

APPLICATION OF AI-BASED FORECASTING ALGORITHMS TO IMPROVE THE RELIABILITY OF SOLAR DIVERTERS

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This paper presents an adaptive control approach for solar diverters based on artificial intelligence, implemented on the STM32F405 microcontroller platform. The proposed solution addresses the problem of inefficient utilization of surplus photovoltaic (PV) energy in household solar power systems without battery storage, where excess generation is often exported to the grid instead of being locally consumed. The developed approach relies on short-term power forecasting to proactively regulate the operation of a triac-based power controller. A hybrid control strategy is introduced, combining conventional phase-angle control and pulse-width modulation techniques with AI-driven prediction. Based on the forecasted power dynamics, the system selects the most appropriate switching strategy and limits the rate of power change, thereby reducing switching losses and thermal stress on power electronic components. The embedded neural model performs two tasks simultaneously: regression for predicting the magnitude of short-term active power variations and binary classification for determining the direction of energy flow (consumption or export). The model is trained using real measurement data obtained from voltage, current, and phase signals, which are processed into feature vectors describing the real-time electrical state of the system. To ensure compatibility with resource-constrained hardware, the model is optimized for memory usage and execution speed using a TinyML approach. Experimental results demonstrate that the proposed system achieves a mean absolute error of 18–23 percent and a root mean square error of 16–21 percent in power variation forecasting, while the classification accuracy of energy flow direction reaches 78–84 percent. These results confirm that AI-based predictive control significantly improves the reliability and lifespan of triac-based solar diverters, enables smoother power regulation, and enhances the overall efficiency of solar energy utilization in household photovoltaic installations without reliance on cloud computing.

Keywords: artificial intelligence; embedded neural networks; Keras; photovoltaic systems; power electronics reliability; predictive control; solar diverter; STM32.

Statement of the problem

In household photovoltaic systems without energy storage, solar panels often generate more electricity during the day than household appliances consume. The excess energy is automatically exported to the public electricity grid, which prevents full utilization of the generated power by the owner.

To avoid such losses and maximize the use of generated energy for local consumption or storage, solar diverters are employed. Their purpose is to «capture» the surplus energy before it is exported to the grid and redirect it to useful local storage loads within the household. By doing so, a solar diverter increases the share of self-consumption, reduces electricity bills, and improves the overall efficiency of solar panels by storing energy in another physical form, such as heating water.

Technically, a solar diverter acts as a power regulator. It monitors the household's energy balance, and when energy export to the grid is detected, it redirects all or part of this flow to local loads. This is typically achieved through a controlled power switch (such as a triac), which allows smooth regulation of the delivered power.

However, under real operating conditions, household loads and solar generation fluctuate irregularly, leading to:

- abrupt changes when appliances switch on or off;

- gradual variations caused by cloud cover or precipitation affecting solar panel output;
- thermal and electrical stress on power electronic components resulting from sudden power surges.

Under simple phase-angle control, such variations increase the load on the triac, causing overheating, accelerated crystal degradation, and reduced device lifetime. To mitigate these effects, conventional methods are typically applied:

- half-cycle control (burst control);
- software filters for power variation rate;
- protection of the power circuit using snubbers and varistors.

However, all these methods are reactive, meaning that the system responds only after a power surge occurs. Therefore, the current challenge is the developing proactive methods for regulating the distribution of generated solar energy. This paper proposes an algorithm that, using artificial intelligence, enables the prediction of power dynamics in advance and selects the optimal method for triac control.

Analysis of the latest achievements on the identified problem

Although net metering systems allow owners to earn revenue from exported electricity, this approach does not ensure full utilization of solar energy and may lead to economic and energy losses. Recent studies have focused on strategies to optimize the use of generated solar energy, including the deployment of solar diverters, energy storage systems, and intelligent load management.

Solar diverters automatically redirect excess energy from photovoltaic systems to internal consumers, such as water heaters, heating systems, or other appliances, thereby increasing self-consumption and reducing reliance on the electricity grid [1]. Energy storage technologies, including batteries and thermal storage, enable temporary shifting of solar energy use, addressing the mismatch between production and consumption [2].

The integration of solar energy into the grid also introduces technical challenges, such as voltage fluctuations, bidirectional power flow, and distribution line overloads [3]. To balance the distribution of solar energy between grid export, storage, and local consumption, optimization algorithms—including genetic algorithms and multi-objective strategies—are applied [4, 5].

Some studies emphasize the need to combine technological solutions, intelligent control strategies, and regulatory mechanisms to improve the efficiency of solar energy distribution. For instance, [6] presents an optimization approach based on a Multiple Mitosis Genetic Algorithm (MMGA) to select the most suitable line capable of accepting excess power from an overloaded feeder.

In [7], Deep Reinforcement Learning approaches are used to balance the distribution of photovoltaic generation between batteries and the grid, while [8] proposes a machine learning model to optimize battery utilization in photovoltaic systems.

Recent trends in embedded artificial intelligence systems involve the use of Tiny Machine Learning (TinyML), which allows the deployment of machine learning models on resource-constrained devices, such as microcontrollers, sensors, and other edge systems [9]. Such models operate without cloud connectivity, performing computations directly on the device with minimal memory usage and energy consumption. The study in [10] comprehensively investigates the application of TinyML models for forecasting solar irradiance and photovoltaic power, considering different model types, input features, prediction horizons, peripheral devices, optimization methods, and practical deployment aspects. In [11], a photovoltaic monitoring system is presented for detecting anomalies and damages using thermal images, employing a TinyML and Edge Computing approach for on-device analysis without transmitting large amounts of data to the cloud.

Overall, research on modern artificial intelligence technologies, including TinyML, for improving the efficiency of automatic control and regulation of solar generation systems demonstrates high potential for optimizing

energy processes, reducing losses, and increasing the effectiveness of energy systems.

Purpose and task statement

The study aims to develop and validate an adaptive AI-based control method for solar diverters that enables short-term power forecasting and optimal triac switching strategy selection in order to improve the reliability, efficiency, and operational lifetime of power electronic components in household photovoltaic systems without energy storage.

Summary of the main material

A Solution Architecture

The proposed algorithm enables the prediction of short-term power dynamics and the selection of the optimal triac control method for upcoming time steps. This approach enhances power electronics reliability, extends component lifespan, and maximizes the effective use of solar energy for household consumption.

The main idea of the approach is to combine traditional triac control methods with artificial intelligence-based analysis and forecasting capabilities. This hybrid principle allows the system to prepare in advance for changes in operating conditions, thereby reducing stress on power components. The solution architecture is proposed as a two-level system (Fig. 1).

The executive controller (STM32F405) manages the BTA40-800B triac. Analog inputs of the executive controller receive voltage and current signals from sensors (0–240 V, 0–30 A, scaled to the 0–3.3 V range). It also receives a zero-crossing signal, which is required to generate control signals for the triac using a driver (e.g., MOC3023). This ensures precise and synchronized load switching.

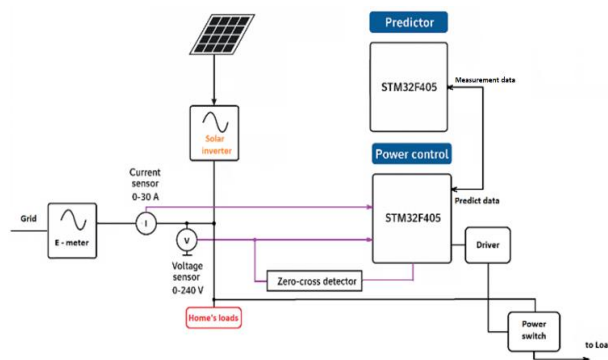


Fig. 1 – Structural diagram of the power and measurement sections of the solar diverter (authorship: this work, based [12])

The controller supports various operating modes:

- Phase-angle control – power regulation under significant load variations;
- Burst control (half-cycle PWM) – switching whole half-cycles on/off during moderate load fluctuations or under stable conditions;

- PWM with rate-of-change limitation – applied during abrupt power changes to adapt quickly without causing thermal or electrical stress on the triac.

The executive microcontroller calculates voltage, current, power, power direction, and power factor, and sends these data to the advisory microcontroller. The advisor analyzes system dynamics using an AI model to forecast system behavior. The AI can classify load conditions as stable, moderately fluctuating, frequently changing, or experiencing sudden power surges.

The advisor’s output is a recommendation on which control mode the executive microcontroller should apply and the allowable rate of power change in upcoming half-cycles for PWM operation.

Let us consider the advisor operation in more detail. It predicts the power change dP , its direction, and the energy flow mode (import or export), denoted as sign. The obtained predictions are transmitted to a processing algorithm that makes a logical selection of the control method. Specifically, depending on the magnitude and sign of dP (for example, if the power change exceeds a threshold, is negative, or falls within a certain range), the algorithm automatically selects the appropriate triac regulation mode. This approach combines intelligent forecasting of the power system state with deterministic control, ensuring adaptability and system stability under varying load and generation conditions.

At the next step, data are sent to the executive controller via the I²C interface in the form of a simple packet (e.g., mode: «phase-angle» 0b00000001, mode: «PWM» without rate limitation 0b00000010, mode: «PWM» with rate limitation 0b10000010, etc.).

Thus, the executive controller remains fully separated from the AI and reliable, while artificial intelligence performs only an advisory function, reducing the likelihood of abrupt transitions and increasing the lifespan of the power electronics. The main benefit of integrating a Keras-based forecasting module reduces thermal and electrical stress on the triac, thereby increasing its service life and the overall system reliability.

At the same time, smoother power regulation is achieved along with reduced harmonic distortion in the grid. Each triac switching event involves transient processes accompanied by energy dissipation (1).

$$Q_{sw} = \int_0^{t_{on}} V(t) \cdot I(t) dt. \quad (1)$$

During abrupt changes of the triac conduction angle or full switching on/off of a high-power load, the switching energy Q_{sw} increases sharply. The accumulated thermal load is calculated as:

$$P_{loss} = f_{sw} * Q_{sw}, \quad (2)$$

where f_{sw} is the switching frequency.

Forecasting the load dynamics allows reducing both the switching energy and the switching frequency, thereby decreasing the thermal power P_{loss} .

We introduce the power change rate as:

$$\frac{dP}{dt} = \frac{P_{k+1} - P_k}{\Delta t}, \quad (3)$$

where:

P_k – power in the current half-period,

P_{k+1} – power in the next half-period,

Δt – duration of the half-period.

If the rate of power change dP/dt is high, the triac must rapidly adjust its firing angle, which imposes stress on the semiconductor. AI-based forecasting allows estimating both the sign and magnitude of dP/dt in advance and "smooths" the transition over several half-periods. This approach increases the triac's lifespan by reducing the integral of thermal losses (4):

$$\Delta P_{loss} = P_{loss}^{classic} - P_{loss}^{predictive} > 0, \quad (4)$$

and the system reliability grows exponentially, as the lifetime of semiconductor devices generally follows the Arrhenius model:

$$L \sim \frac{E_a}{kT}, \quad (5)$$

where even a few degrees reduction in semiconductor junction temperature can significantly multiply the device lifetime.

Using AI as an «advisor» enables the system to:

- reduce peak thermal stress on the triac,
- multiply its operational lifetime,

improve regulation quality (lower harmonic distortion), maximize the utilization of excess solar energy.

B Formation of Input Data for the Model

To train a Keras-based AI model, a dataset representing the system’s current electrical state must be formed. These parameters are used by the AI algorithm to forecast the active power change in the next step, specifically its increment (dP) and the energy flow direction (sign), which indicates whether energy is being consumed or exported.

Voltage and current signals are measured by the STM32F405 microcontroller at a sampling interval of 0.2 seconds for a 50 Hz network. For a single analysis cycle, 400 samples are collected, providing statistically reliable values of the effective parameters.

Within a single cycle, the following sequence of operations is performed.

Digitization of voltage (V_{sample}) and current (I_{sample}) signals through the analog inputs of the microcontroller.

1. Filtering of the DC component using a digital filter that updates DC (Direct Current) offset value: according to (6):

$$Data_{offset\ n+1} = Data_{offset\ n} + \frac{Data_{sample} - Data_{offset\ n}}{ADC\ resolution}, \quad (6)$$

where:

$Data_{offset\ n+1}$ – updated DC offset value;

$Data_{offset\ n}$ – previous DC offset value;

$Data_{sample}$ – current measured signal sample;

ADC resolution – analog-to-digital converter resolution (e.g., 4096 for a 12-bit ADC).

2. Obtaining the AC component centered around zero:

$$Data_{filtered} = Data_{sample} - Data_{offset\ n}. \quad (7)$$

3. Calculation of instantaneous power::

$$P = V_{filtered} \cdot I_{filtered}. \quad (8)$$

After accumulating 400 samples, integration calculations are performed to determine the values of voltage, current, and power, as well as the power factor (PowerFactor).

The calculations are performed according to formulas (9–12):

$$Data_{rms} = K \cdot \sqrt{\frac{\sum Data_{filtered}^2}{N}}, \quad (9)$$

where: K – calibration coefficient, N – number of samples

$$P_{real} = K_V \cdot K_I \cdot \frac{\sum P}{N}, \quad (10)$$

$$P_{apparent} = V_{rms} \cdot I_{rms}, \quad (11)$$

$$PowerFactor = \frac{P}{P_{apparent}}. \quad (12)$$

Because the machine learning model must reflect dynamics of power changes, only those parameters that are directly measured by the executive microcontroller and transmitted via I²C are fed as input:

$$X(t) = [V_{rms}(t), I_{rms}(t), P(t), P_{apparent}(t), PowerFactor(t)]. \quad (13)$$

The goal of the model is to predict the power state at the next time step:

$$Y(t)_m = [dP_{m+1}, sign_{m+1}], \quad (14)$$

where:

dP_{m+1} – predicted power change,

$sign_{m+1}$ – energy flow direction (consumption/export).

Using the forecast data obtained in the format (14), the "advisor" makes decisions on which control mode to use. For example, if the predicted change dP does not exceed 300 W, it is recommended to apply the PWM mode without speed limitations.

The executive microcontroller receives the data on the control method type and other service information every 0.2 seconds via the I²C interface.

C Creation of the AI Model

The goal of this stage was to develop and implement a compact regression neural model capable of predicting changes in active power in the time series of electrical signals. The model is based on measurements obtained from the executive microcontroller, which in turn receives data from voltage and current sensors for further processing. The primary task of the model is to determine the direction of power change – whether it will increase or decrease at the next time step – which is critical for selecting the triac control functions.

To train the model, sequences of input vectors (13) describing the temporal dynamics of the parameters are used. To capture temporal dependence, a sliding window of the six most recent measurements was used, covering a time interval of approximately 1.2 seconds. Thus, to produce the first forecast, the system must accumulate at least six consecutive data cycles. During this period, the model is inactive—the microcontroller only collects valid data in the buffer, ensuring filter stabilization and offset compensation. Full operation of the forecasting system begins 1.2–3 seconds after startup.

This approach ensures forecast stability and eliminates false results during the transient period. After the buffer is filled, the model performs the first prediction of the future power state, according to (14).

Considering the computational limitations of the STM32F405, the model is built with a simplified architecture without redundant layers, ensuring high execution speed and low energy consumption.

The neural network is trained using a combined loss function:

$$L = \alpha \cdot MSE(dP_{pred}, dP_{true}) + \beta \cdot BCE(sign_{pred}, sign_{true}), \quad (15)$$

where the first term minimizes the regression error, and the second improves the accuracy of predicting the power flow direction, allowing simultaneous minimization of the regression error and enhancement of directional classification accuracy.

Mean Squared Error (MSE) penalizes large deviations, training the model to accurately predict the magnitude of power change, and is defined as:

$$MSE(dP_{pred}, dP_{true}) = \frac{1}{N} \sum_{i=1}^N (dP_{pred}^{(i)} - dP_{true}^{(i)})^2, \quad (16)$$

BCE (Binary Cross-Entropy) – binary cross-entropy is calculated as:

$$BCE(sign_{pred}, sign_{true}) = -\frac{1}{N} \sum_{i=1}^N [sign_{true}^{(i)} \log(sign_{pred}^{(i)}) + (1 - sign_{true}^{(i)}) \log(1 - sign_{pred}^{(i)})], \quad (17)$$

where:

$sign_{pred}$ – predicted power direction,

$sign_{true}$ – actual power direction.

The coefficients $\alpha = 0.83$ and $\beta = 0.33$ in the combined loss function were determined empirically to balance the regression (MSE) and classification (BCE) contributions. This combination ensures computational simplicity, high prediction accuracy, and efficient implementation on the STM32F405. Unlike alternative loss functions, it provides stable, fast, and accurate real-time forecasting, with training performed on data covering both stable and abrupt variations in voltage and load.

Figure 3 shows the architecture of the two-output regression-classification neural network for predicting power change and its direction.

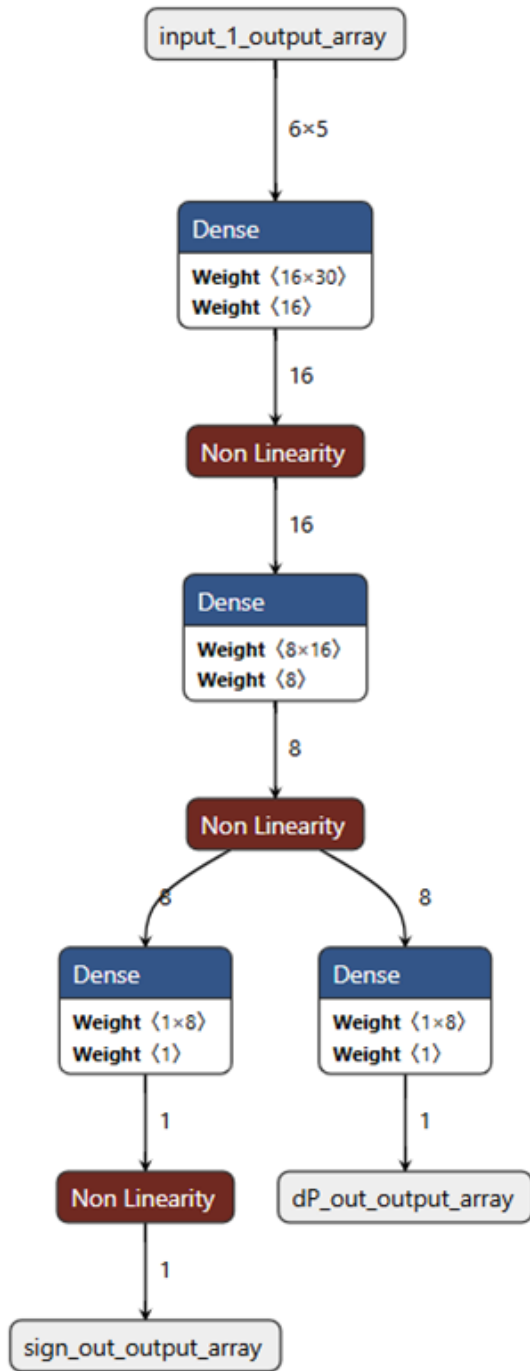


Fig. 3 – Architecture of the two-output regression–classification neural network for predicting power change and its direction (authorship: this work)

Thus, the model learns to respond flexibly to non-stationary processes typical of household loads.

Results and Discussion

The test results indicate that forecast quality is sufficient. The model reproduces power trends during transient conditions and determines the direction of energy flow.

Table 1

Main experimental metrics	
Metric	Value
Mean Absolute Error (for ΔP)	18–23 % of the nominal power
RMSE	16–21 %
Classification accuracy of $sign_{next}$	78–84 %

The model achieves an average prediction error (MAE) of 18–23% of the nominal power, and an RMSE of 16–21%, indicating stable reproduction of power trends during transient conditions. The energy flow direction classification accuracy ($sign_{next}$ feature) is 78–84%, which is an acceptable level for real-time systems without hardware acceleration for neural computations.

Optimization reduced memory use from ~36 kB to 12.5 kB and prediction time to 4.6 ms (in int16 format) demonstrating successful real-time adaptation, including triac control tasks.

The model was optimized, reducing memory usage from approximately 36 kB to about 12.5 kB. The execution time for a single prediction at a clock frequency of 168 MHz is presented in Table 2.

Table 2

Model performance indicators	
Format	Execution time of a single prediction
float32	≈ 18.9 мс
float16	≈ 12.1 мс
Int16	≈ 4.6 мс

It is especially important that the model can adequately respond to short-term load variations without losing prediction stability.

Conclusions

This work presents the process of developing and implementing a compact neural network model for forecasting active power variations on the STM32F405 microcontroller.

Previous approaches to power forecasting in embedded systems were typically based on simplified linear models or filtering algorithms that did not account for temporal dependencies between successive measurements.

The proposed AI model, in contrast, leverages temporal context (sliding window) and combines regression and classification outputs, improving the system’s accuracy and adaptability.

Compared to models deployed on more powerful platforms (e.g., Raspberry Pi or ESP32), the implementation on the STM32F405 demonstrates comparable accuracy with significantly lower power consumption and computational latency.

The developed model:

- generates predictions of both the magnitude and direction of power changes based on five key electrical parameters;
- demonstrates acceptable accuracy for local load control;
- operates without the need for hardware acceleration
- has a small memory footprint (≈ 12.5 kB) and a short prediction execution time (< 5 ms).

The main contribution of this work is demonstrating the feasibility of effectively applying AI approaches on mid-range microcontrollers for energy monitoring and control tasks.

Future research will focus on implementing an adaptive self-learning mechanism during operation and integrating multiple microcontrollers into a network for distributed forecasting.

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ЗАСТОСУВАННЯ ШІ АЛГОРИТМІВ ПРОГНОЗУВАННЯ ДЛЯ ПІДВИЩЕННЯ НАДІЙНОСТІ СОНЯЧНИХ ДИВЕРТОРІВ

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У роботі представлено адаптивний підхід до керування сонячними диверторами на основі штучного інтелекту, реалізований на платформі мікроконтролера STM32F405. Запропоноване рішення спрямоване на розв'язання проблеми неефективного використання надлишкової фотоелектричної (PV) енергії в побутових сонячних електростанціях без акумуляторних накопичувачів, коли надлишок генерації часто експортується до електромережі замість локального споживання. Розроблений підхід базується на короткостроковому прогнозуванні потужності для проактивного регулювання роботи силового контролера на основі симістора. Запропоновано гнучку стратегію керування, яка поєднує традиційне фазо-кутове керування та методи широтно-імпульсної

модуляції з прогнозуванням на основі штучного інтелекту. З урахуванням прогнозованої динаміки потужності система обирає оптимальну стратегію комутації та обмежує швидкість зміни потужності, що дозволяє зменшити втрати на перемикання та теплові навантаження на силові електронні компоненти. Вбудована нейронна модель одночасно виконує дві задачі: регресію для прогнозування величини короткострокових змін активної потужності та бінарну класифікацію для визначення напрямку потоку енергії (споживання або експорт). Навчання моделі здійснюється на основі реальних вимірювальних даних напруги, струму та фазових сигналів, які формують вектори ознак, що описують поточний електричний стан системи. Для забезпечення сумісності з апаратними платформами з обмеженими ресурсами модель оптимізовано за обсягом пам'яті та швидкодією з використанням підходу TinyML. Експериментальні результати показують, що запропонована система досягає середньої абсолютної похибки 18–23 % та середньоквадратичної похибки 16–21 % при прогнозуванні змін потужності, а точність класифікації напрямку потоку енергії становить 78–84 %. Отримані результати підтверджують, що прогнозне керування на основі штучного інтелекту суттєво підвищує надійність і ресурс симісторних сонячних диверторів, забезпечує більш плавне регулювання потужності та підвищує загальну ефективність використання сонячної енергії в побутових фотоелектричних установках без використання хмарних обчислень.

Ключові слова: штучний інтелект; вбудовані нейронні мережі; Keras; фотоелектричні системи; надійність силових електроніки; прогнозне керування; сонячний дивертор; STM32.

Перелік використаних джерел

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