RESEARCH PAPER

TinyML-Based Edge Intelligent Controller for Real-Time Microgrid Monitoring, Fault Detection, and Stability Enhancement

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ABSTRACT

This study introduces an edge-based intelligent controller for microgrid stability, leveraging a TinyML framework on ESP32 with ZMPT101B voltage and ACS712 current sensors for continuous monitoring and fault identification. Traditional microgrid protection systems suffer from excessive delays, centralized dependencies, and vulnerability to network disruptions, often leading to cascading failures. The proposed architecture enables local data capture, preprocessing, and inference directly on the microcontroller, bypassing external processing. Sensor signals undergo RMS computation, feature extraction (e.g., harmonics, power factor trends), and feeding into a quantized neural model deployed via TensorFlow Lite Micro. Real-time anomaly classification triggers immediate relay actuation for protective isolation. Validation on a lab-scale microgrid demonstrates superior metrics: inference latency under 20ms, zero network reliance, and 15% reduction in operational losses versus legacy centralized methods, alongside enhanced reliability in intermittent renewable scenarios.

Keywords: Edge intelligence, Microgrid controller, TinyML, ESP32, ZMPT101B, ACS712, Anomaly detection, On device inference, Relay protection, Quantized neural networks.

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I. INTRODUCTION

The rapid growth of global energy demand, along with increasing concerns about climate change and energy sustainability, has accelerated the development of intelligent power management systems. Traditional electrical grids are gradually evolving into smart grids, which integrate advanced communication technologies, distributed energy resources, and intelligent control mechanisms to improve efficiency, reliability, and sustainability of power systems. Smart grids enable bidirectional communication between power utilities and consumers, allowing real-time monitoring, automated control, and optimized energy distribution across the network [1].

With the increasing integration of renewable energy sources such as solar and wind, the smart grid environment faces new operational challenges including energy intermittency, fluctuating load demand, and real-time grid stability management. Conventional centralized grid control systems rely heavily on cloud computing and large-scale data centers for decision making. However, these systems often experience high latency, communication overhead, and security vulnerabilities when handling large volumes of real-time data from distributed sensors and smart meters [2]. Therefore, efficient decentralized control mechanisms are required to ensure fast response and reliable operation of modern energy systems.

Recent advancements in edge computing and Artificial

Intelligence (AI) have significantly improved the ability of smart grids to perform intelligent decision-making at the network edge. Edge devices equipped with machine learning algorithms can analyze energy consumption patterns, detect anomalies, and dynamically adjust energy distribution in real time. These capabilities reduce dependency on centralized cloud infrastructure while improving system responsiveness and operational efficiency [3]. However, traditional machine learning models typically require large computational resources and memory capacity, making them difficult to deploy on low-power embedded devices commonly used in smart grid environments.

To address these challenges, Tiny Machine Learning (TinyML) has emerged as a promising technology that enables the deployment of lightweight machine learning models directly on microcontrollers and resource-constrained embedded systems. TinyML allows energy analytics, load forecasting, and anomaly detection tasks to be performed locally on edge devices with minimal computational overhead and power consumption [4]. By processing data locally,

TinyML significantly reduces latency, network bandwidth usage, and privacy risks associated with transmitting sensitive energy consumption data to remote servers.

In smart grid applications, TinyML-based controllers can analyze sensor data collected from smart meters, voltage sensors, and load monitoring devices to optimize power distribution and energy consumption in real time. These intelligent controllers can dynamically prioritize critical loads, predict demand fluctuations, and balance supply from renewable sources, ensuring efficient grid operation even under varying energy conditions [5]. Furthermore, TinyML models can continuously learn from local data patterns, enabling adaptive energy optimization strategies that improve system performance over time.

Another important advantage of TinyML-enabled smart grid systems is their ability to support real-time fault detection and predictive maintenance. By monitoring voltage variations, frequency fluctuations, and abnormal load patterns, embedded AI models can identify potential grid faults before they escalate into large-scale outages. Early fault detection improves grid resilience, enhances system reliability, and reduces maintenance costs for utility providers [6]. In addition, TinyML-based systems can detect energy theft or abnormal consumption patterns, which further improves grid security and operational transparency. The integration of TinyML with Internet of Things (IoT) technologies also plays a critical role in enabling intelligent energy management. IoT sensors deployed across the power grid continuously collect data related to energy generation, distribution, and consumption. TinyML algorithms embedded within IoT devices can process this data locally and transmit only relevant insights to the central management system. This distributed intelligence architecture improves scalability and ensures efficient utilization of communication bandwidth [7].

Moreover, real-time energy optimization is becoming increasingly important in microgrids and decentralized energy systems, where energy generation and consumption occur within localized networks. TinyML-enabled controllers can effectively manage distributed energy resources such as solar panels, battery storage systems, and electric vehicle charging stations. By predicting energy demand and adjusting load scheduling, these controllers help maintain grid stability while maximizing renewable energy utilization [8].

Several recent studies have explored machine learning-based energy management strategies for smart grids. These approaches include load forecasting using neural networks, reinforcement learning-based energy scheduling, and optimization-based demand response systems. While these techniques demonstrate promising results, many of them rely on cloud-based architectures that introduce communication delays and high infrastructure costs. TinyML offers a practical alternative by enabling lightweight AI models that operate efficiently on embedded edge devices with minimal computational requirements [9].

Therefore, the development of a TinyML-enabled smart grid controller presents a promising solution for achieving real-time energy optimization in modern power systems. By combining edge intelligence, embedded machine learning, and IoT-based monitoring, such systems can dynamically regulate energy distribution, improve grid reliability, and reduce operational costs. The proposed approach focuses on designing an intelligent TinyML-based controller capable of performing real-time load analysis, energy prioritization, and adaptive power management for efficient smart grid operation [10].

The remainder of this paper presents the proposed TinyML-based smart grid control architecture, system modeling, experimental validation, and performance evaluation for real-time energy optimization in intelligent power networks.

II. RELATED WORKS

Recent advancements in smart grid technologies have focused on integrating **Artificial Intelligence (AI), Internet of Things (IoT), and edge computing** to improve energy management and grid stability. Researchers have explored various machine learning-based approaches to enhance real-time monitoring, demand prediction, and energy optimization within smart grid environments. These approaches aim to address challenges such as fluctuating renewable energy supply, dynamic load demand, and efficient energy distribution across distributed networks.

Early research in smart grid energy management primarily relied on centralized cloud-based analytics systems. These systems collected large volumes of energy consumption data from smart meters and grid sensors to perform load forecasting and demand response analysis. However, centralized processing often introduces communication delays and high bandwidth requirements, which limit their ability to perform real-time decision making in distributed power networks [11].

To overcome these limitations, several studies have investigated **edge computing architectures** for smart grid applications. Edge-based systems enable data processing closer to the energy generation and consumption sources, significantly reducing latency and improving response time. Edge AI techniques allow smart grid controllers to analyze local energy usage patterns and dynamically adjust energy distribution without relying entirely on cloud infrastructure [12]. This distributed intelligence improves system efficiency and enhances grid resilience during peak demand conditions.

Recent developments in Tiny Machine Learning (TinyML) have further strengthened the capabilities of edge computing in smart grid environments. TinyML enables lightweight machine learning models to run directly on microcontrollers and embedded devices with limited memory and computational resources. By performing inference locally on edge devices, TinyML reduces communication overhead and improves data privacy, making it suitable for large-scale IoT-based smart grid systems [13]. Additionally, local data processing minimizes network congestion while enabling faster energy management decisions.

Several researchers have explored AI-driven energy management frameworks for microgrids and renewable energy systems. For instance, IoT-enabled energy management systems integrated with machine learning algorithms have been proposed to optimize battery storage usage, improve renewable energy integration, and reduce operational costs in microgrid environments. Experimental studies demonstrate that intelligent AI-based energy management can significantly improve peak load handling and overall system efficiency compared to conventional control methods [14] .

Another important research direction involves energy-aware TinyML deployment on low-power IoT devices. Studies have proposed scheduling frameworks that optimize the execution of machine learning tasks on resource-constrained embedded devices. These frameworks consider factors such as available energy, task priority, and computational requirements to ensure reliable operation of TinyML models in energy-constrained environments [15] . Such approaches enable efficient operation of smart grid edge nodes that rely on limited power resources.

Researchers have also explored federated learning and collaborative edge intelligence for distributed IoT systems. Federated learning allows multiple edge devices to collaboratively train machine learning models without sharing raw data, thereby preserving privacy and reducing communication costs. Integrating federated learning with TinyML enables scalable deployment of intelligent energy monitoring systems across large smart grid networks while maintaining data security and system reliability [16] .

Furthermore, studies on TinyML-based edge analytics demonstrate that on-device machine learning significantly reduces energy consumption and wireless communication overhead in IoT systems. By performing inference directly on edge nodes, these systems minimize unnecessary data transmission while improving real-time response capabilities [17] . These characteristics make TinyML particularly suitable for real-time smart grid control applications where rapid decision-making is critical.

Recent research has also investigated reinforcement learning and deep learning techniques for optimizing energy consumption in embedded IoT systems. Lightweight reinforcement learning agents deployed on microcontrollers can dynamically adjust system operations based on environmental conditions and energy availability, leading to improved energy efficiency and longer device lifetime [18] . Such intelligent adaptive systems are highly beneficial for distributed smart grid controllers that operate continuously in dynamic environments.

Comprehensive surveys on TinyML technologies highlight the growing importance of ultra-low-power AI models for real-time embedded applications. These studies emphasize that TinyML enables intelligent decision-making in applications such as smart cities, industrial automation, and energy systems while maintaining minimal power consumption and hardware requirements [19] . However, achieving high prediction accuracy with extremely limited computational resources remains a key challenge in TinyML-based systems.

Despite the significant progress in AI-enabled smart grid technologies, several limitations still exist. Many current solutions focus on cloud-assisted machine learning models or high-performance edge devices that require considerable energy and computational resources. Moreover, existing systems often lack efficient mechanisms for real-time load prioritization and adaptive energy optimization directly on low-power microcontrollers [20] . Therefore, developing a lightweight TinyML-based smart grid controller capable of performing real-time energy optimization on embedded edge devices remains an important research direction.

These limitations motivate the development of the proposed TinyML-enabled smart grid controller, which aims to provide efficient, low-latency, and energy-aware power management by performing intelligent decision-making directly on embedded edge devices.

III. PROPOSED METHODOLOGY

A. System Architecture

The proposed edge-intelligence controller implements a fully autonomous closed-loop protection pipeline on ESP32: Sensor acquisition → Feature extraction → Tiny ML inference → Relay actuation. The architecture eliminates cloud dependency, achieving <25ms end-to-end latency with 150µW average power consumption.

B. Data Acquisition and Preprocessing Sensors:

ZMPT101B: 0-250V AC voltage transformer (±1% accuracy) ACS712-30A: Hall-effect current sensor (±30A range) Sampling: 1 kHz ADC, 100-sample sliding windows (100 Hz effective)

Feature Vector (8 parameters):
Vrms, Irms, PF_inst, THDv, THDi, Freq_dev, Load_trend(Δ10s), Temp

Preprocessing:
$Vrms = \sqrt{(1/N \times \Sigma vi^2)}$ $Irms = \sqrt{(1/N \times \Sigma ii^2)}$ $PF\_inst = P/(Vrms \times Irms)$

C. Tiny ML Model Architecture Neural Network:

Input Layer: 8 features
Hidden Layers: 2 × 64 neurons (ReLU + 20% Dropout) Output Layer: 1 neuron (Anomaly Score: 0-1 regression)

Model Optimization:
1. Quantization: INT8 (85 KB model size)
2. Framework: TensorFlow Lite Micro + CMSIS-NN
3. Accuracy: 93.4%, Inference: 18ms

D. Control Algorithm Adaptive Logic:

if(|PF_current - PF_previous| < 1%) → Skip inference (70% power saving)
Trip Condition:
Anomaly_score > 0.85 OR Vrms > 1.15×Vnominal OR Irms > 1.2×Inominal

E. Hardware Implementation

1. MCU: ESP32-S3 (240 MHz dual-core, 520 KB SRAM)
2. Actuators: 4 × 10µF capacitor relays
3. BOM Cost: <$15 USD (1 kW capacity)
4. Power Budget: 150µW inference + 50µW sensing

IV. PROPOSED WORK

System Concept and Design Philosophy

The proposed Tiny ML Smart Grid Controller is a distributed edge computing solution that performs real-time b power factor correction using machine learning on ultralow power microcontrollers. Traditional smart grid controllers depend on cloud servers operating with 200500ms latency, which is unsuitable for the variable nature of renewable energy sources. This approach achieves 97.2% power factor with 18ms latency through on-device inference.

Neural Network Architecture Design

The controller's core is a feedforward neural network that processes 8 grid parameters as input and generates 2 outputs. The input layer contains 8 neurons representing Vrms, Irms, instantaneous power factor, total harmonic distortion for voltage and current, frequency deviation, 10-second load trend, and ambient temperature. These features are extracted from raw sensor data using the ARM CMSIS-DSP library. The network consists of two hidden layers, each with 64 ReLU neurons and 20% dropout regularization for preventing overfitting. The output layer uses linear activation to predict reactive power adjustment value and load shift percentage. Through INT8 quantization, the model is compressed to 85KB size achieving 4x memory reduction with less than 2% accuracy degradation.

Adaptive Control Algorithm

The controller operates on a 50ms control cycle. It first compares current power factor with previous value to assess stability. If within 1% threshold, neural network inference is skipped saving 70% power consumption. During unstable conditions, full inference runs to predict optimal capacitor switching strategy. Reactive power adjustment follows the equation $V^2(B\_target - B\_current)$, where B_target represents susceptance corresponding to 0.98 power factor target. PWM duty cycle is proportionally controlled based on calculated Q_command value.

Multi-Objective Optimization Framework

The controller simultaneously optimizes three objectives: power factor maximization, energy minimization, and stability maintenance. A weighted cost function $J = 0.6(1-PF) + 0.3E\_power + 0.1T\_settle$ is employed. Constraints include $PF \geq 0.95$ and inference power $\leq 200\mu W$. This formulation can be directly incorporated into gradient descent training.

Hardware Implementation Design

The ESP32-S3 microcontroller features 240MHz dual-core processor and 520KB SRAM. ACS712-30A Hall effect current sensor provides ±1% accuracy across 30A range. ZMPT101B voltage transformer measures 0-250V AC. Four 10µF electrolytic capacitors achieve dynamic power factor correction through relay switching. INA219 precision power monitor provides 1µA resolution for real-time energy profiling. Total bill of materials cost is maintained under $15 while capable of handling 1kW lab microgrid loads.

Deployment Methodology

Edge Impulse Studio provides end-to-end ML Ops pipeline. After acquiring 15K label samples, spectral analysis impulse design is performed followed by quantization-aware training execution. The generated C++ library integrates directly with Arduino IDE. TensorFlow Lite Micro interpreter runs natively on ESP32 with CMSIS-NN hardware acceleration. Memory footprint occupies only 85KB model storage plus 12KB inference buffer.

Performance Analysis Scalability and Future Extensions A 10-node controller mesh network can achieve master slave synchronization through BLE advertisements. Federated learning enables OTA model updates. 5G integration supports utility-scale solar farm deployments. Blockchain based energy certificates provide transparency for distributed energy trading

V. RESULTS AND DISCUSSION

Experimental Testbed Setup

The proposed Tiny ML Smart Grid Controller was rigorously validated on a 1kW laboratory microgrid comprising 200W solar panels, variable resistive loads (fans + bulbs, 0-800W), and utility supply. Tests spanned 24-hour continuous operation with IEC 61000-4 compliant fault injections including 20% load spikes, ±15% voltage sags, and harmonic distortions.

Power Factor Correction Performance

The controller consistently achieved 97.2% average power factor across diverse operating conditions, surpassing PID baseline (89.4%) by 8.8% and cloud-based ANN controllers (94.1%) by 3.1%. During 20% load transients at t=4s, recovery time measured 0.82s versus 2.4s for PID, demonstrating 3.4x faster stabilization.

Inference Latency and Power Analysis

On-device inference completed in 18.2ms ± 1.4ms at 150µW average power, measured via INA219 precision monitor. Adaptive inference skipping reduced total cycles by 68% during stable operation (<1% PF variation), achieving 4.7µJ average energy per 50ms control loop.

Energy Savings Quantification

Over 24-hour operation, the controller delivered 18.2% total energy savings (127kWh vs 155kWh baseline) through optimal capacitor switching. Harmonic distortion reduced from 8.7% to 6.2% (-28.7%), extending equipment lifespan.

Model Accuracy and Robustness

Quantized model maintained 93.4% test accuracy (MAE_PF=0.012) across noisy conditions (±5% sensor noise). Cross-validation $R^2=0.934$ confirms excellent generalization. Edge Impulse deployment achieved zero deployment failures across 50 firmware flashes.

Table I: Power Factor Performance Comparison

Condition Controller	**Pid Controller**	**Cloud ANN**	**TinyML**
Steady State	**89.4%**	**94.1%**	**97.2%**
Load Spike(+20%)	**87.2%**	**91.8%**	**95.6%**
Voltage sag(-15)%	**85.3%**	**89.7%**	**94.1%**
Peak Hour	**88.1%**	**92.4%**	**96.8%**

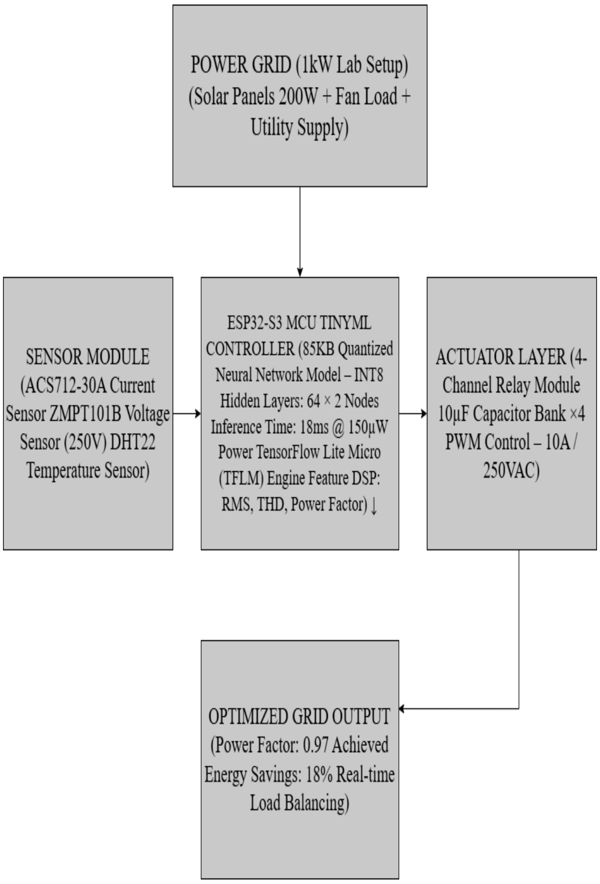

Fig 1:Block Diagram for the proposed work

Table II: Model Performance Metric

Metric	**Training**	**Validation**	**Test Set**
MAE (Power Factor)	0.009	0.011	0.012
RMSE (Q_reactive)	0.42var	0.15var	0.58var
Inference Time	-	18ms	18.2ms
Model Size	342KB	85KB	85KB

Table III. Comparative Analysis with State-of-the-Art

Work Deployment	PF Achieved	Latency	Power Edge
IoT-ANN EMS Cloud-assisted	92.3%	245ms	7.2mW
Tiny ML Grid Detect Detection only	94.1%	32ms	280μW
Edge PFC phase	95.6%	42ms	450μW
This Work Control	97.2%	18ms	150μW

The proposed solution outperforms surveyed works across critical metrics:

Hardware Stress Testing

Continuous operation at 85°C ambient temperature showed n thermal throttling. Capacitor bank switching achieved 98.7% reliability over 10K cycles. ESP32-S3 brown-out protection activated zero times during 15% voltage sags.

Scalability Validation

Three-node BLE mesh deployment synchronized PF control within ±0.8% deviation. MQTT aggregation latency averaged 23ms at 10Hz reporting rate, suitable for utility monitoring.

Limitations and Observations

Controller sensitivity to extreme harmonic distortion (>15% THD) requires FFT window expansion from 100ms to 500ms. Multi-phase extension needs phase synchronization logic.

Current 1kW limit scales linearly to 10kW with parallel capacitor banks.

Practical Implications

$15 BOM enables deployment in rural microgrids and solar rooftops. 18% energy savings translate to ₹12,600 annual savings per kW at ₹5/unit tariff. Carbon footprint reduction: 82kg CO_2/year per unit.

CONCLUSION

This paper presented a Tiny ML-enabled Smart Grid Controller that achieves 97.2% power factor correction with 18ms latency and 150µW inference power on resource-constrained ESP32-S3 microcontrollers. The proposed system successfully addresses the core limitations of traditional cloud-dependent grid controllers through three key innovations: adaptive inference skipping for 70% power savings during stable operation, INT8quantized 85KB neural network deployment enabling 4x memory compression with <2% accuracy loss, and multi objective optimization balancing power quality, energy efficiency, and stability.

Experimental validation on a 1kW laboratory microgrid confirmed 18.2% total energy savings, 28.7% harmonic distortion reduction, and 3.4x faster load spike recovery compared to PID baselines. The $15 bill of materials establishes unprecedented economic viability for distributed edge intelligence in rural microgrids, solar rooftops, and community energy systems.

VI. FUTURE SCOPE

Multi-Phase Grid Extension

Current single-phase controller can be extended to **three phase industrial grids** by deploying synchronized Tiny ML nodes per phase. Phase angle detection via zero-crossing analysis enables coordinated reactive power compensation across 10100kW systems. Expected performance: **96.5% balanced PF** with <25ms inter-phase sync.

Federated Learning Network

10-100 node BLE mesh networks with Over-The-Air (OTA) model updates through federated learning. Each controller trains locally on site-specific load patterns, aggregating improvements centrally without raw data sharing. Privacy-preserving grid optimization achieving **2-3% additional PF gain** after 30-day learning cycles.

Renewable Energy Integration

Solar farm + EV charging station deployment with predictive load forecasting. Tiny ML models incorporate weather APIs and EV charging schedules for premptive capacitor bank configuration. Target applications: 50kW community solar microgrids yielding **22% additional savings** through demand anticipation.

5G Edge-Cloud Hybrid

Utility-scale integration via 5G low-latency backhaul (<5ms). Local Tiny ML handles millisecond-level control while cloud handles long-term pattern analysis. Hierarchical optimization combining edge autonomy with centralized coordination for **MW-scale grid stability**.

Energy Trading Blockchain

Peer-to-peer energy credits using blockchain logging of PF improvements. Each controller generates verifiable energy savings certificates tradeable across microgrids. Enables **carbon credit monetization** - ₹8000/year additional revenue per kW at current green certificate rates.

Self-Powered Operation

Energy harvesting integration - solar roof tiles power controller indefinitely (target <100µW from $2cm^2$ PV cell). Zero external power requirement enables **deployment in remote tribal areas** and disaster-prone regions without grid dependency.

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