Neural Network-Based MPPT on Edge Devices

A Feasibility Study & Research Framework for Replacing Classical Solar Tracking Algorithms with Machine Learning on the Raspberry Pi Zero Platform

Focus Area: Embedded AI & Power Electronics

Hardware Target: Raspberry Pi Zero / Zero 2 W

Application: Solar Photovoltaic MPPT

1. Executive Summary & Research Motivation

Solar Photovoltaic (PV) harvesting relies fundamentally on Maximum Power Point Tracking (MPPT) to maintain optimal power output despite continuous variations in solar irradiance and temperature. Traditional heuristic algorithms—most notably **Perturb & Observe (P&O)** and **Incremental Conductance (IncCond)**—suffer from inherent steady-state power oscillations, slow dynamic response during rapid cloud cover, and failure under **Partial Shading Conditions (PSC)** where local power peaks trap classical tracking loops.

This research proposal investigates deploying a lightweight **Artificial Neural Network (ANN)** onto an ultra-low-power single-board computer (Raspberry Pi Zero) to perform intelligent, high-speed MPPT. By framing power tracking as a multi-variable non-linear regression problem, an edge neural network predicts the global maximum power point voltage (V_{mpp}) or converter duty cycle (D_{mpp}) in a single direct forward pass, eliminating iterative step searches and drastically reducing dynamic harvesting losses.

2. Comparative Analysis: Classical vs. Neural Network MPPT

Traditional algorithms operate as closed-loop iterative gradient search routines. In contrast, Neural Network approaches act as function approximators mapping sensor states directly to peak efficiency parameters.

Performance Indicator	Perturb & Observe (P&O)	Incremental Conductance	Neural Network (Edge AI)
Steady-State Behavior	Continuous oscillation around peak; perpetual micro-power loss.	Damped oscillation, but vulnerable to sensor noise.	**Zero steady-state oscillation**; settles precisely at predicted peak point.
Dynamic Weather Response	Slow step-by-step convergence; can track in wrong direction during fast transients.	Moderate tracking speed; bound by fixed step size.	**Instantaneous single-pass mapping** ($O(1)$ time complexity) upon state update.
Partial Shading (PSC)	Gets permanently trapped in *Local Maxima* (losing 20%–40% power yield).	Fails to identify Global Maximum without costly wide-sweep routines.	**Global Peak Detection**; learns complex multi-peaked P-V characteristic curves.
Sensor Requirements	Voltage (V_{pv}) & Current (I_{pv}) only.	Voltage (V_{pv}) & Current (I_{pv}) only.	Flexible: V, I electrical inputs, or combined with Irradiance (G) & Temp (T).
Compute Complexity	Extremely low (runs on basic 8-bit microcontrollers).	Low (basic arithmetic conditionals).	Moderate; requires lightweight matrix inference engine (TFLite / ONNX).

Core Advantage of Edge AI MPPT

In steady state, classical P&O continually steps the duty cycle up and down ($D \pm \Delta D$) to detect direction, shedding 1%–3% of total harvested energy daily. An NN model evaluates sensor inputs and outputs the exact optimal value directly, holding the converter at peak power with zero perturbation losses.

3. Hardware Architecture & Raspberry Pi Zero Feasibility

Deploying high-frequency power electronics control on a Linux-based SBC presents unique architectural challenges. Linux non-deterministic OS scheduling introduces microsecond control jitter, which is unacceptable for direct high-frequency PWM switching (e.g., 50 kHz – 100 kHz).

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RASPBERRY PI ZERO CONTROL ENGINE | | | | [ Sensors ] ---> High-Speed ADC ---> [ Quantized NN
Model ] ---> Duty Cycle Output| | (V_pv, I_pv) (SPI Interface) (ONNX / TFLite Runtime)
(D_mpp) | +---------------------------------------------------------------------
+---------+ | Hardware PWM / I2C| v
+-------------------------------------------------------------------------------+ | POWER
STAGE & DC-DC CONVERTER | | [ Solar Panel Array ] ===> [ Buck/Boost Converter ] ===> [ Output
Load / Battery ]| | (MOSFET Gate Driver) |
+-------------------------------------------------------------------------------+
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Key Hardware Engineering Considerations:

- **Dual-Core Compute Power:** The Raspberry Pi Zero 2 W (quad-core ARM Cortex-A53 @ 1GHz) handles lightweight matrix inference in under **0.5 milliseconds** using 64-bit SIMD instructions.

- **Hardware PWM Offloading:** To bypass Linux OS kernel jitter, the duty cycle output must drive the hardware PWM register directly (`/sys/class/pwm/`) or communicate via I2C/SPI with a dedicated slave switching controller (e.g., RP2040 or STM32).
- **Analog Sensing Interfacing:** Because the Pi Zero lacks integrated ADCs, high-resolution external ADCs (such as the ADS1115 or MCP3008 via SPI) are required to capture panel voltage (V_{pv}) and current (I_{pv}) at 1 kSPS or higher.

4. Promising Niche Research Directions

To make a significant academic or industrial contribution, this project can be structured around three high-value specialized research vectors:

ANGLE A **Sensorless Electrical-Only NN**

Eliminates expensive weather sensors (Pyranometers & Thermal sensors). The NN is trained to implicitly infer atmospheric conditions purely from high-rate electrical derivatives (V_{pv}, I_{pv}, dP/dV), driving down overall hardware BOM costs while maintaining high accuracy.

ANGLE B **Hybrid Coarse-Fine Architecture**

Combines AI speed with classical precision. The Neural Network acts as a *Global Estimator* that instantly jumps to the global peak region during transient weather shifts, while a micro-step P&O routine fine-tunes the absolute apex in steady state.

ANGLE C **On-Device Reinforcement Learning (Self-Healing MPPT)**

Solar panels degrade by roughly 0.5%–0.8% annually, accumulate dust, and develop localized hot spots. Rather than using a static offline-trained network, an **On-Device Q-Learning or Actor-Critic Reinforcement Learning agent** running on the Pi Zero continuously adapts its control policy over months of operation, auto-tuning for panel aging and environmental degradation.

5. Data Strategy & Mathematical Foundations

Neural networks require representative training data mapping input states to maximum power targets. The photovoltaic solar cell characteristic is governed by the single-diode physics model:

$$I = I_{ph} - I_0 \cdot [\, \exp(\, q \cdot (V + I \cdot R_s) / (n \cdot k \cdot T)\,) - 1\,] - (V + I \cdot R_s) / R_{sh}$$

Data acquisition can be structured across three distinct tiers:

1. **Synthetic Mathematical Sweeps:** Simulating thousands of P-V and I-V curve variations across temperature ranges ($10°C$ - $65°C$) and irradiance levels (100 - $1000\ W/m^2$) to extract the ground-truth optimal duty cycle (D_{mpp}).
2. **Empirical Weather Profiling:** Integrating high-resolution time-series solar data from the *NREL National Solar Radiation Database (NSRDB)* to expose the network to realistic cloud-cover transitions.
3. **Hardware Bench Logging:** Using a controllable electronic load or MOSFET bench rig to sweep physical PV panel curves under real daylight conditions.

6. Experimental Validation & Testing Roadmap

To rigorously demonstrate the superiority of the Neural Network MPPT controller over classical approaches, the experimental testbed should execute three quantitative benchmarks:

- **1. Dynamic Tracking Efficiency (η_{mppt}):** Evaluated using integrated energy capture over a standard dynamic test sequence (EN 50530 standard curve):

$$\eta_{mppt} = [\int_0^T P_{actual}(t)\, dt / \int_0^T P_{theoretical\_max}(t)\, dt] \times 100\%$$

- **2. Transient Step-Response Latency:** Measuring recovery time (in milliseconds) required to relocate the peak when irradiance drops by 50% instantaneously.
- **3. Multi-Peak Global Power Tracking under PSC:** Testing harvesting yield when 30% of the panel array is shaded, creating multiple local maxima on the P-V curve.

7. Implementation Roadmap

Phase 1: Simulation & Offline Training

Generate synthetic single-diode datasets; train Multi-Layer Perceptron (MLP) model; quantize weights to INT8 precision for TFLite/ONNX.

Phase 2: Hardware Interfacing & Bench Test

Wire SPI ADC (MCP3008/ADS1115) to Pi Zero; interface DC-DC Buck converter with hardware PWM driver; verify inference latency (<1ms).

Phase 3: Comparative Benchmarking

Run side-by-side harvesting tests against P&O algorithm under synthetic shade and transient lighting; record dynamic yield and efficiency gains.