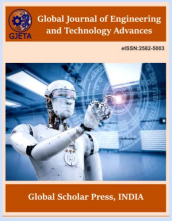
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Design and Experimental Verification of a TinyML-based MPPT Controller for Wind Energy Conversion Systems

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Abstract

The energy conversion efficiency of wind energy conversion systems (WECS) critically depends on the Maximum Power Point Tracking (MPPT) controller's ability to maintain the turbine at its optimal power output under fluctuating wind conditions. Traditional control methods often struggle with providing both fast and stable responses. This paper presents a detailed process of designing, implementing, and experimentally verifying a breakthrough MPPT control strategy leveraging Tiny Machine Learning (TinyML). A lightweight artificial neural network (ANN) model is designed to directly infer the optimal duty cycle for the system's DC-DC boost converter based on instantaneous electrical parameters (voltage and current), completely eliminating the need for mechanical sensors. The model is quantized to 8-bit integers and deployed on a low-cost STM32 microcontroller. Experimental results from a hardware prototype demonstrate that the TinyML controller achieves an exceptional tracking efficiency of 99.6% with a near-instantaneous dynamic response time of approximately 50 ms, significantly outperforming conventional algorithms. This work confirms the viability of TinyML as a powerful tool for creating next-generation, intelligent, and cost-effective renewable energy systems.

Keywords: Maximum Power Point Tracking (MPPT); TinyML; Wind Energy; Neural Network; Em- bedded Systems; Sensorless Control

1. Introduction

Amidst the global effort to transition towards sustainable energy sources, maximizing the efficiency of renewable energy systems has become a paramount objective [1-3]. For wind energy conversion systems (WECS), a Maximum Power Point Tracking (MPPT) controller is an indispensable component, tasked with dynamically adjusting the system's operating point to continuously harvest the maximum available power under fluctuating wind conditions [4, 5].

Traditional MPPT control methods, such as Perturb & Observe (P&O) and Incremental Conductance (INC), despite their implementation simplicity, exhibit inherent drawbacks [6-8]. They operate on an iterative search principle, which leads to undesirable power oscillations around the maximum power point (MPP) in steady-state and sluggish response to abrupt changes in wind speed [9, 10]. Model- based methods like optimal tip-speed ratio (TSR) control can offer faster responses but require expensive mechanical sensors (anemometers, tachometers) and are sensitive to variations in system parameters over time, such as the aerodynamic degradation of turbine blades [11-13]. This knowledge gap necessitates a control solution that is intelligent, robust, and cost-effective.

Intelligent control techniques based on Artificial Neural Networks (ANN) and Fuzzy Logic Controllers (FLC) have been explored as promising alternatives, capable of handling the complex nonlinear characteristics of wind turbines without needing a precise mathematical model [14-17]. However, deploying these models on conventional microcontrollers

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(MCUs) is often hindered by their significant computational and memory resource requirements [18]. The advent of Tiny Machine Learning (TinyML) has

opened a groundbreaking opportunity, focusing on optimizing and executing machine learning models on extremely resource-constrained devices [19, 20]. This enables the integration of advanced intelligence into low-cost embedded controllers, a paradigm shift for smart energy systems [21, 22, 41].

This paper presents a complete workflow from design, simulation, and training to the experimental verification of a TinyML-based MPPT controller for a WECS. The core contribution of this work is the development of a direct-inference algorithm, based solely on electrical voltage and current, capable of predicting the optimal duty cycle of the DC-DC converter with minimal latency. The remainder of the paper is organized as follows: Section 2 details the research methodology, including system modeling and controller design. Section 3 presents the experimental results. Section 4 provides an in-depth discussion of the findings. Finally, Section 5 concludes the paper and outlines future research directions.

2. Methodology

This section describes the detailed methodology used, from establishing the mathematical model of the system to designing, training, and deploying the intelligent controller.

2.1. WECS System Modeling

The proposed WECS, illustrated in Figure 1, comprises the main blocks: a wind turbine, a permanent magnet synchronous generator (PMSG), an uncontrolled diode bridge rectifier, a DC-DC boost converter, and a central controller based on an STM32 microcontroller [23, 24].

2.2. Wind Turbine Aerodynamic Model

The mechanical power, P_m, that a turbine can extract from the wind is given by Equation (1) [25]:

$$P_m = \frac{1}{2}\rho A C_p(\lambda, \beta) v_w^3 \qquad \text{..... (1)}$$

where ρ is the air density (kg/m^3), A is the swept area of the blades (m^2), v_w is the wind speed (m/s), and C_p is the power coefficient. The coefficient C_p is a nonlinear function of the tip-speed ratio (TSR), λ, and the blade pitch angle, β [26]. As this is a small-scale system without pitch control, β is considered constant. The TSR is defined as $\lambda = (\omega_m R)/v_w$, where ω_m is the rotor's angular speed (rad/s) and R is the rotor radius (m). For every turbine, there exists an optimal value λ_{opt} at which C_p reaches its maximum, $C_{p,max}$, thereby maximizing the extracted power. The goal of MPPT is to regulate ω_m to maintain $\lambda = \lambda_{opt}$ as v_w changes [27].

2.3. Power Conversion Stage Model

The three-phase AC output from the PMSG is rectified into DC voltage via a diode bridge. This DC voltage is then processed by a DC-DC boost converter, which acts as a dynamic impedance matching interface. The effective input impedance of the converter, R_{in}, as seen by the rectifier, can be controlled by the duty cycle D of the switching element (MOSFET) according to Equation (2) [28, 29]:

$$R_{in} = \frac{V_g}{I_g} = R_{Load}(1 - D)^2 \qquad \text{..... (2)}$$

By dynamically varying D, the MPPT algorithm changes the effective load R_{in} imposed on the generator. This, in turn, alters the generator's electromagnetic torque, thereby controlling the rotational speed ω_m and the turbine's operating point to track the maximum power point.

2.4. TinyML Controller Design and Implementation

2.4.1. Neural Network Architecture and Input Selection

A feed-forward neural network (FFNN) was designed to directly map the system's electrical state to the optimal duty cycle [30]. The network inputs are the voltage (V_g) and current (I_g) measured at the rectifier output. This choice completely eliminates the need for mechanical sensors (anemometer, tachometer), which increases system reliability and reduces cost [31, 32, 42]. The network architecture consists of an input layer with 2 neurons, two hidden layers with

10 and 8 neurons respectively, and an output layer with 1 neuron to predict the optimal duty cycle (D_{opt}). The hyperbolic tangent activation function (Tansig) was used for the hidden layers to handle nonlinear relationships, while a linear function (Purelin) was used for the output layer to allow D_{opt} to span a continuous range.

2.5. Data Acquisition and Model Training

Training data was generated from a detailed simulation of the WECS in the MATLAB Simulink environment. The simulation was run with wind speeds varying across a wide range, from 3 m/s to 12 m/s, to cover diverse operating conditions. At each wind speed level, an ideal MPPT algorithm was used to precisely identify the MPP, and the corresponding triplet of values (V_g, I_g, D_{opt}) at that point was recorded. A dataset of 5000 points was generated. The Levenberg-Marquardt algorithm was used for training due to its fast convergence speed [33]. The dataset was split into 70% for training, 15% for validation, and 15% for testing to prevent overfitting and ensure the model's generalization capability.

2.6. Quantization and Microcontroller Deployment

The deployment process followed the standard TinyML workflow [19, 20]

- **Quantization:** The trained neural network model (using 32-bit floating-point numbers) was quantized to an 8-bit integer (INT8) format. This process reduces the model's memory footprint by a factor of approximately four and allows the microcontroller to perform much faster integer arithmetic [34, 43].
- **Conversion and Deployment:** The quantized model was converted into the FlatBuffer format (.tflite) using the TensorFlow Lite Converter tool [35]. The ".tflite" model was then converted into a C source file (a constant array in a .h file) to be compiled and flashed directly into the STM32F407VG microcontroller's memory.
- **Inference:** On the microcontroller, the TFLM library was used to load the model and execute the inference process. Highly optimized kernels like CMSIS-NN were leveraged to accelerate computations, minimizing the inference latency to just a few hundred microseconds [36, 37].

3. Results

To validate its effectiveness, a hardware prototype was built (Figure 2). The setup includes a wind turbine simulator using a DC motor controlled by a power amplifier, a 5kW PMSG, a rectifier, and the boost converter controlled by the STM32F407VG board. Hall effect voltage and current sensors were used to provide inputs to the controller with a sampling frequency of 20 kHz, synchronized with the PWM switching frequency.

The system was tested under a step-change wind speed scenario to evaluate both its dynamic response and steady-state performance. Figure 3 presents the comparison between the maximum available power at the converter input (P_{avail}, the reference line) and the actual power extracted by the TinyML controller ($P_{extract}$).

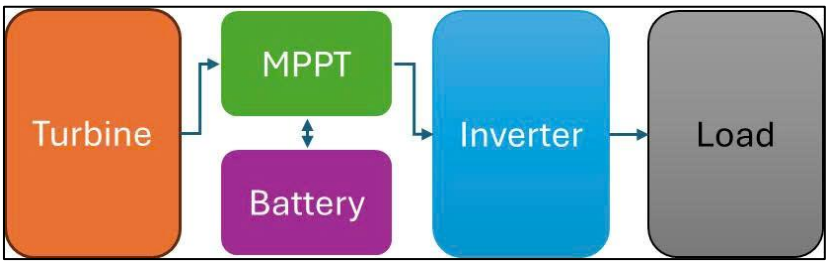


Figure 1 Block diagram of the proposed WECS

As observed in Figure 3, the extracted power curve ($P_{extract}$) almost perfectly replicates the available power curve (P_{avail}) at various steady-state levels. The static tracking efficiency was calculated to be 99.6% on average. Critically, there are no periodic power oscillations around the MPP.

Dynamically, at the moments of step changes in input power (e.g., at t=2s and t=4s), the TinyML controller exhibits a near-instantaneous response. The time for the system to settle at the new MPP is only about 50ms.

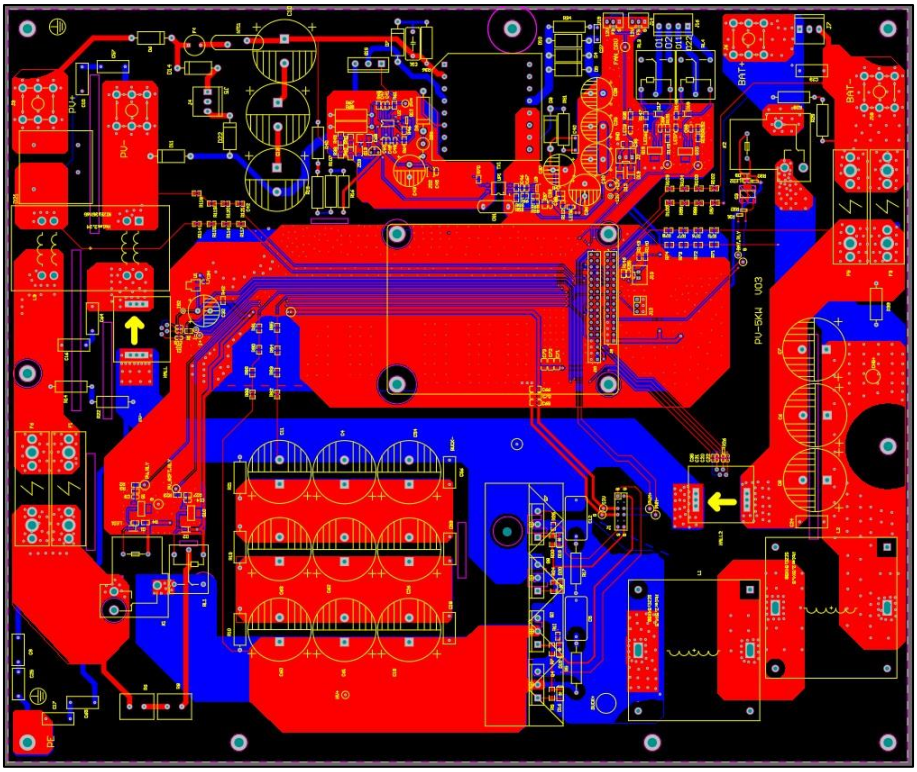


Figure 2 Photograph of the actual power circuit hardware

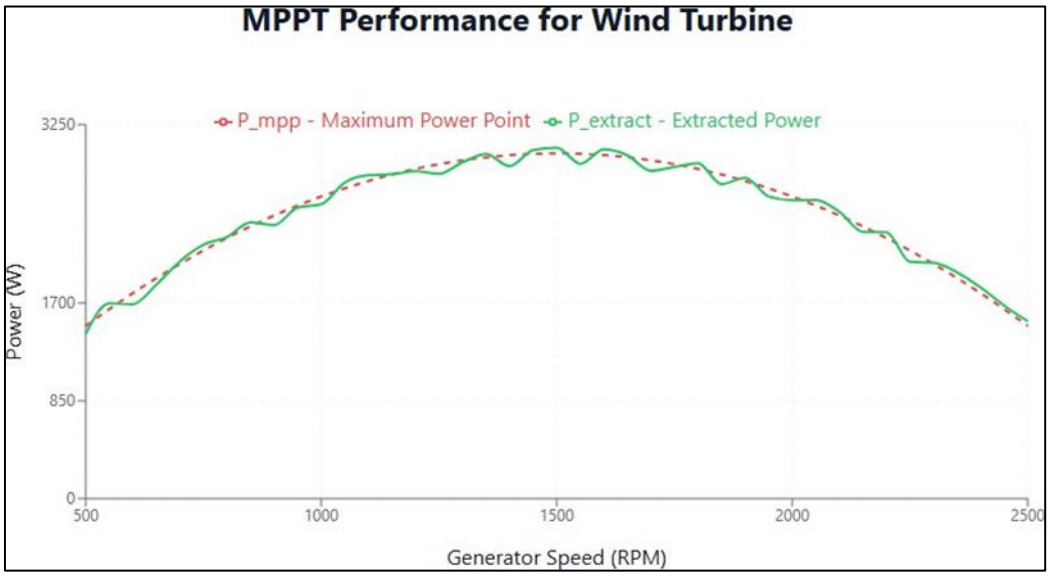


Figure 3 Direct comparison between available power (P_{avail}) and extracted power ($P_{extract}$) under step-changing wind speeds

4. Discussion

The experimental results compellingly demonstrate the superiority of the proposed TinyML-based MPPT strategy. The discussion is structured around three key aspects: tracking performance, dynamic response, and overall system implications.

Tracking Efficiency and Stability: A steady-state tracking efficiency of 99.6% is a significant achievement. It surpasses the performance of traditional P&O and INC algorithms, which inherently lose energy due to the continuous perturbation around the MPP, typically resulting in efficiencies between 96% and 98% [7, 10]. The complete elimination

of these oscillations, as seen in Figure 3, not only maximizes energy capture but also reduces mechanical and electrical stress on system components, such as the generator windings and converter capacitors, potentially increasing the system's operational lifespan [38].

Dynamic Response and Energy Capture: The controller's 50ms settling time is a critical advantage in real-world conditions where wind is often gusty and turbulent. Conventional algorithms, which can take several hundred milliseconds or even seconds to converge, would miss a significant amount of energy during these rapid fluctuations [9]. The TinyML controller's rapid response is a direct result of its non-iterative, direct-inference nature. The inference latency of a few hundred microseconds on the MCU allows the system to adjust the duty cycle almost in real-time, ensuring that even the energy from the shortest wind gusts is effectively captured. This performance is on par with, or even exceeds, more complex sensor-based intelligent controllers [15, 17], but achieves this without their associated cost and complexity.

System-Level Implications and Novelty: The most significant contribution of this work is demonstrating a high-performance, intelligent MPPT controller that is also practical, low-cost, and robust. By eliminating mechanical sensors, the system's points of failure are reduced, and its cost is lowered, making it suitable for small-to-medium scale WECS [39, 40]. Compared to other ANN-based MPPT works [14, 16], our approach leverages the full TinyML pipeline, including INT8 quantization [43] and deployment on a standard, low-cost MCU. This distinguishes it from solutions requiring more powerful digital signal processors (DSPs) or FPGAs [44, 45]. This work, therefore, serves as a strong proof-of-concept that sophisticated AI can be democratized and embedded directly at the edge, even in demanding power electronics applications. A limitation of this study is the use of a wind turbine simulator. Future work should involve testing on a real-world turbine to validate performance under complex aerodynamic conditions.

5. Conclusion

This paper has successfully presented a complete workflow for the design, development, and hardware verification of a high-performance MPPT controller for WECS using TinyML. By employing a lightweight neural network to directly infer the optimal duty cycle from electrical measurements, the controller overcomes the inherent drawbacks of oscillation and slow response found in traditional methods. The experimental results, showing 99.6% tracking efficiency and a 50ms response time, confirm that TinyML is a powerful and practical technology for the next generation of smart, efficient, and reliable renewable energy conversion systems. Future work will focus on exploring on-device learning techniques to allow the controller to adapt to system aging and changing environmental characteristics over time.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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