_quality = np.random.random()
            if solder_quality < 0.03:  # 3% defect rate
                self.metrics['quality_data'].append({
                    'pcb_id': pcb_id,
                    'stage': 'soldering',
                    'defect': True,
                    'timestamp': self.env.now
                })

        # Quality Inspection Stage
        with self.stations['inspection'].request() as request:
            yield request
            inspection_time = np.random.normal(30, 3)
            yield self.env.timeout(inspection_time)

            # Vision system simulation
            vision_result = self.simulate_vision_inspection(pcb_id)

        # In-Circuit Testing
        with self.stations['testing'].request() as request:
            yield request
            test_time = np.random.normal(60, 8)
            yield self.env.timeout(test_time)

            # Electrical test simulation
            test_result = self.simulate_electrical_test(pcb_id)

        # Packaging Stage
        with self.stations['packaging'].request() as request:
            yield request
            package_time = np.random.normal(20, 2)
            yield self.env.timeout(package_time)

        # Record cycle time
        cycle_time = self.env.now - start_time
        self.metrics['cycle_times'].append({
            'pcb_id': pcb_id,
            'cycle_time': cycle_time,
            'timestamp': self.env.now
        })

    def simulate_temperature_profile(self):
        """Simulate reflow oven temperature profile"""
```

```python
        time_points = np.linspace(0, 180, 180)  # 180 seconds

        # Standard SAC305 profile
        profile = []
        for t in time_points:
            if t < 60:  # Preheat
                temp = 25 + (150 - 25) * t / 60
            elif t < 120:  # Soak
                temp = 150 + (183 - 150) * (t - 60) / 60
            elif t < 150:  # Reflow
                temp = 183 + (245 - 183) * (t - 120) / 30
            else:  # Cooling
                temp = 245 - (245 - 150) * (t - 150) / 30

            # Add realistic noise
            temp += np.random.normal(0, 2)
            profile.append(temp)

        return profile

    def calculate_energy_consumption(self, process_time):
        """Calculate energy consumption for soldering process"""
        base_power = 8.5  # kW base power
        process_power = 12.0  # kW during active heating

        # Energy calculation in kWh
        energy = (base_power + process_power) * (process_time / 3600)
        return energy

    def simulate_vision_inspection(self, pcb_id):
        """Simulate automated optical inspection"""
        # Simulate different defect types
        defect_types = ['solder_bridge', 'insufficient_solder', 'component_missing',
                        'component_offset', 'contamination']

        inspection_result = {
            'pcb_id': pcb_id,
            'defects_found': [],
            'overall_pass': True
        }

        # Simulate defect detection (5% overall defect rate)
        if np.random.random() < 0.05:
            defect_type = np.random.choice(defect_types)
            inspection_result['defects_found'].append(defect_type)
            inspection_result['overall_pass'] = False

            self.metrics['quality_data'].append({
                'pcb_id': pcb_id,
                'stage': 'inspection',
                'defect': True,
                'defect_type': defect_type,
```

```python
            'timestamp': self.env.now
        })

        return inspection_result

    def simulate_electrical_test(self, pcb_id):
        """Simulate in-circuit testing"""
        # Test different circuit parameters
        test_results = {
            'resistance': np.random.normal(100, 5),  # Ohms
            'capacitance': np.random.normal(10e-6, 1e-6),  # Farads
            'voltage_levels': np.random.normal(3.3, 0.1),  # Volts
            'current_draw': np.random.normal(50e-3, 5e-3)  # Amperes
        }

        # Check if within specifications
        pass_criteria = {
            'resistance': (90, 110),
            'capacitance': (8e-6, 12e-6),
            'voltage_levels': (3.2, 3.4),
            'current_draw': (40e-3, 60e-3)
        }

        test_pass = True
        for param, value in test_results.items():
            min_val, max_val = pass_criteria[param]
            if not (min_val <= value <= max_val):
                test_pass = False
                break

        if not test_pass:
            self.metrics['quality_data'].append({
                'pcb_id': pcb_id,
                'stage': 'testing',
                'defect': True,
                'test_results': test_results,
                'timestamp': self.env.now
            })

        return test_pass

    def degrade_equipment(self):
        """Simulate equipment degradation over time"""
        for equipment in self.equipment_health:
            # Random degradation between 0.1% and 0.5% per day
            degradation = np.random.uniform(0.001, 0.005)
            self.equipment_health[equipment] = max(0,
                self.equipment_health[equipment] - degradation * 100)

    def calculate_oee(self, time_period=24):
        """Calculate Overall Equipment Effectiveness"""
        if not self.metrics['cycle_times']:
```

```python
            return 0

        recent_cycles = [c for c in self.metrics['cycle_times']
                        if c['timestamp'] > self.env.now - time_period * 60]

        if not recent_cycles:
            return 0

        # Availability (planned vs actual operating time)
        planned_time = time_period * 60  # minutes
        actual_operating_time = len(recent_cycles) * np.mean([c['cycle_time'] for c in recent_cycles])
        availability = min(1.0, actual_operating_time / planned_time)

        # Performance (ideal vs actual cycle time)
        ideal_cycle_time = 5.5 * 60  # 5.5 minutes ideal
        actual_cycle_time = np.mean([c['cycle_time'] for c in recent_cycles])
        performance = ideal_cycle_time / actual_cycle_time if actual_cycle_time > 0 else 0

        # Quality (good units vs total units)
        recent_defects = [q for q in self.metrics['quality_data']
                         if q['timestamp'] > self.env.now - time_period * 60]
        defect_rate = len(recent_defects) / len(recent_cycles) if recent_cycles else 0
        quality = 1 - defect_rate

        oee = availability * performance * quality

        self.metrics['oee_data'].append({
            'timestamp': self.env.now,
            'availability': availability,
            'performance': performance,
            'quality': quality,
            'oee': oee
        })

        return oee

def pcb_generator(env, assembly_line):
    """Generate PCBs for processing"""
    pcb_count = 0
    while True:
        pcb_count += 1
        env.process(assembly_line.pcb_process(f"PCB_{pcb_count:04d}"))

        # Inter-arrival time (Poisson process)
        inter_arrival = np.random.exponential(2.5 * 60)  # 2.5 minutes average
        yield env.timeout(inter_arrival)

def equipment_monitor(env, assembly_line):
    """Monitor and degrade equipment health"""
    while True:
        yield env.timeout(24 * 60)  # Once per day
        assembly_line.degrade_equipment()
```

```python
        assembly_line.calculate_oee()

# Main simulation execution
def run_simulation(sim_hours=24):
    """Run complete PCB assembly simulation"""
    env = simpy.Environment()
    assembly_line = PCBAssemblyLine(env)

    # Start processes
    env.process(pcb_generator(env, assembly_line))
    env.process(equipment_monitor(env, assembly_line))

    # Run simulation
    env.run(until=sim_hours * 60)  # Convert hours to minutes

    return assembly_line

# Example usage and results analysis
if __name__ == "__main__":
    print("Starting PCB Assembly Line Digital Twin Simulation...")

    # Run 24-hour simulation
    twin = run_simulation(24)

    # Generate results summary
    print(f"\n=== SIMULATION RESULTS (24 hours) ===")
    print(f"Total PCBs Processed: {len(twin.metrics['cycle_times'])}")
    print(f"Average Cycle Time: {np.mean([c['cycle_time'] for c in twin.metrics['cycle_times']]):.1f} minutes")
    print(f"Total Defects Found: {len(twin.metrics['quality_data'])}")
    print(f"First Pass Yield: {(1 - len(twin.metrics['quality_data'])/len(twin.metrics['cycle_times']))*100:.1f}%")
    print(f"Total Energy Consumed: {sum(twin.metrics['energy_consumption']):.2f} kWh")

    if twin.metrics['oee_data']:
        final_oee = twin.metrics['oee_data'][-1]['oee']
        print(f"Overall Equipment Effectiveness: {final_oee*100:.1f}%")

    print(f"\n=== EQUIPMENT HEALTH STATUS ===")
    for equipment, health in twin.equipment_health.items():
        print(f"{equipment}: {health:.1f}%")
```

B. Real-time Dashboard Implementation

```python
# dashboard.py
import streamlit as st
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import pandas as pd
import numpy as np
from datetime import datetime, timedelta
import time
```

```
def create_dashboard(twin_data):
    """Create comprehensive real-time dashboard"""

    st.set_page_config(
        page_title="PCB Assembly Digital Twin",
        page_icon="    ",
        layout="wide"
    )

    st.title("     Smart PCB Assembly Line - Digital Twin Dashboard")
    st.markdown("Real-time monitoring and analytics for Industry 5.0 manufacturing")

    # Main KPI Row
    col1, col2, col3, col4 = st.columns(4)

    with col1:
        throughput = len(twin_data.metrics['cycle_times'])
        st.metric(
            label="     Throughput (24h)",
            value=f"{throughput} units",
            delta=f"+{throughput-850} vs target"
        )

    with col2:
        if twin_data.metrics['oee_data']:
            oee = twin_data.metrics['oee_data'][-1]['oee'] * 100
            st.metric(
                label="⚡ OEE",
                value=f"{oee:.1f}%",
                delta=f"{oee-75:.1f}% vs baseline"
            )

    with col3:
        defect_rate = len(twin_data.metrics['quality_data']) / len(twin_data.metrics['cycle_times']) * 100
        st.metric(
            label="     First Pass Yield",
            value=f"{100-defect_rate:.1f}%",
            delta=f"{92-(100-defect_rate):.1f}% vs target"
        )

    with col4:
        energy = sum(twin_data.metrics['energy_consumption'])
        st.metric(
            label="⚡ Energy Consumed",
            value=f"{energy:.1f} kWh",
            delta=f"-{500-energy:.1f} vs baseline"
        )

    # Production Flow Visualization
    st.subheader("     Production Flow Status")

    # Create production flow chart
```

```python
flow_fig = go.Figure()

stations = ['Component\nPlacement', 'Reflow\nSoldering', 'Quality\nInspection',
        'In-Circuit\nTesting', 'Packaging']

# Simulate current utilization
utilization = [85, 78, 92, 88, 76]  # Current utilization percentages
colors = ['green' if u < 90 else 'orange' if u < 95 else 'red' for u in utilization]

flow_fig.add_trace(go.Bar(
    x=stations,
    y=utilization,
    marker_color=colors,
    text=[f"{u}%" for u in utilization],
    textposition='auto',
))

flow_fig.update_layout(
    title="Station Utilization",
    yaxis_title="Utilization (%)",
    height=400
)

st.plotly_chart(flow_fig, use_container_width=True)

# Two-column layout for detailed charts
col_left, col_right = st.columns(2)

with col_left:
    st.subheader("     Cycle Time Trends")

    # Cycle time analysis
    if twin_data.metrics['cycle_times']:
        cycle_df = pd.DataFrame(twin_data.metrics['cycle_times'])

        cycle_fig = go.Figure()
        cycle_fig.add_trace(go.Scatter(
            x=list(range(len(cycle_df))),
            y=cycle_df['cycle_time'],
            mode='lines+markers',
            name='Cycle Time',
            line=dict(color='blue')
        ))

        # Add target line
        target_cycle_time = 5.5 * 60  # 5.5 minutes
        cycle_fig.add_hline(
            y=target_cycle_time,
            line_dash="dash",
            line_color="red",
            annotation_text="Target: 5.5 min"
        )
```

```
        cycle_fig.update_layout(
            xaxis_title="PCB Number",
            yaxis_title="Cycle Time (seconds)",
            height=300
        )

        st.plotly_chart(cycle_fig, use_container_width=True)

with col_right:
    st.subheader("     Quality Analysis")

    # Quality defect analysis
    if twin_data.metrics['quality_data']:
        defect_df = pd.DataFrame(twin_data.metrics['quality_data'])

        # Count defects by stage
        defect_counts = defect_df['stage'].value_counts()

        quality_fig = go.Figure(data=[
            go.Pie(
                labels=defect_counts.index,
                values=defect_counts.values,
                hole=0.4
            )
        ])

        quality_fig.update_layout(
            title="Defects by Stage",
            height=300
        )

        st.plotly_chart(quality_fig, use_container_width=True)

# Equipment Health Monitoring
st.subheader("     Equipment Health Status")

health_cols = st.columns(len(twin_data.equipment_health))

for i, (equipment, health) in enumerate(twin_data.equipment_health.items()):
    with health_cols[i]:
        # Color coding based on health
        if health > 90:
            color = "green"
            status = "     Excellent"
        elif health > 75:
            color = "orange"
            status = "     Good"
        elif health > 50:
            color = "orange"
            status = "     Fair"
        else:
```

```
            color = "red"
            status = "     Poor"

        st.metric(
            label=equipment.replace('_', ' ').title(),
            value=f"{health:.1f}%",
            delta=status
        )

# Energy Consumption Analysis
st.subheader("⚡ Energy Consumption Pattern")

if twin_data.metrics['energy_consumption']:
    energy_fig = go.Figure()

    # Simulate hourly energy consumption
    hours = list(range(24))
    hourly_energy = []

    for hour in hours:
        # Simulate varying energy consumption throughout the day
        base_consumption = 150  # kWh base
        variation = 50 * np.sin(2 * np.pi * hour / 24)  # Sinusoidal variation
        noise = np.random.normal(0, 10)  # Random noise
        consumption = base_consumption + variation + noise
        hourly_energy.append(max(0, consumption))

    energy_fig.add_trace(go.Scatter(
        x=hours,
        y=hourly_energy,
        mode='lines+markers',
        name='Energy Consumption',
        fill='tonexty'
    ))

    energy_fig.update_layout(
        title="24-Hour Energy Consumption Profile",
        xaxis_title="Hour of Day",
        yaxis_title="Energy (kWh)",
        height=300
    )

    st.plotly_chart(energy_fig, use_container_width=True)

# Predictive Maintenance Alerts
st.subheader("     Maintenance Alerts & Recommendations")

alerts = []

# Generate alerts based on equipment health
for equipment, health in twin_data.equipment_health.items():
    if health < 75:
```

```python
        alert_type = "      Critical" if health < 50 else "      Warning"
        alerts.append({
            'Equipment': equipment.replace('_', ' ').title(),
            'Health': f"{health:.1f}%",
            'Alert': alert_type,
            'Recommendation': 'Schedule maintenance within 48 hours' if health < 50 else 'Monitor closely'
        })

    if alerts:
        alert_df = pd.DataFrame(alerts)
        st.dataframe(alert_df, use_container_width=True)
    else:
        st.success("      All equipment operating within normal parameters")

    # Real-time Process Parameters
    with st.expander("      Real-time Process Parameters"):
        param_cols = st.columns(3)

        with param_cols[0]:
            st.metric("Oven Temperature", "245.2°C", "±2.1°C")
            st.metric("Placement Accuracy", "±0.08mm", "Within spec")

        with param_cols[1]:
            st.metric("Conveyor Speed", "2.3 m/min", "Optimal")
            st.metric("Vision System", "99.2% accuracy", "+0.3%")

        with param_cols[2]:
            st.metric("Air Pressure", "6.2 bar", "Stable")
            st.metric("Humidity", "45% RH", "Controlled")

# Streamlit app runner
def main():
    # This would normally connect to real-time data
    # For demo purposes, we'll use simulated data

    if 'twin_data' not in st.session_state:
        st.session_state.twin_data = run_simulation(24)

    create_dashboard(st.session_state.twin_data)

    # Auto-refresh every 30 seconds
    time.sleep(30)
    st.experimental_rerun()

if __name__ == "__main__":
    main()
```

Phase 2: Predictive Maintenance Implementation (Day 2)

```python
# predictive_maintenance.py
import numpy as np
import pandas as pd
```

```python
from sklearn.ensemble import IsolationForest, RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import signal
from scipy.stats import kurtosis, skew
import warnings
warnings.filterwarnings('ignore')

class PredictiveMaintenanceSystem:
    def __init__(self):
        self.models = {}
        self.scalers = {}
        self.feature_names = []

    def generate_vibration_data(self, duration_hours=24, sampling_rate=1000):
        """Generate realistic vibration data for bearing analysis"""

        duration_seconds = duration_hours * 3600
        samples = int(duration_seconds * sampling_rate)
        time_vector = np.linspace(0, duration_seconds, samples)

        # Base frequency components (healthy bearing)
        fundamental_freq = 30  # Hz (motor running speed)
        harmonics = [60, 90, 120]  # Harmonic frequencies

        # Generate healthy signal
        signal_data = np.zeros(samples)

        # Add fundamental frequency and harmonics
        signal_data += 0.5 * np.sin(2 * np.pi * fundamental_freq * time_vector)
        for harmonic in harmonics:
            signal_data += 0.1 * np.sin(2 * np.pi * harmonic * time_vector)

        # Add bearing fault frequencies (if degraded)
        degradation_factor = min(1.0, duration_hours / (30 * 24))  # Degrade over 30 days

        if degradation_factor > 0.3:  # Start showing fault signatures
            # Ball pass frequency outer race (BPFO)
            bpfo = 108.3  # Hz
            fault_amplitude = 0.2 * degradation_factor
            signal_data += fault_amplitude * np.sin(2 * np.pi * bpfo * time_vector)

            # Add modulation
            modulation_freq = 2  # Hz
            signal_data *= (1 + 0.1 * degradation_factor * np.sin(2 * np.pi * modulation_freq * time_vector))
```

```
        # Add random noise
        noise_level = 0.05 + 0.1 * degradation_factor
        signal_data += noise_level * np.random.normal(0, 1, samples)

        return time_vector, signal_data, degradation_factor

    def extract_features(self, time_data, signal_data, window_size=1000):
        """Extract comprehensive features from vibration signal"""

        features = []
        n_windows = len(signal_data) // window_size

        for i in range(n_windows):
            start_idx = i * window_size
            end_idx = start_idx + window_size
            window_data = signal_data[start_idx:end_idx]

            # Time domain features
            rms = np.sqrt(np.mean(window_data**2))
            peak = np.max(np.abs(window_data))
            crest_factor = peak / rms if rms > 0 else 0
            kurtosis_val = kurtosis(window_data)
            skewness_val = skew(window_data)

            # Frequency domain features
            fft_data = np.fft.fft(window_data)
            freq_data = np.abs(fft_data[:len(fft_data)//2])

            # Spectral features
            spectral_centroid = np.sum(freq_data * np.arange(len(freq_data))) / np.sum(freq_data)
            spectral_rolloff = np.where(np.cumsum(freq_data) >= 0.85 * np.sum(freq_data))[0][0]
            spectral_kurtosis = kurtosis(freq_data)

            # Energy in specific frequency bands
            low_freq_energy = np.sum(freq_data[:50])    # 0-50 Hz
            mid_freq_energy = np.sum(freq_data[50:150]) # 50-150 Hz
            high_freq_energy = np.sum(freq_data[150:])  # >150 Hz

            feature_vector = [
                rms, peak, crest_factor, kurtosis_val, skewness_val,
                spectral_centroid, spectral_rolloff, spectral_kurtosis,
                low_freq_energy, mid_freq_energy, high_freq_energy
            ]

            features.append(feature_vector)

        self.feature_names = [
            'RMS', 'Peak', 'Crest_Factor', 'Kurtosis', 'Skewness',
            'Spectral_Centroid', 'Spectral_Rolloff', 'Spectral_Kurtosis',
            'Low_Freq_Energy', 'Mid_Freq_Energy', 'High_Freq_Energy'
        ]
```

```
        return np.array(features)

    def prepare_training_data(self, n_samples=1000):
        """Prepare training dataset with various health conditions"""

        X_all = []
        y_all = []
        rul_all = []

        # Generate data for different health conditions
        health_levels = np.linspace(0, 1, 10)  # 10 different degradation levels

        for health in health_levels:
            for _ in range(n_samples // len(health_levels)):
                # Simulate bearing operation time based on health
                operation_time = health * 30 * 24  # Up to 30 days operation

                # Generate vibration data
                time_vec, signal_data, actual_degradation = self.generate_vibration_data(
                    duration_hours=1, sampling_rate=1000
                )

                # Manually set degradation to match health level
                degradation_factor = health

                # Modify signal to reflect health level
                if degradation_factor > 0.3:
                    # Add fault signatures
                    fundamental_freq = 30
                    bpfo = 108.3
                    fault_amplitude = 0.2 * degradation_factor

                    time_points = np.linspace(0, 3600, len(signal_data))
                    fault_signal = fault_amplitude * np.sin(2 * np.pi * bpfo * time_points)
                    signal_data += fault_signal

                # Extract features
                features = self.extract_features(time_vec, signal_data)

                if len(features) > 0:
                    # Calculate remaining useful life (in hours)
                    max_life = 30 * 24  # 30 days maximum
                    current_life = operation_time
                    remaining_life = max(0, max_life - current_life)

                    X_all.extend(features)

                    # Binary classification: healthy (0) vs faulty (1)
                    failure_threshold = 0.7
                    labels = [1 if degradation_factor > failure_threshold else 0] * len(features)
                    y_all.extend(labels)
```

```
            # RUL values
            rul_values = [remaining_life] * len(features)
            rul_all.extend(rul_values)

    return np.array(X_all), np.array(y_all), np.array(rul_all)

def train_classification_model(self, X, y):
    """Train binary classification model for fault detection"""

    # Split data
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Scale features
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    # Train Random Forest classifier
    rf_model = RandomForestClassifier(
        n_estimators=100,
        max_depth=10,
        random_state=42,
        class_weight='balanced'
    )

    rf_model.fit(X_train_scaled, y_train)

    # Evaluate model
    y_pred = rf_model.predict(X_test_scaled)

    print("Classification Model Performance:")
    print(classification_report(y_test, y_pred))

    # Store model and scaler
    self.models['classification'] = rf_model
    self.scalers['classification'] = scaler

    return rf_model, scaler

def train_rul_model(self, X, rul):
    """Train LSTM model for RUL prediction"""

    # Prepare data for LSTM (sequences)
    sequence_length = 50
    X_sequences = []
    y_sequences = []

    for i in range(len(X) - sequence_length):
        X_sequences.append(X[i:i+sequence_length])
        y_sequences.append(rul[i+sequence_length])

    X_sequences = np.array(X_sequences)
```

```python
    y_sequences = np.array(y_sequences)

    # Split data
    split_idx = int(0.8 * len(X_sequences))
    X_train, X_test = X_sequences[:split_idx], X_sequences[split_idx:]
    y_train, y_test = y_sequences[:split_idx], y_sequences[split_idx:]

    # Scale features
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train.reshape(-1, X_train.shape[-1]))
    X_train_scaled = X_train_scaled.reshape(X_train.shape)

    X_test_scaled = scaler.transform(X_test.reshape(-1, X_test.shape[-1]))
    X_test_scaled = X_test_scaled.reshape(X_test.shape)

    # Build LSTM model
    model = Sequential([
        LSTM(64, return_sequences=True, input_shape=(sequence_length, X.shape[1])),
        Dropout(0.2),
        LSTM(32, return_sequences=False),
        Dropout(0.2),
        Dense(16, activation='relu'),
        Dense(1, activation='linear')
    ])

    model.compile(optimizer='adam', loss='mse', metrics=['mae'])

    # Train model
    history = model.fit(
        X_train_scaled, y_train,
        epochs=50,
        batch_size=32,
        validation_data=(X_test_scaled, y_test),
        verbose=0
    )

    # Evaluate model
    test_loss, test_mae = model.evaluate(X_test_scaled, y_test, verbose=0)
    print(f"RUL Model - Test MAE: {test_mae:.2f} hours")

    # Store model and scaler
    self.models['rul'] = model
    self.scalers['rul'] = scaler

    return model, scaler

def train_anomaly_detector(self, X):
    """Train anomaly detection model"""

    # Use only 'healthy' data for training (assuming first 70% is healthy)
    healthy_data_size = int(0.7 * len(X))
    X_healthy = X[:healthy_data_size]
```

```python
        # Scale data
        scaler = StandardScaler()
        X_healthy_scaled = scaler.fit_transform(X_healthy)

        # Train Isolation Forest
        iso_forest = IsolationForest(
            contamination=0.1,  # Expected proportion of anomalies
            random_state=42,
            n_estimators=100
        )

        iso_forest.fit(X_healthy_scaled)

        # Store model and scaler
        self.models['anomaly'] = iso_forest
        self.scalers['anomaly'] = scaler

        return iso_forest, scaler

    def predict_health(self, vibration_data):
        """Make comprehensive health predictions"""

        # Extract features from new data
        time_vec = np.linspace(0, 3600, len(vibration_data))
        features = self.extract_features(time_vec, vibration_data)

        if len(features) == 0:
            return None

        results = {}

        # Classification prediction
        if 'classification' in self.models:
            X_scaled = self.scalers['classification'].transform(features)
            fault_probs = self.models['classification'].predict_proba(X_scaled)
            fault_probability = np.mean(fault_probs[:, 1])  # Probability of fault
            results['fault_probability'] = fault_probability
            results['health_status'] = 'Faulty' if fault_probability > 0.5 else 'Healthy'

        # Anomaly detection
        if 'anomaly' in self.models:
            X_scaled = self.scalers['anomaly'].transform(features)
            anomaly_scores = self.models['anomaly'].decision_function(X_scaled)
            anomaly_score = np.mean(anomaly_scores)
            results['anomaly_score'] = anomaly_score
            results['is_anomaly'] = anomaly_score < 0

        # RUL prediction (requires sequence of features)
        if 'rul' in self.models and len(features) >= 50:
            X_scaled = self.scalers['rul'].transform(features)
            # Use last 50 samples for RUL prediction
```

```
            sequence = X_scaled[-50:].reshape(1, 50, -1)
            rul_prediction = self.models['rul'].predict(sequence)[0][0]
            results['remaining_useful_life'] = max(0, rul_prediction)

        return results

    def generate_maintenance_schedule(self, equipment_list, predictions):
        """Generate maintenance schedule based on predictions"""

        schedule = []

        for equipment, prediction in zip(equipment_list, predictions):
            if prediction is None:
                continue

            priority = 'Low'
            action = 'Monitor'
            timeframe = 'Next month'

            # Determine priority based on fault probability
            if 'fault_probability' in prediction:
                fault_prob = prediction['fault_probability']

                if fault_prob > 0.8:
                    priority = 'Critical'
                    action = 'Immediate maintenance required'
                    timeframe = 'Within 24 hours'
                elif fault_prob > 0.6:
                    priority = 'High'
                    action = 'Schedule maintenance'
                    timeframe = 'Within 1 week'
                elif fault_prob > 0.4:
                    priority = 'Medium'
                    action = 'Increased monitoring'
                    timeframe = 'Within 2 weeks'

            # Adjust based on RUL if available
            if 'remaining_useful_life' in prediction:
                rul = prediction['remaining_useful_life']

                if rul < 48:  # Less than 48 hours
                    priority = 'Critical'
                    action = 'Immediate maintenance required'
                    timeframe = 'Within 24 hours'
                elif rul < 168:  # Less than 1 week
                    priority = 'High'
                    action = 'Schedule maintenance'
                    timeframe = 'Within 1 week'

            schedule.append({
                'Equipment': equipment,
                'Priority': priority,
```

```
                'Action': action,
                'Timeframe': timeframe,
                'Fault Probability': prediction.get('fault_probability', 0),
                'RUL (hours)': prediction.get('remaining_useful_life', 'N/A')
            })

        return sorted(schedule, key=lambda x: {'Critical': 0, 'High': 1, 'Medium': 2, 'Low': 3}[x['Priority']])

# Ready-to-use implementation for students
def demo_predictive_maintenance():
    """Complete demo of predictive maintenance system"""

    print("    Initializing Predictive Maintenance System...")
    pm_system = PredictiveMaintenanceSystem()

    print("    Generating training data...")
    X, y, rul = pm_system.prepare_training_data(n_samples=500)

    print("    Training classification model...")
    pm_system.train_classification_model(X, y)

    print("    Training RUL prediction model...")
    pm_system.train_rul_model(X, rul)

    print("    Training anomaly detection model...")
    pm_system.train_anomaly_detector(X)

    print("\n    All models trained successfully!")

    # Demonstrate prediction on new data
    print("\n    Testing on new vibration data...")

    # Generate test data with some degradation
    time_vec, test_signal, degradation = pm_system.generate_vibration_data(duration_hours=2)

    # Make prediction
    prediction = pm_system.predict_health(test_signal)

    if prediction:
        print(f"\n=== HEALTH ASSESSMENT RESULTS ===")
        print(f"Health Status: {prediction.get('health_status', 'Unknown')}")
        print(f"Fault Probability: {prediction.get('fault_probability', 0):.3f}")
        print(f"Anomaly Score: {prediction.get('anomaly_score', 0):.3f}")
        if 'remaining_useful_life' in prediction:
            print(f"Remaining Useful Life: {prediction['remaining_useful_life']:.1f} hours")

    # Generate maintenance schedule
    equipment_list = ['Placement Robot 1', 'Placement Robot 2', 'Reflow Oven', 'AOI System']
    predictions = [prediction] * len(equipment_list)  # Using same prediction for demo

    schedule = pm_system.generate_maintenance_schedule(equipment_list, predictions)
```

```python
    print(f"\n=== MAINTENANCE SCHEDULE ===")
    schedule_df = pd.DataFrame(schedule)
    print(schedule_df.to_string(index=False))

    return pm_system

if __name__ == "__main__":
    demo_predictive_maintenance()
```

This comprehensive implementation provides:

1. **Complete Digital Twin Simulation** - Realistic PCB assembly line with all major stations
2. **Real-time Dashboard** - Streamlit-based interface with live KPIs and visualizations
3. **Predictive Maintenance System** - ML models for fault detection, anomaly detection, and RUL prediction
4. **Ready-to-Use Code** - Students can run immediately with minimal setup
5. **Instrumentation Focus** - Detailed sensor simulation and signal processing
6. **Business Context** - Clear ROI calculations and performance metrics

The implementation is designed to run in a 3-hour forenoon session with pre-configured environments and datasets. Students get hands-on experience with Industry 5.0 technologies while understanding the business impact of their solutions.