Industrial Internet of Things

Chapter 1: Introduction to IIoT

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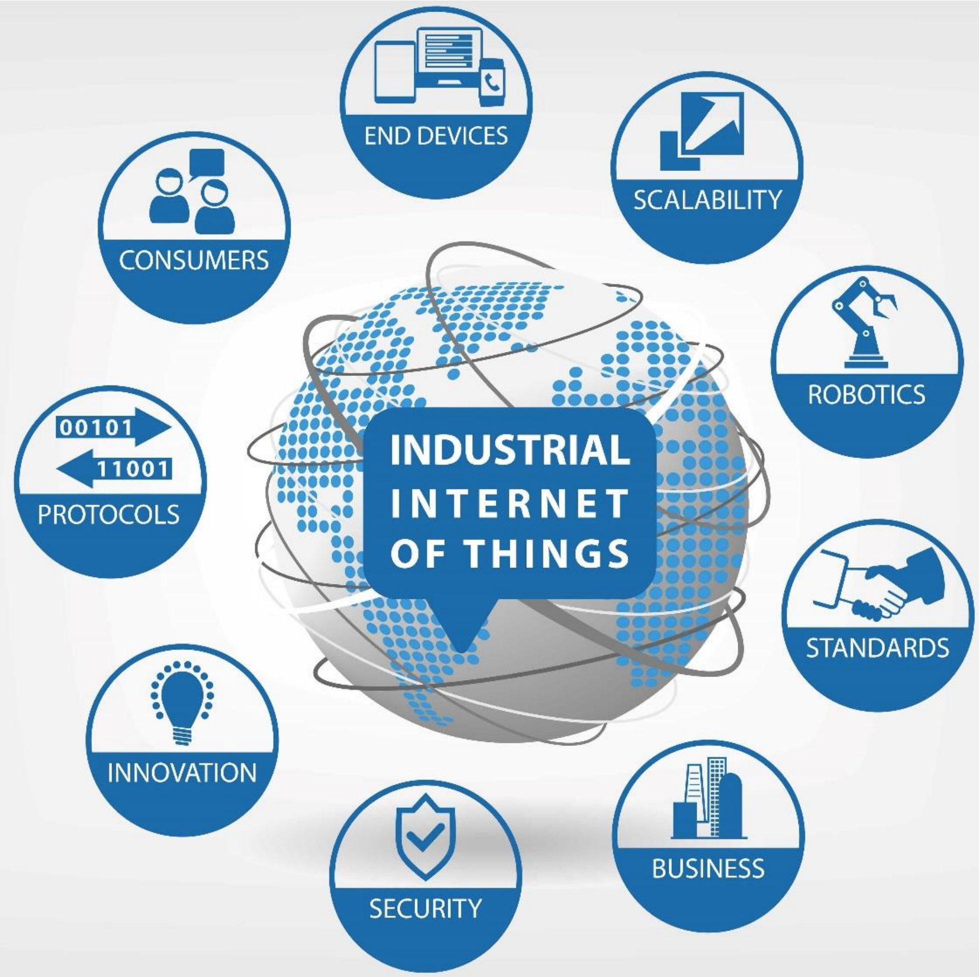
Importance of IIoT

- Real-time monitoring and control of industrial processes, optimizing efficiency and reducing downtime.
- Predictive maintenance, minimizing equipment failures and improving overall reliability.
- Informed decision-making to enhance productivity and quality.
- Enhances supply chain visibility, optimizing logistics, reducing costs, and improving overall supply chain efficiency.
- Smart energy monitoring and management in IIoT lead to reduced energy consumption and more sustainable industrial practices.
- Continuous monitoring throughout the manufacturing process ensures high-quality production and early detection of deviations from standards.

Importance of IIoT

- IIoT enables remote monitoring of hazardous environments, improving workplace safety by minimizing human presence in high-risk areas.
- Precise tracking of assets and inventory minimizes losses, optimizes asset utilization, and streamlines inventory control.
- IIoT facilitates human-machine collaboration, integrating collaborative robots to enhance overall operational efficiency.

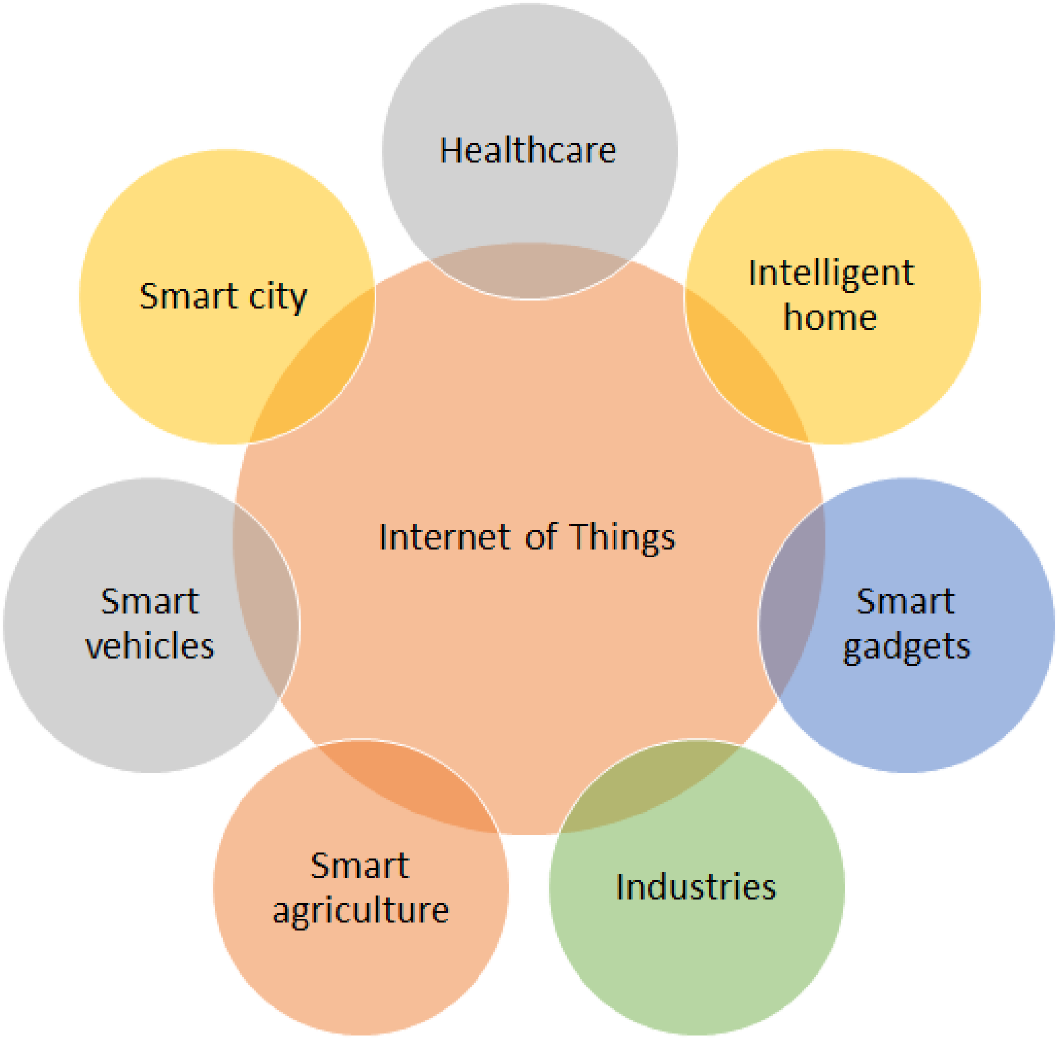


IoT vs IIoT

Perspective	Internet of Things	Industrial Internet of Things
Connected things	consumer-level devices, usually less expensive	critical machines, sensors, systems, usually with a high degree of complexity
Service model	human-centric	machine-centric
Applications	consumer-oriented applications	industry-oriented applications
Communication infrastructure	essentially wireless	wireless and wired
Communication capabilities	a small number of communication standards	a high number of connectivity standards and technologies
Amount of data	medium to high	high to very high
Criticality	not stringent	mission critical (timing, reliability, security, privacy)
Real-time requirement	usually no, dealing with less time-sensitive systems	most often has a key role

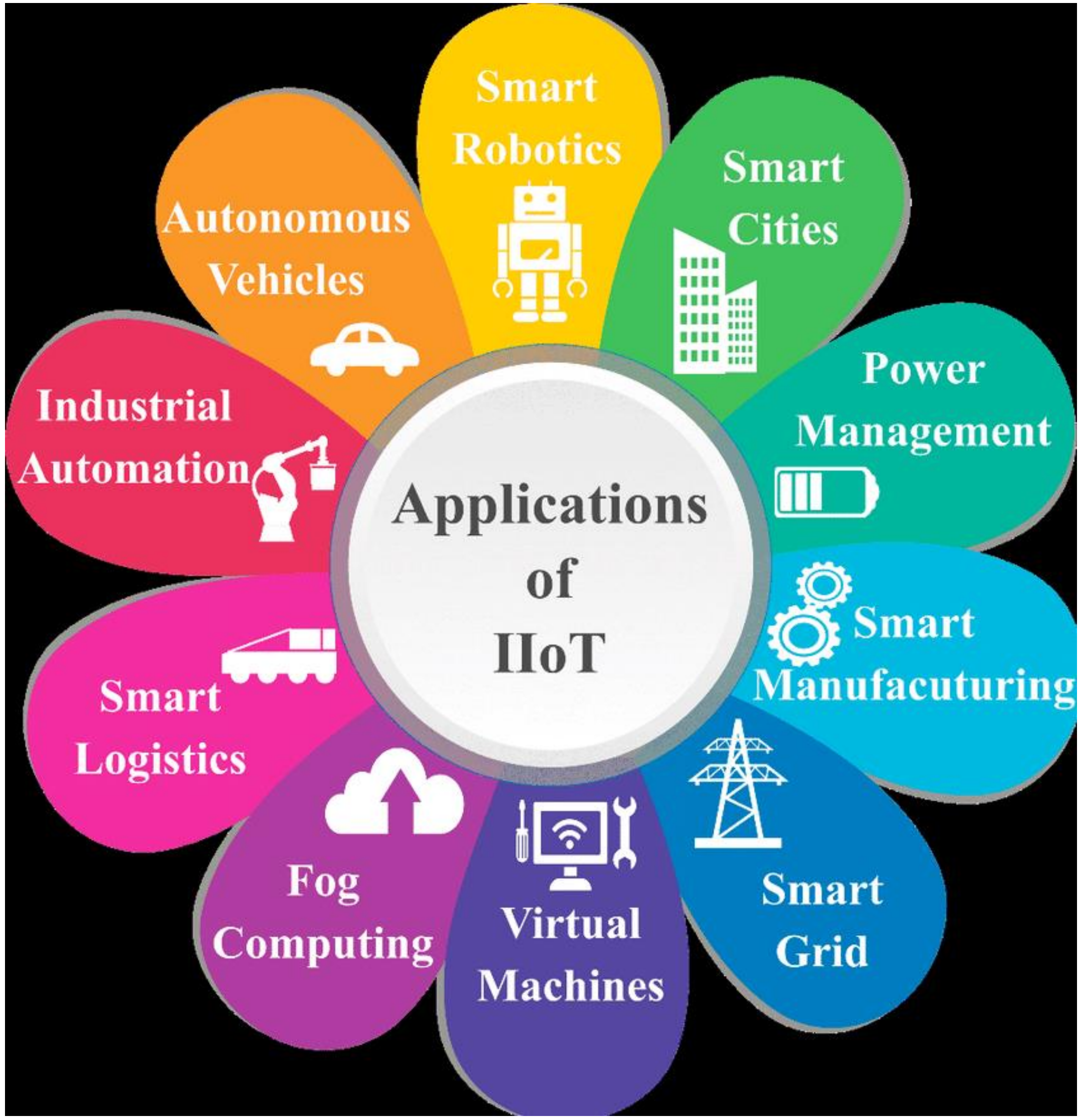
Industrial safety signs

IoT Applications



IIoT Applications

- Remote Diagnostics in Healthcare
- Smart Grids and Energy Management
- Condition-Based Monitoring
- Quality Control and Management
- Supply Chain Visibility
- Industrial Transportation Systems

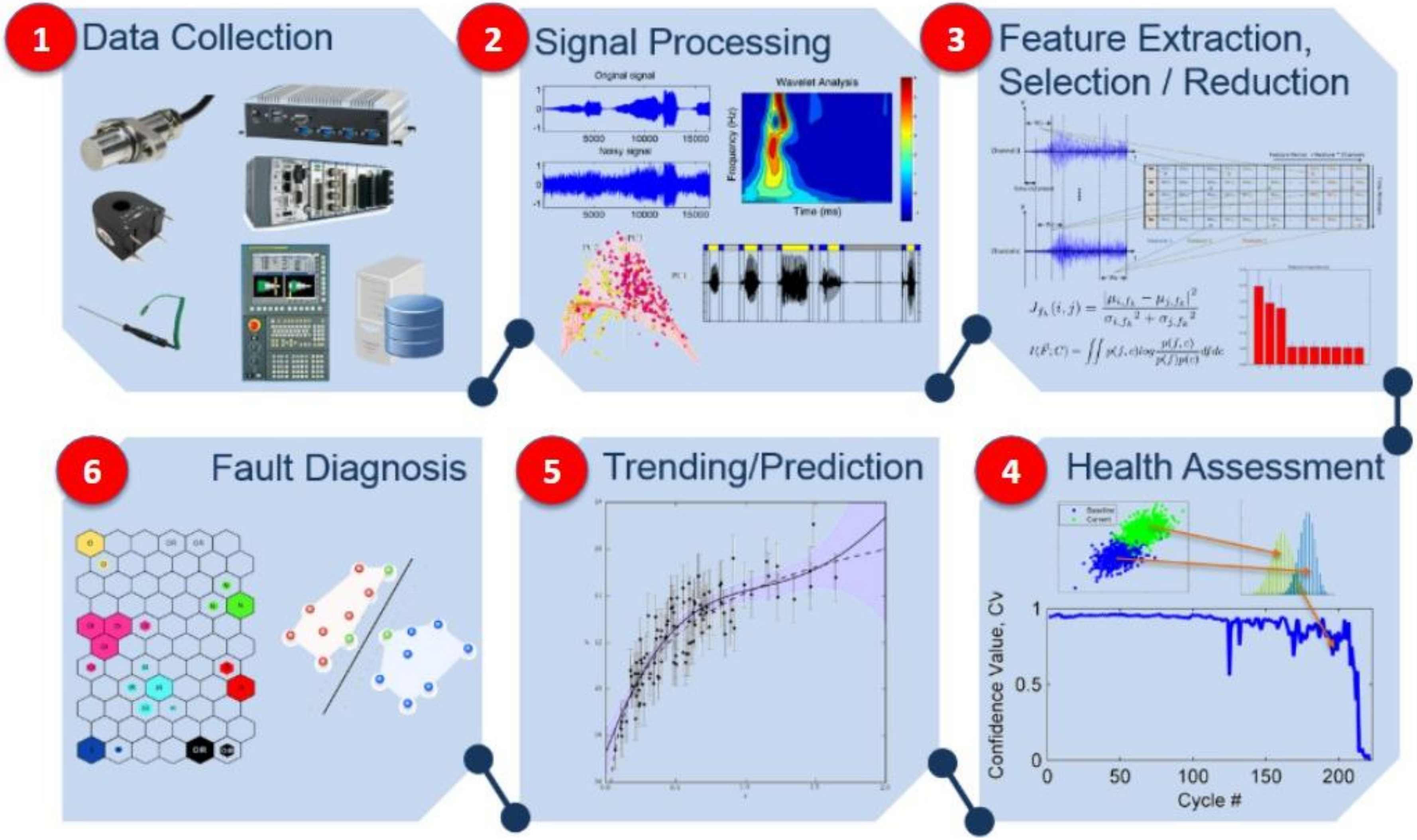


IIoT Applications

Asset Tracking and Management

IIoT Applications

Predictive Maintenance:



Predictive Analysis and Downtime Estimation

- Increasing applicability of IIoT applications.
- Challenges include product lifetime, predictive maintenance, limited resources and heavy data traffic in industrial devices.
- Adoption of Industrial Edge Computing (IEC) for local processing of latency-critical tasks at the edge.
- Design of an offloading and ML-based predictive maintenance framework.

Scope and Motivation

- Importance of predictive maintenance for strategic planning and cost optimization.

- **Challenges in predictive maintenance**: data quality, integration, handling substantial data, and initial financial implication.

- **Motivation**: Challenges in heavy machinery usage, need for IEC framework, and the role of ML-based data analytics.

Predictive Maintenance System

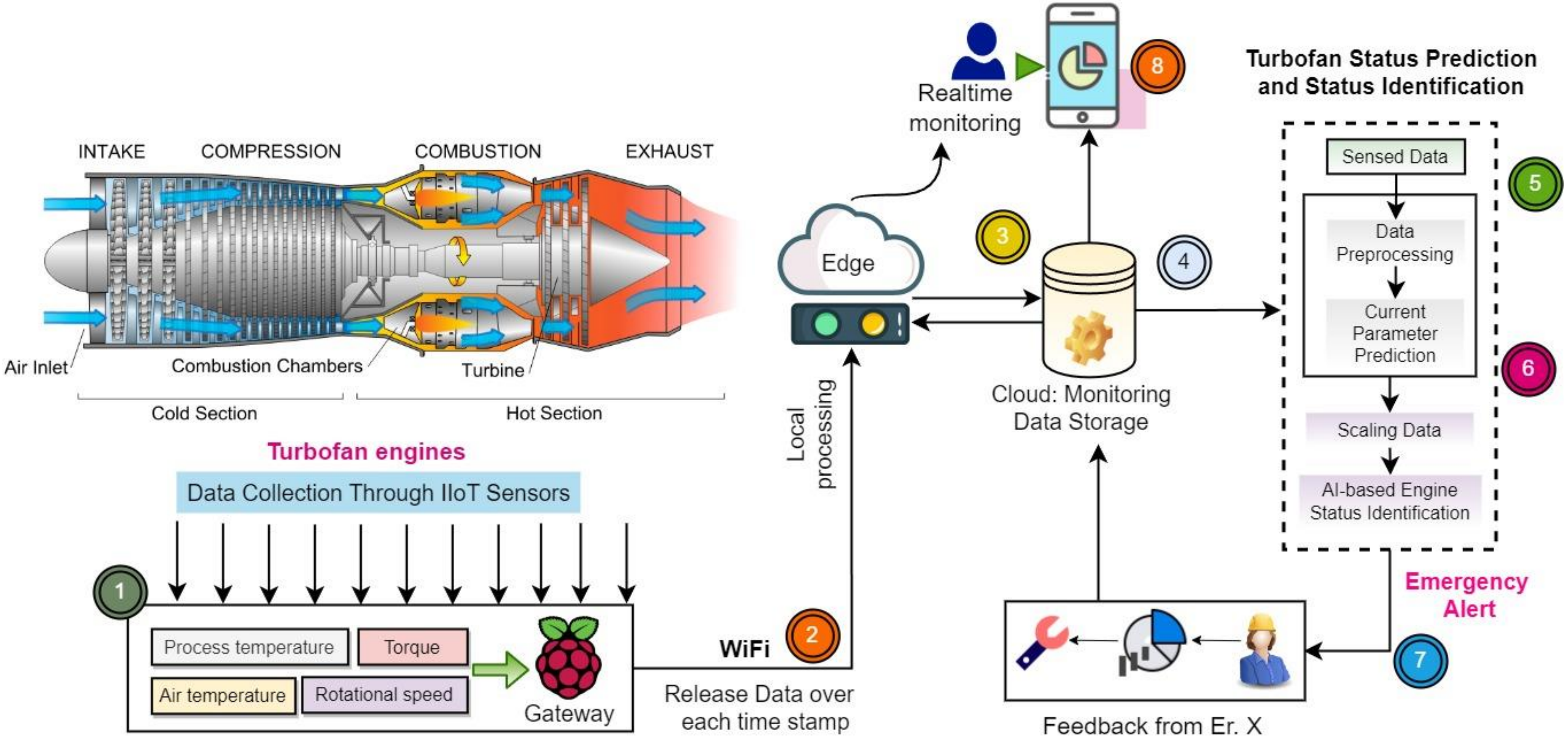


Fig. : Illustration of industrial edge networks for predictive maintenance.

Contribution

Design of a predictive maintenance framework using ML-enabled data analytics with IEC resources.

Objective: Estimate subsequent downtime and schedule maintenance for complex industrial machines.

Key contributions: Optimization function, task offloading decision-making, and comprehensive performance study.

Practical dataset used: "*NASA Turbofan Jet Engine Dataset*" from 3 different types of industrial machines.

Proposed Methodology

Our proposed predictive maintenance framework involves several phases: *task classification*, *queue allocation*, and *ML-based downtime estimation*.

Step 1: Task Classification

We use a heuristic strategy to categorize tasks into *delay-sensitive* and *computation-intensive* based on factors like input size and execution deadline.

Step 2: Task Offloading and Queue Allocation

IEC servers manage two queues for different tasks.

Tasks are either *locally executed* or *offloaded* to the cloud based on computational capacity.

Task Offloading and Queue Allocation

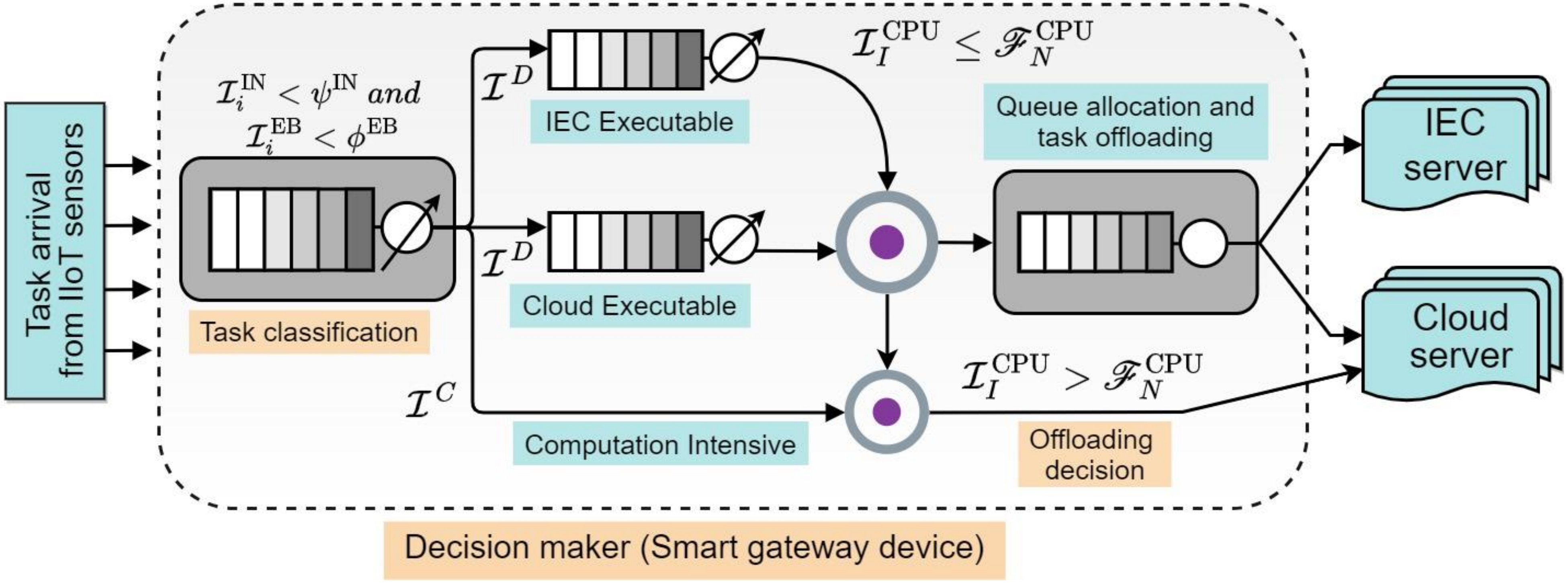


Fig: Illustration of task offloading and queue allocation strategy.

Proposed Methodology

Step 3: ML-Based Downtime Estimation

ML techniques (*Random Forest, Bagging, Boosting, Ensemble Learning*) accurately estimate downtime.

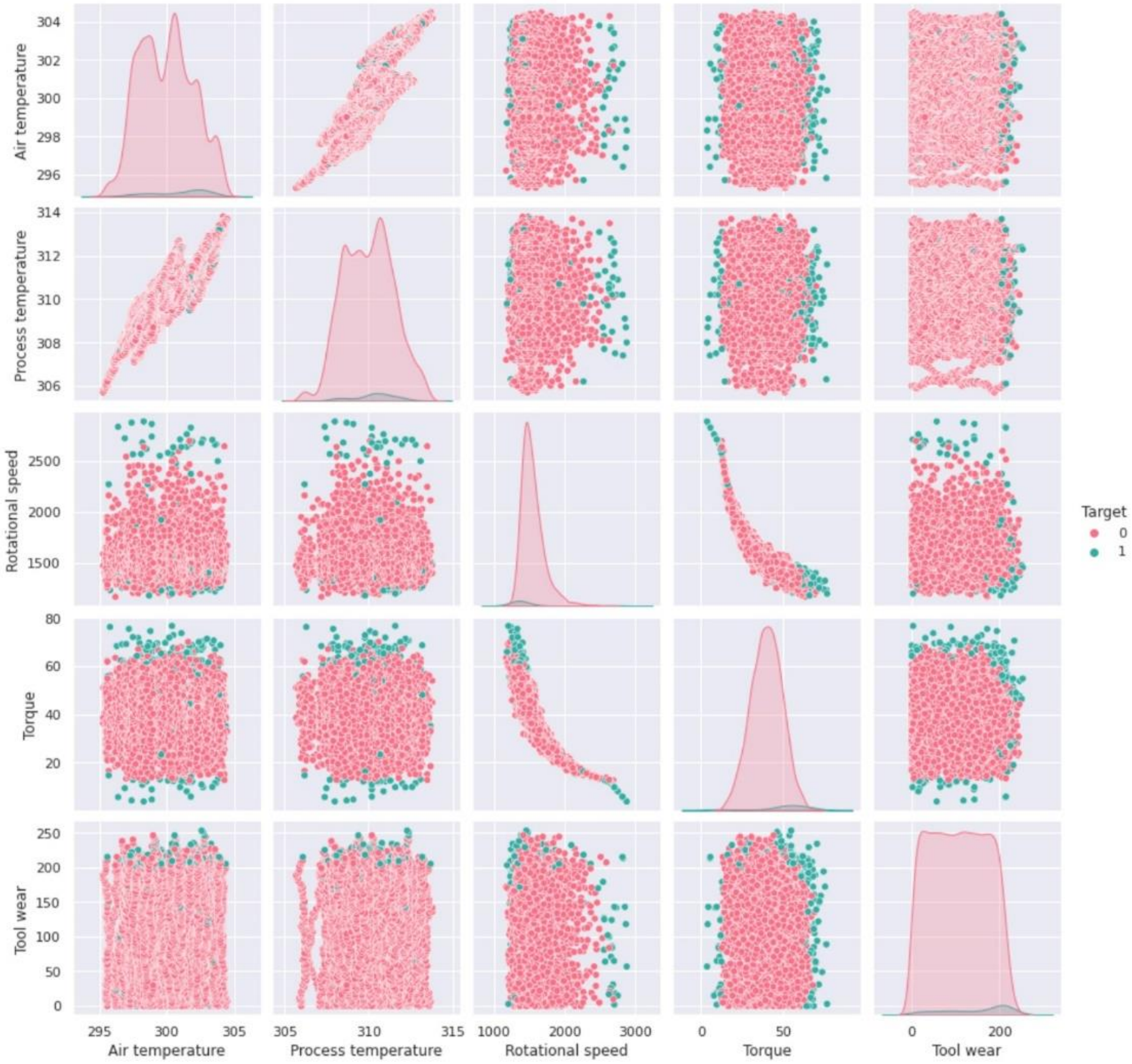
Supervised ML involves training models on labeled datasets for better decision-making.

Simulation Setup

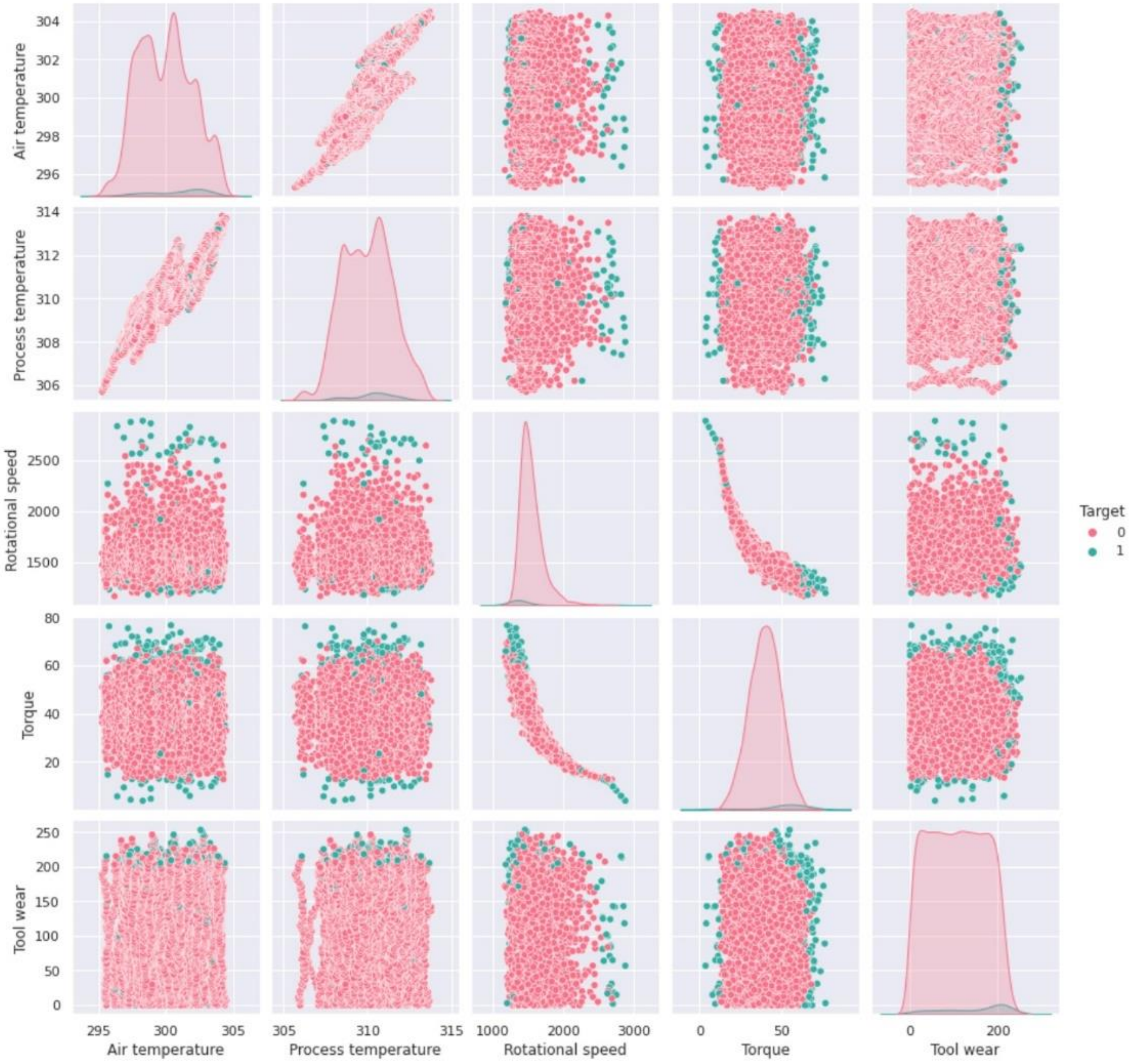
Number of tasks: 50, 100, 150, 200, 250, 300.
Number of Industrial Machines: 20.
Number of IEC Servers: 10.
Number of Cloud Servers: 2.
Task Offloading Decision Threshold: 0.5.
Available bandwidth between devices: 20 MBps.
Power consumption for computation at IEC server: 0.5 mW.
Power consumption for computation at Cloud server: 10 mW.
"NASA Turbofan Jet Engine Dataset" is used for estimating the lifetime and next maintenance of industrial machines.
Google Colab environment utilized for the entire experiment.

Dataset

- **NASA Turbofan Jet Engine Dataset**: 10,000 entries from 3 industrial machine types.
- **Engine Size Distribution**: 60% large, 30% medium, 10% small engines.
- **Class Imbalance**: 96.7% no failure, 3.3% failure labels.
- **Failure Reasons**: 1.1% power, 1.0% toolware, 0.8% overstrain, 0.5% high heat dissipation.
- **Dataset Features**: 6 key parameters (Air temperature, Process temperature, Rotational speed, Torque, Tool wear, Target), 2 output levels (failure, no failure), facilitating comprehensive machine behavior evaluation



Dataset


Air temperature
Process temperature
Rotational speed
Torque
Tool wear
Target
0
1
295
300
305
310
315
1000
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3000
0
50
200
304
302
298
296
314
312
308
306
2500
1500
80
60
40
20
250
150
100

Performance Analysis

Execution Delay Analysis:
Task completion rate impacts execution delay on different devices.
IEC servers regulate end-to-end execution delay within a limit.
Proposed offloading strategy reduces overall execution delay with task volume.

Energy Consumption Trends:
IIoT sensors attempt execution on devices but offload due to limitations.
Delay-sensitive tasks directed to IEC servers, reducing computation overhead.
Computation-intensive tasks assigned to cloud servers, increasing energy consumption.

Computation Cost Evaluation:
Total computation cost comparison with existing strategies (Wang's, Mao's, Din's).
Significant improvement in performance with lower overall computation cost.
Consideration of end-to-end costs and execution costs on various computing devices

Predictive Analysis and Downtime Estimation

- Aim to enhance machine longevity and reduce downtime in industrial operations.
- Usage of balanced ML models: andom forests, bagging, boosting, ensemble learning.
- Training the model involved 1000 iterations for balanced prediction.
- Dataset divided into 80% training and 20% test samples for model evaluation.
- Accuracy Results: Random Forests (97.8%), Bagging (97.33%), Boosting (86.7%), Ensemble Learning (96.15%).
- Standard scaling and sampling techniques employed to enhance estimation accuracy.
- Bagging technique shows higher performance improvement in cross-validation.
- Despite overall accuracy enhancement, average prediction accuracy increased from 83% to 87%.

Thank You!