# High Level Design (HLD)

# Smart Grid Management: AI-Powered Predictive Maintenance and Demand Forecasting

# Contents

# Abstract

The Smart Grid Management: AI-Powered Predictive Maintenance and Demand Forecasting system is designed to enhance the reliability, efficiency, and sustainability of modern power grids. This High-Level Design (HLD) document outlines an IoT-based real-time monitoring and AI-driven predictive maintenance system that utilizes sensors to gather critical parameters such as temperature, voltage, and current from grid components.

The collected data is processed using machine learning models, ensemble learning, and federated learning to detect faults, predict failures, and optimize demand forecasting. The system features a Data Acquisition System (DAQ) with ESP32 microcontrollers, MLX90614 temperature sensors, voltage and current sensors, and GPS modules for geo-tagging assets. Additionally, Dynamic Thresholding is implemented to classify operational states into normal, warning, and critical levels, enabling an Early Warning System (EWS) for fault prevention.

The proposed architecture integrates cloud storage, real-time dashboards, and automated notifications for proactive grid management. By leveraging AI-powered analytics and IoT technology, the system ensures real-time fault detection, reduced downtime, and improved grid efficiency. This HLD provides a structured approach to the system's architecture, component interactions, and implementation strategies, laying the foundation for a scalable, intelligent, and industry-ready smart grid solution.

# 1. Introduction

The rapid expansion of power grids, combined with increasing energy demands, has led to greater operational challenges, including equipment failures, unplanned outages, and safety risks. One of the primary concerns in modern power systems is thermal stress and overloading, which significantly contribute to transformer failures, circuit breaker malfunctions, and other grid-related disruptions. To mitigate these risks, real-time fault detection and predictive maintenance have become essential for ensuring grid stability, reliability, and efficiency.

This project presents Interlard, an IoT-based Smart Grid Management System that integrates fault detection, predictive maintenance, and early warning mechanisms using MLX90614 thermal infrared sensors, voltage sensors, and current sensors. By leveraging machine learning algorithms such as Support Vector Machine (SVM) and Ensemble Learning,

classifying normal, warning, and critical operating conditions.

Furthermore, the system employs real-time data acquisition (DAQ) and cloud-based monitoring to facilitate remote diagnostics and proactive decision-making. This enables utilities and grid operators to detect anomalies before they escalate into critical failures, thereby minimizing downtime, maintenance costs, and energy losses.

Why this High-Level Design Document?

The purpose of this High-Level Design (HLD) document is to provide an architectural overview of the Smart Grid Management: AI-Powered Predictive Maintenance and Demand Forecasting system. The document outlines system design, component interactions, and functionality to guide development and implementation.

## 1.1Scope

This project aims to enhance grid reliability and efficiency by integrating IoT-based real-time monitoring, AI-driven predictive maintenance, and demand forecasting. The system will collect data from various grid components using temperature sensors (MLX90614), voltage sensors, and current sensors, process it using machine learning models, and generate insights for fault detection and early warnings.

## 1.2 Definitions

2. **Smart Grid**: An advanced electrical grid that integrates digital communication, IoT, and AI-based analytics to enhance efficiency, reliability, and sustainability.
3. **Predictive Maintenance**: A proactive approach that uses AI and historical data to anticipate equipment failures before they occur.
4. **Fault Detection**: The identification of irregularities or malfunctions in power grid components using real-time data and AI-driven algorithms.

5. **Dynamic Thresholding**: A statistical method that categorizes grid parameters (temperature, voltage, current) into **normal, warning, and critical** levels based on real-time sensor data.
6. **Early Warning System (EWS)**: A mechanism that alerts grid operators about potential failures, allowing for preventive actions.
7. **Data Acquisition System (DAQ):** The hardware and software combination that collects, processes, and transmits sensor readings for analysis.

# 2. General Description

### Product Perspective

The Smart Grid Management: AI-Powered Predictive Maintenance and Demand Forecasting system is designed to enhance the reliability and efficiency of power grids by leveraging IoT, AI, and Federated Learning. The system incorporates real-time monitoring, fault detection, early warning, and predictive maintenance to prevent equipment failures and optimize power distribution.

## 2.1 Problem Statement

Aging power grids suffer from overheating, overvoltage, and equipment failures, leading to unplanned downtime, energy wastage, and financial losses. Traditional maintenance methods are reactive, addressing faults after they occur, which increases operational costs and grid instability.

## 2.2 Proposed Solution

This project introduces an IoT-based real-time monitoring system integrated with AI-driven fault detection and demand forecasting. The system consists of:

- ESP32 with sensors (MLX90614, voltage, current, and GPS) for real-time data collection.
- Federated Learning-based AI models for predictive maintenance.
- Early Warning System (EWS) for proactive issue resolution.
- A cloud-integrated visualization dashboard using Streamlit.

## 2.3 Future Scope

AI-Edge Computing: Implementing AI models directly on ESP32 for faster fault detection.

Blockchain for Grid Security: Securing grid data using blockchain for tamper-proof logging.

Integration with Smart Meters: Enhancing energy forecasting through smart meters.

Grid Expansion: Scaling the model to industrial and renewable energy grids.

## 2.4 Technical Requirements

| **Component** | **Specification** |
|---|---|
| Microcontroller | ESP32 (WiFi-enabled) |
| Temperature Sensor | MLX90614 (Infrared) |
| Voltage Sensor | 0-25V Measurement Range |
| Current Sensor | 0-30A Capacity |

| | |
|---|---|
| Communication | WiFi, HTTP API |
| Cloud Storage | Google Firebase |
| AI Model | Ensemble Learning, Federated Learning |
| Web Dashboard | Streamlit |
| Power Supply | 5V DC |

## 2.5 Data Requirements

Sensor Data: Ambient & core temperature, voltage, current readings.

Fault Logs: Historical faults from substations.

## 2.6 Tools Used

| Category | Tools |
|---|---|
| Programming | Python, C++ (Arduino) |
| AI/ML | Scikit-learn, TensorFlow |
| IoT | ESP32, Google Firebase, Google Apps Script |
| Data Visualization | Streamlit, Power BI |
| Communication | WiFi, HTTP API |

## 2.7 Hardware Requirement

| Component | Description |
|---|---|
| Microcontroller | ESP32 (for data collection & transmission) |
| Temperature Sensor | MLX90614 (for real-time thermal monitoring) |
| Voltage Sensor | 0-25V (for measuring electrical fluctuations) |
| Current Sensor | 0-30A (for load assessment) |
| GPS Module | NEO-6M (for asset tracking) |
| OLED Display | TFT SPI 128x160 V1.1 (for local monitoring) |

## 2.8Constraints

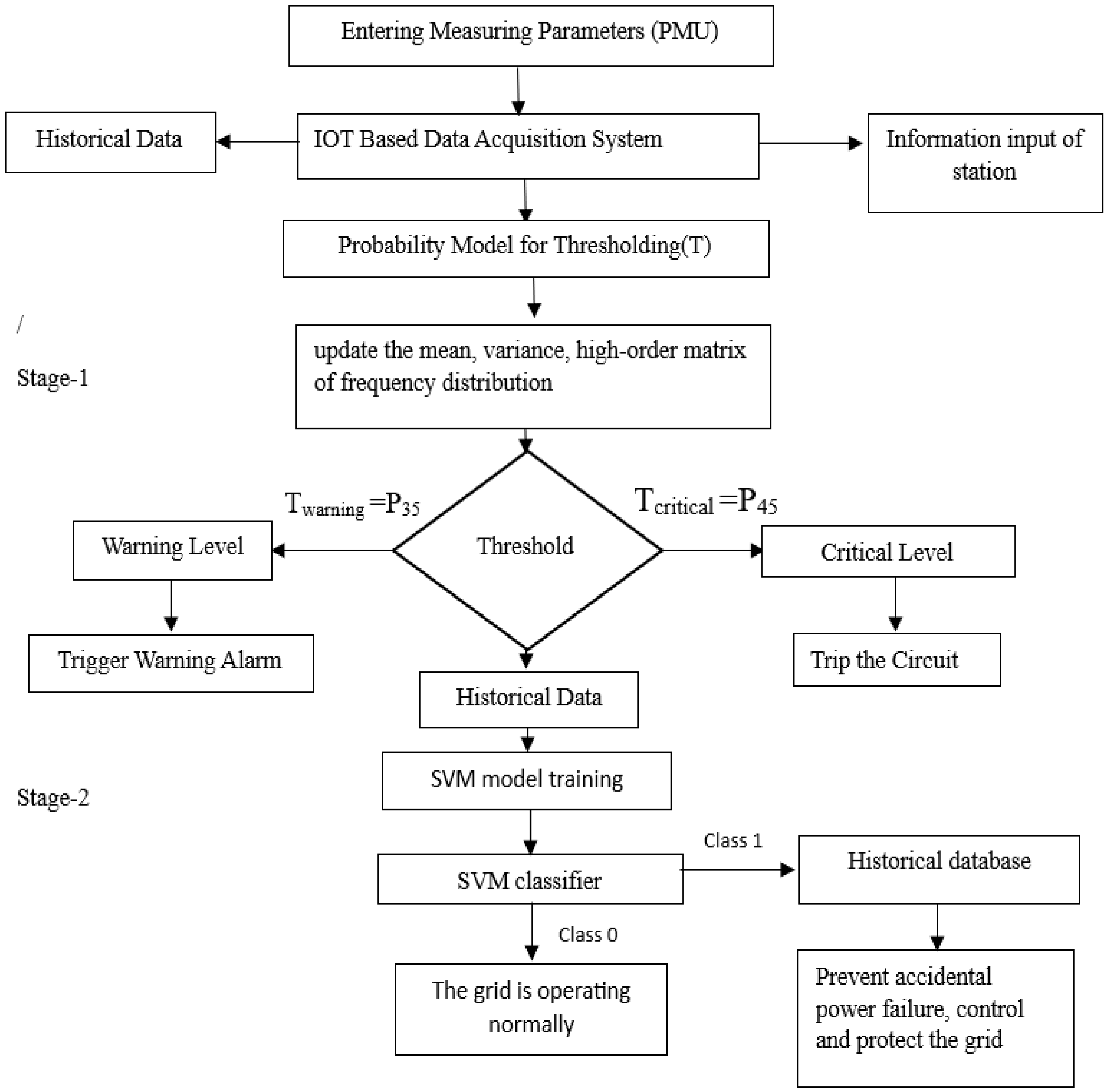
1. Data Latency: WiFi-based communication may introduce delays.
2. Model Training Complexity: Federated Learning requires distributed computing resources.
3. Energy Consumption: IoT sensors must balance power efficiency with real-time monitoring.

## 2.9Assumptions

1. Reliable WiFi connectivity is available at substations.
2. Historical fault data is available for training AI models.

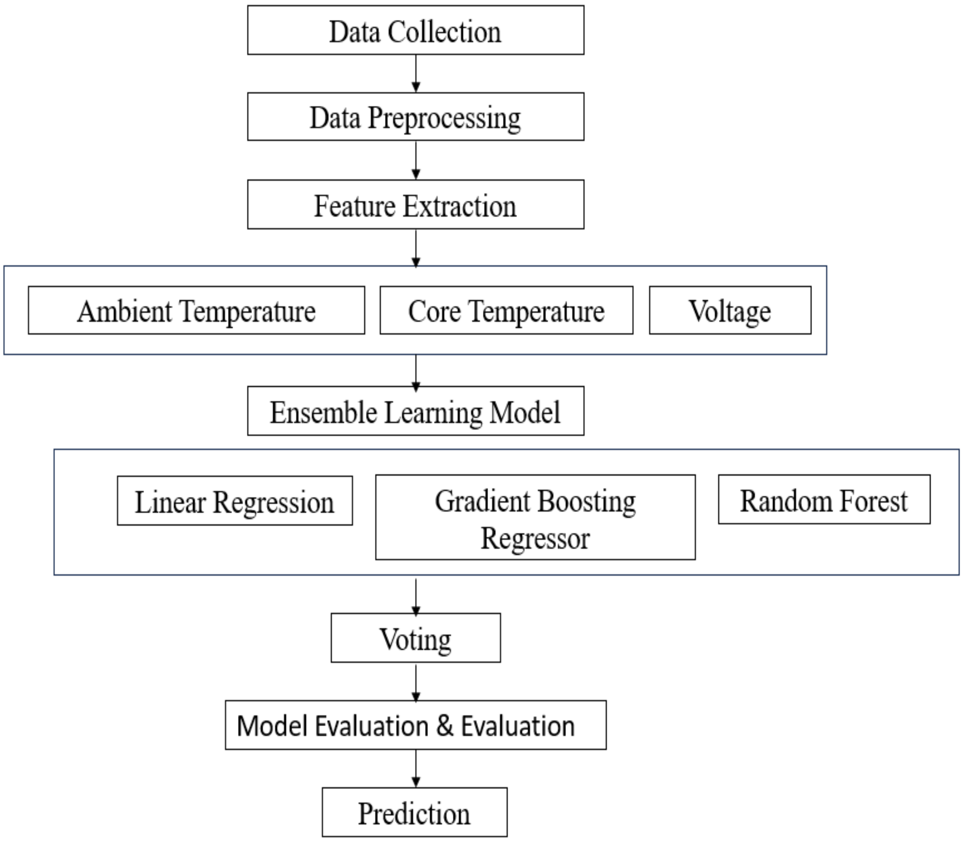
## Design Details

1. Process Flow

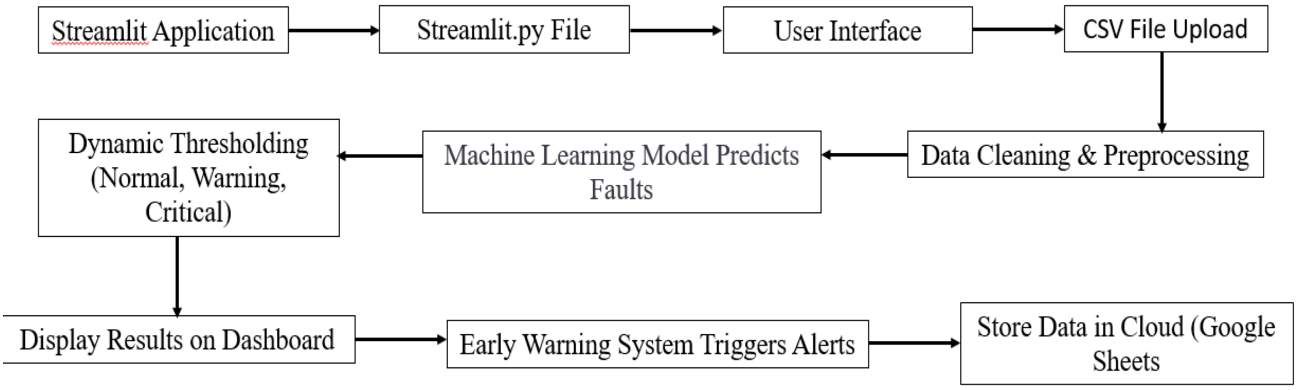



## Proposed Methodology

### 2.9.1 Model Training and Evaluation




### 2.9.2 Deployment Process




## 2.10 Event Log

| | Timestamp | Ambient Temperature | Core Temperature | Voltage | Output | Fault Count | Health Score |
|---|---|---|---|---|---|---|---|
| 1 | 11/12/2024 0:38:45 | 27.51 | 30.05 | 0 | 0 | 9 | 23.41 |
| 2 | 11/12/2024 0:39:08 | 27.75 | 28.83 | 0 | 0 | 7 | 29.66 |
| 3 | 11/12/2024 0:39:31 | 27.85 | 29.09 | 0 | 0 | 0 | 50.55 |
| 4 | 11/12/2024 0:39:55 | 27.91 | 29.25 | 0 | 0 | 3 | 41.48 |
| 5 | 11/12/2024 9:26:08 | 26.89 | 26.47 | 0 | 0 | 6 | 33.68 |
| 6 | 11/12/2024 9:26:31 | 26.89 | 26.49 | 0 | 0 | 2 | 45.68 |
| 7 | 11/12/2024 9:26:54 | 26.95 | 26.83 | 3.3 | 0 | 7 | 40.45 |
| 8 | 11/12/2024 9:27:58 | 26.73 | 27.17 | 3.3 | 0 | 1 | 58.45 |
| 9 | 11/12/2024 9:28:21 | 26.83 | 27.09 | 3.3 | 0 | 9 | 34.43 |
| 10 | 11/12/2024 9:28:44 | 26.85 | 27.37 | 0 | 0 | 7 | 30.44 |
| 11 | 11/12/2024 9:29:07 | 26.93 | 27.73 | 3.19 | 0 | 0 | 60.88 |
| 12 | 11/12/2024 9:29:30 | 27.03 | 28.07 | 3.07 | 0 | 8 | 36.38 |
| 13 | 11/12/2024 9:29:53 | 27.03 | 28.23 | 2.98 | 0 | 7 | 39.06 |
| 15 | 11/12/2024 9:30:39 | 27.13 | 28.19 | 0 | 0 | 3 | 42.09 |
| 16 | 11/12/2024 9:31:03 | 27.15 | 28.27 | 3.11 | 0 | 9 | 33.39 |
| 17 | 11/12/2024 9:31:26 | 27.17 | 28.27 | 3.28 | 0 | 1 | 57.89 |
| 18 | 11/12/2024 9:31:50 | 27.09 | 28.37 | 3.3 | 0 | 8 | 36.96 |

2.11 Error Handling

## Performance

## 2.12 Reusability

The system architecture is modular and scalable, allowing integration into different grid infrastructures.

Components such as IoT sensors, AI models, and cloud storage can be reused across various power distribution networks.

The Federated Learning approach ensures adaptability to new datasets without requiring significant reconfiguration.

The Early Warning System (EWS) can be repurposed for other industrial applications like factory automation and HVAC monitoring.

## **2.13 Application Compatibility**

The system supports multi-platform integration, including cloud-based dashboards (Streamlit), embedded microcontrollers (ESP32), and edge computing devices.

Compatible with existing SCADA (Supervisory Control and Data Acquisition) systems for real-time data visualization.

Interoperable with different sensor types, including MLX90614 (temperature), voltage, and current sensors.

Can be deployed in renewable energy grids, industrial power systems, and traditional electrical substations.

## 2.14 Resource Utilization

Optimized IoT Data Transmission: Uses efficient communication protocols (HTTP API, MQTT) to reduce bandwidth usage.

Cloud and Edge Computing Balance: Computational tasks are distributed between edge devices (ESP32) and cloud servers for low-latency processing.

Power Efficiency: ESP32 operates in low-power mode to minimize energy consumption.

Minimal Hardware Requirements: Uses low-cost microcontrollers and sensors to keep deployment affordable.

## 2.15 Deployment

Flexible Deployment Models: Supports on-premise, cloud-based, and hybrid deployments.

Plug-and-Play Integration: Designed for quick installation and minimal manual intervention.

Automated Updates: AI models and firmware can be remotely updated without disrupting operations.

Security Measures: Implements data encryption, authentication protocols, and access control for secure deployment

# 3 Dashboards

The system includes a **real-time monitoring dashboard** that provides an interactive visualization of key grid parameters and fault detection insights.

**10.1 Key Features of the Dashboard**

- **Live Data Streaming:** Displays real-time temperature, voltage, and current readings.
- **Fault Detection Alerts:** Highlights critical conditions using **color-coded indicators (Normal, Warning, Critical)**.
- **Historical Data Analysis:** Allows operators to compare past trends with real-time performance.
- **Predictive Analytics:** Displays **ML-based forecasts** for demand and maintenance needs.
- **Health Score Visualization:** Assigns a **health rating** to each grid component based on operational conditions.
- **Geolocation Tracking:** Uses **GPS data** to map faults and optimize response times.

## 3.8Key Performance Indicators (KPI)

The system's effectiveness will be measured using the following **KPIs:**

**11.1 Operational KPIs**

- **Fault Detection Accuracy (%)**: Measures how accurately AI models detect faults.
- **Mean Time to Detect (MTTD) (s)**: Time taken to identify a fault.
- **Mean Time to Repair (MTTR) (min)**: Time required to resolve detected issues.
- **Power Outage Reduction (%)**: Compares downtime before and after system deployment.

**11.2 Predictive Maintenance KPIs**

- **Failure Prediction Accuracy (%)**: Measures the AI's ability to predict faults before they occur.
- **Maintenance Cost Reduction (%)**: Tracks cost savings due to predictive maintenance.

**11.3 Demand Forecasting KPIs**

- **Load Forecasting Accuracy (%)**: Evaluates the precision of AI-based demand forecasting.
- **Peak Load Management Efficiency (%)**: Measures improvements in power distribution.
-

## Conclusion

The Smart Grid Management: AI-Powered Predictive Maintenance and Demand Forecasting system is a cutting-edge solution designed to enhance grid reliability, efficiency, and sustainability. By integrating IoT-based sensor networks, AI-driven fault detection, and federated learning, the system provides real-time monitoring, predictive analytics, and early warning capabilities.

This approach reduces unplanned outages, optimizes maintenance schedules, and improves grid resilience against failures. With features like a health score index, dynamic thresholding, and cloud-based dashboards, the system empowers power operators with data-driven decision-making.

Future enhancements include blockchain-based data security, edge AI deployment, and integration with industrial power networks to further revolutionize the energy sector.