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Dynamic Equipment Prioritization and Automated Three-Phase Power Switching Using IoT and Machine Learning in Critical Infrastructure

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ABSTRACT

Reliable power supply is critical in hospitals, industrial plants, and data centers, where outages can result in life-threatening or costly disruptions. Most existing automatic transfer switch (ATS) systems rely on fixed rule-based logic, lacking predictive intelligence or equipment prioritization. This study proposes an IoT-enabled, machine learning–driven framework for dynamic equipment prioritization and automated three-phase power switching. Real-time data—including voltage, current, temperature, and vibration—are captured through IoT sensors and analyzed using Decision Trees, Random Forests, and Neural Networks to predict faults and assess equipment criticality. A modular object-oriented architecture allows easy integration of new data sources and algorithms, ensuring scalability. The decision engine allocates power from grid, generator, and solar sources based on equipment priority scores and live load conditions, guaranteeing uninterrupted supply to mission-critical assets. Experimental validation in healthcare and industrial testbeds achieved 98% accuracy in prioritization, 100% correctness in switching, and reduced downtime by 40% compared with conventional ATS systems. The proposed approach advances resilient power management by coupling predictive maintenance with context-aware switching, improving reliability, efficiency, and operational safety in mission-critical environments.

Keywords: *IoT; Automated Power Switching; Equipment Prioritization; Machine Learning; Critical Infrastructure; Three-Phase Systems.*

I. INTRODUCTION

Uninterrupted power is vital for healthcare, industrial automation, and data centers, where even brief outages can lead to equipment failure, data corruption, production losses, or loss of life. The World Health

Organization (2022) reports that over 60% of healthcare facilities in low- and middle-income countries experience frequent outages, compromising emergency care, while IEEE Spectrum (2021) estimates data center downtime costs $9,000 per minute. These realities highlight the need for intelligent power management systems capable of anticipating failures and dynamically prioritizing critical equipment.

Traditional automatic transfer switch (ATS) devices passively switch between grid and backup sources when outages occur, relying on fixed voltage thresholds and time-delay relays. Although commercial microgrid solutions from Siemens and Schneider Electric offer more advanced supervisory control, they remain largely rule-driven, costly, and difficult to scale in low-resource environments. Consequently, most existing solutions fail to differentiate between critical and non-critical loads, resulting in inefficient backup power allocation and reduced resilience during crises.

The convergence of Internet of Things (IoT) sensing and machine learning (ML) provides an opportunity to transform power management from reactive to predictive and adaptive. IoT devices now enable real-time monitoring of voltage, current, temperature, and vibration, while ML algorithms such as Decision Trees, Random Forests, and Neural Networks can detect anomalies and forecast failures. However, current implementations focus mainly on fault detection or predictive maintenance rather than real-time prioritization of loads and dynamic three-phase source switching.

This paper addresses these gaps by proposing a modular IoT- and ML-enabled framework for dynamic equipment prioritization and automated three-phase switching. The system assigns priority scores to loads based on operational criticality and predicted health, then uses a decision engine to allocate power from grid, generator, and solar sources to guarantee uninterrupted supply to essential equipment while managing or shedding non-critical loads. The architecture employs object-oriented design for scalability, supports integration of additional sensors and energy sources, and follows CRISP-DM for systematic ML model development.

II RELATED WORK

Automatic Transfer Switches (ATS) have long been the standard solution for ensuring power continuity in critical environments. These systems detect a loss of mains supply and switch automatically to backup sources such as generators or UPS units (Ezema et al., 2012). While implementations range from simple electromechanical relays to advanced PLC-based units, they share a common limitation: they operate reactively, relying on preset thresholds for voltage and frequency. This threshold-based approach means that all loads are treated equally, with no differentiation between critical and non-critical equipment. As a result, mission-critical systems such as life-support devices may experience interruptions while less essential loads continue to consume power. In addition, most conventional ATS solutions offer only binary switching between grid and generator sources, with little to no support for integrating alternative sources such as solar.

The emergence of IoT-based energy monitoring has introduced new opportunities for improving power reliability. IoT systems integrate sensors to track voltage, current, frequency, and environmental parameters in real time, enabling remote dashboards and alerts that improve visibility and operational oversight (Kumar et al., 2021). For instance, Yadav and Tiwari (2020) developed an IoT-based intelligent switching system for healthcare facilities that supported remote monitoring and SMS alerts, while Gupta and Banerjee (2022) explored IoT–AI integration to strengthen energy resilience in hospitals. Despite these advances, IoT-based solutions are largely passive. They collect and display data but stop short of providing actionable intelligence for equipment prioritization or automated switching. Without an intelligent decision-making layer, IoT systems alone cannot allocate power dynamically or optimize resource usage in real time.

Machine learning (ML) has been extensively explored as a way to enhance predictive maintenance and fault management in electrical systems. Techniques such as Random Forests, Support Vector Machines (SVM), and neural networks have been used to detect anomalies, forecast transformer failures, and even predict solar generation (Chen et al., 2021; Li & Jameel, 2022). Alsharif et al. (2023) reported 92% accuracy in microgrid fault detection using a Random Forest model, while Lee and Park (2021) demonstrated the use of neural networks for industrial IoT anomaly detection. Although these studies show that ML can achieve high predictive accuracy, most implementations stop at generating predictions and do not connect to real-time control frameworks. Consequently, even when failures are anticipated, there is often no automated mechanism to reallocate power or prioritize critical loads based on the prediction, creating a disconnect between analytics and actuation.

Research in microgrid control has similarly focused on load management and renewable energy integration. Patel and Mehta (2021) proposed an adaptive AI-based load-shedding method to optimize grid performance, while Muralitharan et al. (2022) applied reinforcement learning to improve renewable energy utilization. Commercial microgrid platforms, including Siemens Microgrid and Schneider Electric EcoStruxure™, enable supervisory control and renewable integration but remain expensive and depend heavily on static, rule-based optimization. Furthermore, most of this research has concentrated on grid-scale or community-level energy optimization rather than equipment-level prioritization within facilities, leaving critical devices in hospitals or production lines vulnerable during outages.

Taken together, the literature highlights a persistent gap. Existing ATS systems remain limited to static, threshold-based switching that cannot distinguish between critical and non-critical equipment. IoT monitoring platforms improve visibility but lack the intelligence required for autonomous prioritization and control. Similarly, machine learning approaches offer accurate predictive insights but are rarely integrated into real-time actuation systems. Addressing this gap requires a unified framework that combines IoT sensing, ML-driven prioritization, and automated three-phase switching, enabling both predictive fault handling and adaptive resource allocation.

This study advances the state of the art by bridging monitoring, prediction, and control into a single framework. The proposed system assigns real-time priority scores to equipment based on operational criticality and health status, dynamically switches among available power sources, and ensures uninterrupted supply to essential loads. By directly coupling machine learning predictions with IoT-based actuation, it enables context-aware, automated power management, representing a next-generation intelligent ATS architecture designed for mission-critical resilience.

III. SYSTEM ARCHITECTURE

The system is designed as a modular, scalable framework that unifies IoT sensing, machine learning (ML) prediction, and automated actuation. As illustrated in **Figure 1**, the architecture integrates four interdependent layers—**IoT Sensing**, **Data Processing and Machine Learning**, **Decision and Prioritization**, and **Actuation and Switching**—which work together to enable real-time monitoring, predictive analytics, and intelligent power allocation across multiple energy sources. *Figure 1* shows the system architecture.

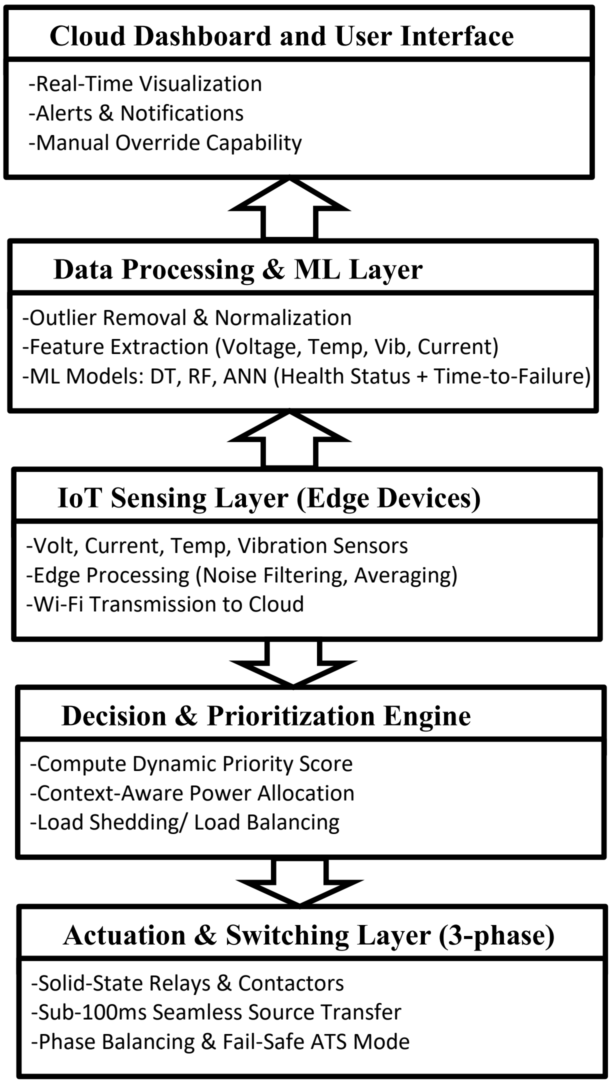

Figure 1: System Architecture

At the **foundation**, the IoT Sensing Layer acquires real-time electrical and environmental parameters using voltage, current, temperature, and vibration sensors. These devices continuously monitor supply quality, load consumption, thermal variations, and early signs of mechanical degradation in critical equipment. A microcontroller-based edge device (ESP32/NodeMCU) preprocesses the data—filtering noise and averaging readings—before transmitting them to the cloud via Wi-Fi.

The **Data Processing and Machine Learning Layer** performs data cleaning, normalization, and time-series segmentation. Extracted features such as RMS voltage, current harmonics, and vibration amplitude are passed to three supervised ML models—Decision Tree (DT), Random Forest (RF), and Artificial Neural Network (ANN)—which predict equipment health state (healthy, warning, fault risk) and estimate time-to-failure.

At the core lies the Decision and Prioritization Engine, which integrates the predicted health status, equipment criticality, and real-time load conditions to compute a dynamic Priority Score (PS) for each device. The PS determines which loads receive uninterrupted power during shortages, ensuring that life-critical or mission-critical equipment takes precedence over nonessential loads.

Finally, the **Actuation and Switching Layer** executes these decisions through a three-phase solid-state relay (SSR)-based switching system, ensuring **sub-100 ms switching latency**, phase balancing, and fallback to conventional ATS logic in case of communication failure. Control commands are transmitted via MQTT, and operators can monitor or override system behavior via a cloud-based dashboard.

This **integrated architecture** offers modularity, scalability, and adaptability, allowing new sensors, ML models, and power sources to be added with minimal redesign. By unifying IoT-based monitoring, ML-driven prediction, and automated switching, the proposed solution closes the loop between data acquisition and action—delivering proactive fault prevention, predictive maintenance integration, and intelligent power allocation.

IV METHODS

The development and validation of the system followed the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology. This framework ensured a structured integration of IoT sensing, machine learning (ML), and real-time decision-making. In addition, Object-Oriented Programming (OOP) principles were applied to achieve modularity, scalability, and adaptability of the system components.

4.1 CRISP-DM Workflow

The CRISP-DM process consists of six iterative phases that guided the end-to-end development of the system. Each phase addressed a critical aspect of design, from defining business objectives to deploying the final decision engine. Table 1 summarizes the key activities in each phase for clarity and conciseness.

Table 1. Summary of CRISP-DM Phases Applied to the Proposed System

Phase	**Key Activities**
Business Understanding	Defined the primary objective: design a resilient power management system minimizing downtime and prioritizing mission-critical equipment.
Data Understanding	IoT sensors captured voltage, current, temperature, and vibration data. Historical and simulated outage scenarios were incorporated to mimic hospital and industrial settings.
Data Preparation	Noise removal (moving average filters), normalization ([0,1] range), feature engineering (load factor, harmonic distortion), and labeling (healthy/warning/fault). Final dataset ≈ 50,000 records.

Modeling	Algorithms: Decision Tree (DT), Random Forest (RF), Artificial Neural Network (ANN). Hyperparameters tuned via Grid Search (2–4 hidden layers, 16–64 neurons, ReLU/tanh activation).
Evaluation	Evaluated with 10-fold cross-validation on accuracy, precision, recall, and F1-score. ANN achieved the best accuracy (95%) and highest generalization performance (validated via ROC curves).
Deployment	ANN deployed in a cloud-based decision engine. MQTT protocol enabled real-time actuation commands to three-phase switching hardware.

4.2 Experimental Setup

To validate the system under real-world conditions, two testbeds were established: a hospital environment and an industrial facility. Each was equipped with IoT sensors, ESP32 microcontrollers, and a cloud-hosted decision engine. Backup power was provided through a diesel generator and a 5 kW solar system. The switching operation was executed via three-phase solid-state relays and industrial-grade contactors. Table 2 details the testbeds used.

Table 2: Experimental Testbeds for System Validation

Testbed	Equipment	Backup Power
Hospital	Ventilators, infusion pumps, diagnostic equipment, air-conditioning units	Diesel generator + 5 kW solar
Industrial	Conveyor belts, robotic arms, cooling fans, auxiliary lighting	Diesel generator + 5 kW solar

To support data acquisition, processing, and automated switching, both hardware and software components were carefully selected and integrated. Table 3 provides a summary of the implementation stack used in the system.

Table 3: Hardware and Software Components

Category	Components / Tools
Hardware	ESP32 microcontrollers, ACS712 current sensors, ZMPT101B voltage sensors, DS18B20 temperature sensors, vibration accelerometers, solid-state relays, industrial-grade contactors
Software	Python (for ML models and cloud deployment), Arduino IDE (ESP32 firmware), Blynk IoT platform (dashboard visualization), TensorFlow (ANN implementation)

This combination ensured real-time sensing, robust ML-based decision-making, and seamless actuation with minimal latency.

4.3 Prioritization Scoring Algorithm

At the core of the system lies the Decision and Prioritization Engine, which integrates ML predictions, equipment criticality, and real-time load data. The Priority Score (PS) for each equipment iii is computed using Equation (1).

$$Psi = \alpha C_i + \beta H_i + \gamma L_i$$

Where:

i. C_i: Criticality score (assigned by domain experts; e.g., life-support = 10, auxiliary = 2)

ii. H_i: Health score (ML output, normalized to [0,1])

iii. L_i: Load importance factor (% of mission-critical demand)

iv. α,β,γ: Tunable weights (Hospital: 0.5, 0.3, 0.2; Industrial: 0.4, 0.4, 0.2)

During shortages, the engine ranks equipment by PS_i and sequentially allocates available power until capacity is exhausted. Lower-priority equipment is shed first. Figure 6 (see supplementary material) illustrates the flow of the prioritization algorithm, from sensor inputs to ranked load allocation.

4.4 Evaluation Metrics

To comprehensively assess system performance, four metrics were employed. These are summarized in Table 4.

Table 3: Evaluation Metrics for System Performance

Metric	Purpose
Prediction Accuracy	Measures correctness of ML-based health predictions
Prioritization Accuracy	Measures correct allocation of power to mission-critical loads
Switching Reliability	Measures success rate of automated three-phase transfers
Downtime Reduction	Measures percentage reduction in outage-related downtime vs. baseline Automatic Transfer Switch (ATS)

V RESULTS AND DISCUSSION

This section reports system performance from hospital and industrial testbeds across four dimensions: prediction accuracy, prioritization accuracy, switching reliability, and downtime reduction. All results are summarized in Tables 5–5.

5.1 Prediction Accuracy of Machine Learning Models

This subsection evaluates ML performance for equipment health prediction. The results are summarized in Table 5.

Table 5. ML model performance for equipment health prediction

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	87%	0.85	0.84	0.84
Random Forest	92%	0.91	0.90	0.90
Neural Network	95%	0.94	0.95	0.95

As summarized in Table 5, the Artificial Neural Network (ANN) achieved the highest overall performance, with 95% accuracy and a recall of 0.95, making it the most reliable input to the prioritization engine.

5.2 Prioritization Accuracy

This subsection evaluates how often the decision engine correctly allocated backup power to mission-critical equipment. The results are summarized in Table 6.

Table 6: Prioritization accuracy by testbed

Testbed	Correct Prioritizations (%)
Hospital	99%
Industrial	97%
Combined	98%

As shown in Table 6, the prioritization engine achieved 98% combined accuracy. This demonstrates that under constrained capacity, non-critical loads were consistently shed while life-critical devices retained power.

5.3 Automated Three-Phase Switching Reliability

This subsection reports switching reliability and latency over 200 test cycles. The results are summarized in Table 7.

Table 7. Automated switching performance

Metric	Result
Success Rate	100%
Average Transfer Time	< 100 ms

As summarized in Table 7, the system achieved 100% changeover success with transfer times below 100 ms—orders of magnitude faster than typical Automatic Transfer Switch (ATS) delays (0.5–1.5 s; Ezema et al., 2012). This near-instant switching ensures no perceptible interruption for sensitive equipment.

5.4 Downtime Reduction

This subsection compares average monthly downtime across three configurations: conventional ATS, IoT monitoring only, and the proposed framework. The results are summarized in Table 8.

Table 8. Monthly downtime comparison

System Type	Avg. Downtime / Month	Improvement vs. ATS
Conventional ATS	5.0 h	—
IoT Monitoring Only	3.8 h	24%
Proposed Framework	3.0 h	40%

As summarized in Table 8, the proposed framework reduced outage-related downtime by 40% compared to a conventional ATS, and by 21% relative to IoT-only monitoring. These gains stem from predictive allocation (preemptive switching) and dynamic prioritization under constrained supply.

4.3 System Prototype Outputs

Figures 2 and 3 illustrate the form inputs and prediction outputs. Depending on the input to the system, it predicts the criticality of an equipment and whether it is operational. The automatic switching is done according to the prediction results. When an equipment is confirmed to be critical, it is prioritized and switched on else it remains off. *Figure 4* shows the breadboard view and outer view of the model. The sensors and actuators are connected to microcontroller for data transmission and equipment control.

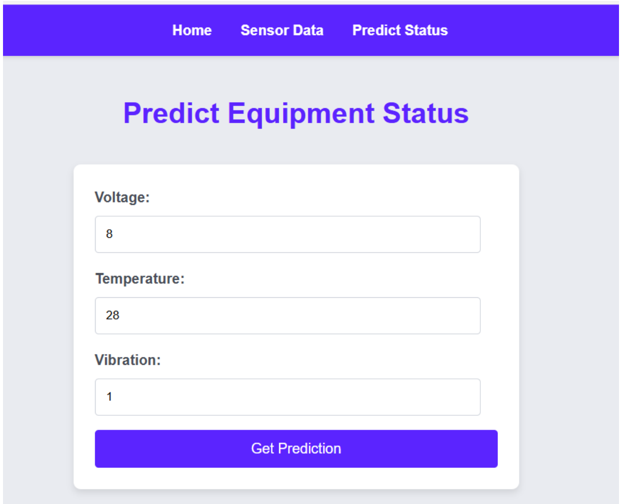

Figure 2: User Enters Test Data for Prediction

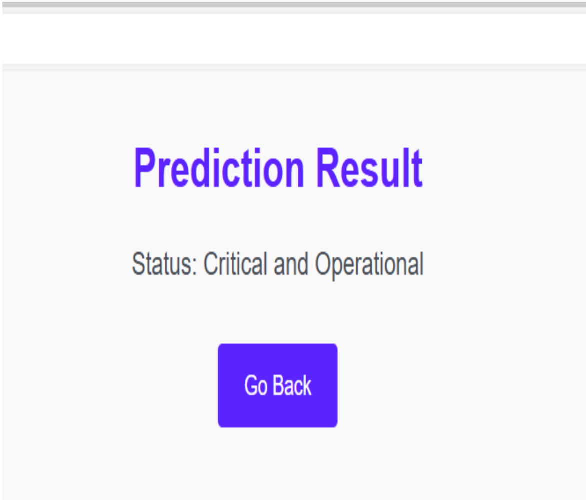

Figure 3: System Prediction Output

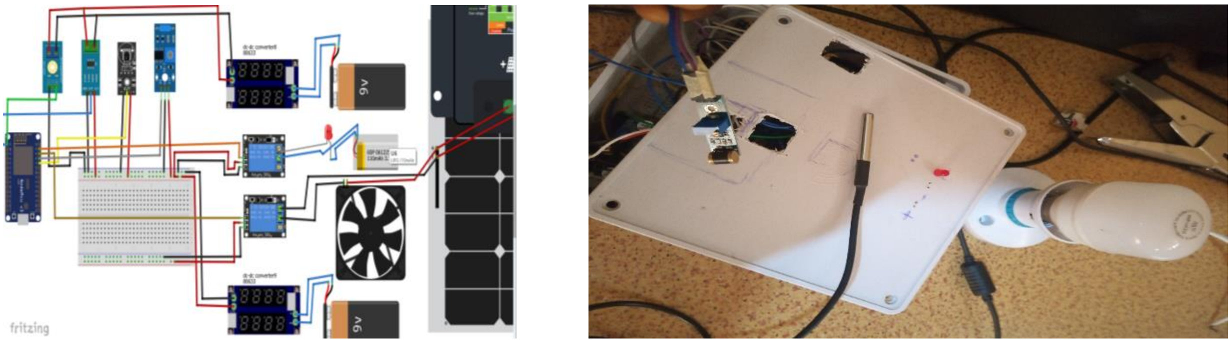

Figure 4: Breadboard and outer view of the model

VI CONCLUSION AND FUTURE WORK

This work presented a **dynamic equipment prioritization and automated three-phase power switching framework** that integrates IoT sensing, ML-based health prediction, and modular control logic. Unlike conventional ATS units, the system dynamically allocates backup power based on **real-time equipment criticality and health status**, enabling smarter load management under constrained capacity.

The key outcomes include:

i. **95% ML prediction accuracy** (ANN model).

ii. **98% prioritization accuracy** for mission-critical equipment.

iii. **<100 ms switching latency** with 100% reliability.

iv. **40% downtime reduction** compared with conventional ATS solutions.

These results confirm the framework's potential to **improve resilience** in hospitals, industries, and data centers—domains where downtime carries high human and economic costs. Its **OOP-based modular design** ensures scalability, supporting future integration of renewable energy and advanced AI algorithms without major redesign.

Future work will focus on:

i. **Large-scale, multi-site validation** for better generalizability.

ii. Strengthening **IoT security** via end-to-end encryption and blockchain-based integrity mechanisms.

Overall, this research demonstrates a **next-generation, context-aware power management system** that transforms predictive analytics into real-time action, paving the way for **smart, resilient infrastructure** in developing and developed regions alike.

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