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# AN ARTIFICIAL NEURAL NETWORK–BASED APPROACH FOR HARMONIC COMPONENTS PREDICTION IN GRID-CONNECTED PV SYSTEMS

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## Abstract

With the increasing penetration of solar photovoltaic (PV) generation, non-sinusoidal current components can be injected into the grid due to power-electronic conversion, degrading power quality and potentially affecting system stability. In practical mitigation, response delays can reduce the effectiveness of active filtering; therefore, fast prediction of harmonic distortion is valuable for enabling adaptive control. This study investigates an artificial neural network (ANN) model to predict total harmonic distortion (THD) and harmonic components in a grid-connected PV system using only two environmental inputs: solar irradiance and ambient temperature. The model was trained and tested using measurements from a 6.4 kW PV setup at the Department of Electrical Engineering, IOE Pulchowk Campus. Based on the recorded measurements, THD under the observed operating conditions ranged from 9.12% to 32.45%. The proposed ANN achieved an overall prediction accuracy of 83% on the available datasets, demonstrating that a lightweight model driven by minimal environmental features can provide timely harmonic estimates. These results support the feasibility of using ANN-based prediction as a foundation for real-time monitoring and adaptive harmonic filtering in PV-connected distribution systems.

**Keywords:** Total harmonic distortion, ANN, Grid-connected PV, Harmonic prediction

## 1. Introduction

The Renewable Energy Sources(RES) sector has undergone rapid transformation in recent times mostly due to mitigation of the effect on the environment and reduction in the consumption of fossil fuels and other non renewable resources. The PV-technology has been one of the top choices among the renewable sources due to its cost effectiveness over time, scalability, need for minimal maintenance along with the advantages mentioned above. According to the International Energy Agency Photovoltaic Power Systems Programme (IEA-PVPS), global PV cumulative capacity grew to 1.6 TW in 2023, up from 1.2 TW in 2022, with between 407.3 GW to 446 GW of new PV systems commissioned in 2023 alone(IEA Photovoltaic Power Systems Programme, 2024).

Harmonics are the wave signals having frequencies(integral multiples of frequencies) other than the fundamental frequency. These harmonics distort the pure sine wave of voltage or current, causing distortion. Harmonics are caused by non linear loads devices that don't draw current smoothly but in pulses. Examples include variable frequency drives, battery chargers, computers, and switching power supplies. These devices change the shape of current waveform to become distorted causing harmonics in the system. Voltage harmonics are present due to the flow of these current harmonics through the systems impedance.

For instance, an inverter consists of semiconductor devices which perform various switching operations to change flow of current creating voltage waveforms. Operation of these switches in switching mode causes rapid transition of on and off states causing sharp rise and fall time in voltage and current resulting distorted sinusoidal waveform. Similarly, variable frequency drives have AC as input and convert it into DC, then creating variable frequency input for motor control. This process causes it to draw current irregularly resulting distortion.

Harmonics causes severe impacts on power quality, equipment stability and operational reliability. Transformer

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overheating is a major problem caused by harmonics which results in increased eddy current losses with additional winding copper losses and higher hysteresis losses. This consequences speeding up insulation degradation leading potential premature failure. Harmonic currents increases transmission losses reducing system efficiency. Distribution systems with 10% THDV may suffer 2–15% losses in transformers, 6% losses in generators and 15–16% losses in capacitors (Das et al., 2014).

The electrical engineering societies have established standards to regulate harmonic distortion levels. The IEEE 519 standard is widely adopted, particularly in North America, providing recommendations for limiting harmonic voltage and current distortion at the point of common coupling (PCC) between the electrical system operator and users(Hoevenaars, 2014). This standard recognizes the dual responsibility of electricity users not to degrade voltage quality by drawing distorted currents, and of utilities to provide users with near sine wave voltage(Hoevenaars, 2014).

Active Shunt Filters, also known as shunt active filters, are the effective solution for power quality problems. A shunt active filter is a power electronics device connected in parallel with non-linear loads to mitigate harmonics at point of common coupling (PCC). The basic principle of operation involves injecting harmonic components that are equal in magnitude but opposite in phase (180° shifted) to the harmonics produced by non-linear loads(Mohod et al., 2020) (Afonso et al., 2000). This process results in harmonic cancellation, making the current source nearly sinusoidal.

Active shunt filters are effective for harmonic mitigation but face critical challenges from time delays in their control systems. These delays-introduced by digital signal processing (DSP), sensor measurements, and computational lags-significantly degrade stability, compensation accuracy, and operational reliability. Time delays destabilize ASFs by altering the phase characteristics of the control loop. Li and Liu (Li and Liu, 2013) demonstrated that delays as small as 0.5 ms can reduce the delay margin-the maximum tolerable delay before instability-by 40% in typical grid-connected systems.

Due to the recent advancement in artificial intelligence(AI), harmonic mitigation and effect of time delay in the active shunt filters have been greatly reduced. Recent studies have increasingly integrated machine learning (ML) and deep learning into shunt active power filter (SAPF) control loops to improve reference current generation, DC-link regulation, and dynamic harmonic extraction under rapidly varying nonlinear loads (Chahine, 2024). For PV-integrated SAPFs, ML-assisted adaptive controllers have been reported to significantly accelerate transient response and improve harmonic identification accuracy compared with classical adaptive schemes, while keeping source-current THD within standard limits (Jai and Ouassaid, 2024).

Similarly, deep learning–driven hybrid SAPF controllers (e.g., ANN/GRU/LSTM-based designs) have been evaluated for harmonic detection and compensation, showing high prediction accuracy and effective THD reduction under practical operating conditions (Ali et al., 2022). In parallel, predictive control strategies have also been demonstrated in simulation and hardware-in-the-loop setups to suppress harmonics (Sapkota et al., 2024). Overall, the literature indicates a clear trend toward data-driven and predictive controllers to mitigate time-delay effects and enhance SAPF performance.

Existing Deep Learning architectures for harmonic mitigation rely exclusively on electrical measurements (voltage/current waveforms), neglecting the causal relationship between environmental conditions and harmonic generation in renewable-integrated grids (Sugavanam et al., 2021) (Liu et al., 2024). No prior studies explicitly use solar irradiance and temperature as inputs for harmonic prediction, despite their direct impact on PV output and inverter switching behavior. While unsupervised DL methods effectively identify daily harmonic patterns, their 10-minute sampling intervals fail to capture sub-second transients caused by cloud cover (de Oliveira, 2023), necessitating the high-resolution measurement.

There have been studies in harmonic prediction using neural networks considering environmental parameters (Žnidarec et al., 2019), but to the best of the author's knowledge, there has been no such harmonic prediction using only solar irradiance and ambient temperature with high-resolution data, with a simple yet multi-neuron neural network to best predict the total harmonic distortion (THD) and harmonic components.

This paper is organized into mainly three parts, with each part having or not having a subdivision. Part 1 presents the introduction to the topic of the paper, background, a literature review, and research gap. Part 2 describes the proposed methodology, experimental setup, system description, and analysis of the power quality. In Part 3, the model results, discussion on results, and concluding remarks based on the obtained results are provided.

## 2. Methodology

### 2.1. Description of Site

For the purpose of this study, a grid-connected PV system installed on the rooftop of the Department of Electrical Engineering, Pulchowk Campus, Laltipur, Nepal (27° 40′ 56.55″ N latitude and 85° 19′ 5.95″ E longitude) is selected as the case study site. The gird connected PV system has the rated capacity of 6.4 kW and primarily supplies power to

Table 1. Configuration and electrical characteristics of the installed solar PV system

| **Parameter** | **Specification** |
|---|---|
| PV module manufacturer | Trina Solar |
| PV module model | TSM–400DE09 |
| Rated power per module ($P_{max}$) | 400 W |
| Number of PV modules | 16 |
| Total installed PV capacity | 6.4 kW |
| Maximum power voltage ($V_{mp}$) | 34.2 V |
| Maximum power current ($I_{mp}$) | 11.70 A |
| Open-circuit voltage ($V_{oc}$) | 41.2 V |
| Short-circuit current ($I_{sc}$) | 12.28 A |
| Maximum system voltage | 1500 V (IEC) |
| Power tolerance | 0 to +5 W |
| Rated conditions | STC (1000 W/m$^2$, 25°C, AM 1.5) |

the local electrical load within the Department of Electrical Engineering. The electrical characteristics are based on manufacturer specifications under standard test condition are tabulated in the Table 1.

## 2.2. Approach

For the measurement of the data, a power analyzer was used at the point of common coupling (PCC) of the PV system. The power quality was measured using the Elcontrol NanoVIP Cube power analyzer (Elcontrol Energy). As mentioned in (Elcontrol Energy), the NanoVIP provides advanced power quality measurement, including full traditional energy analysis (V, I, P, Q, S, F, PF, THD%, instantaneous values, minimum/maximum/average, and absorbed/generated energy meters for each three-phase system), along with harmonic components up to the 50th order.

The solar irradiance and ambient temperature were obtained from a weather station located in Khumaltar, Lalitpur, Nepal, and provided by the Government of Nepal's Department of Hydrology and Meteorology (DHM) at 10-minute intervals. Harmonic and THD measurements were recorded in real time at the PV point of common coupling using the Elcontrol NanoVIP Cube power analyzer. To create the final dataset for ANN training, the power-analyzer measurements were aggregated into 10-minute windows aligned with the DHM timestamps, and each aggregated harmonic/THD record was paired with the corresponding irradiance and temperature values. Measurements were collected under varying weather conditions, including partly cloudy and sunny days, to capture a wider range of operating variability. Figure 1 shows the PV system installed on the rooftop of the Department of Electrical Engineering, and Figure 2 and Figure 3 shows the point of common coupling where the power analyzer was connected to measure power quality.

From the fifteen+ parameters recorded by the power analyzer, preprocessing selectively extracted total harmonic distortion (THD) and individual harmonic components using Nano Studio software. The final compiled dataset incorporated solar irradiance, ambient temperature,

Figure 1. A 6.4 kW grid-connected PV sytem loacted on rooftop of Department of Electrical Engineering

Figure 2. Point of common coupling

Figure 3. Power analyzer connected at point of common coupling

THD, and harmonic components, providing a optimized foundation for model training.

## 2.3. Model Architecture

For training the model, solar irradiance and ambient temperature are used as input parameters. Using the minimum number of parameters ensures there is no overfitting, improves computational efficiency, enables faster training, and leads to better optimization. As seen in the Figure 4, the correlation between current amplitude and THD (Total Harmonic Distortion) is very high, which justifies the selection of solar irradiance as the key input features. Also the corrleation between ambient temperature and THD is also acceptable as in Figure 5 (Žnidarec et al., 2019).

Using a Random Forest Regressor for further analysis showed that solar irradiance contributed approximately 58% of the model's predictive capability, while ambient temperature contributed for approximately 42% in Figure 6. From the correlation coefficient and Random Forest Regressor (RFR), use of solar irradiance and ambient temperature as the input parameter is validated ,which keeps the model correct and compuatitonally efficient.

The neural network used for predicting harmonic components (including Total Harmonic Distortion, and individual harmonics) is a fully connected feedforward model implemented using TensorFlow/Kears. Model summary is shown in Table 2 and in Figure 7

## 2.4. Model Summary

The neural network architecture begin with an input layer (shape=(2,)) that accepts two numerical features-here in this case, solar irradiance and ambient temperature.

Table 2. Neural Network Architecture

| Layer | Type | Units | Activation | Purpose |
|---|---|---|---|---|
| Input | Dense | 2 | – | Input Parameters:Temp & radiation |
| 1 | Dense | 128 | ReLU | Feature learning |
| 2 | Dense | 96 | ReLU | Feature Abstraction |
| 3 | Dense | 256 | ReLU | Deep features extraction |
| 4 | Dense | 160 | ReLU | Final Hidden layer |
| Output | Dense | 3 | Linear | THD& harmonic prediction |

The model contains four hidden layers, all utilizing Rectified Linear Unit (ReLU) activation functions to capture complex non-linear relationship between input parameters and harmonic distortion patterns. To mitigate overfitting, dropout regularization is applied after each dense layer, with shallow layers using a dropout rate of 0.2 and deeper layers employing a more aggressive 0.4 rate. The output layer consists of three neurons with linear activation, designed to predict continuous harmonic values through regression.

With a learning rate of 0.01 and adaptive moment estimation for effective gradient descent while preserving training stability, the model uses the Adam optimizer. We use Mean Absolute Error (MAE) for the loss function because it provides robustness against outliers that are frequently found in harmonic measurement data. Although convergence tracking tracks training accuracy, MAE and Root Mean Square Error (RMSE) metrics are used for primary evaluation because they offer a more insightful interpretation of the model's predictive performance for continuous harmonic values. This optimization setup, which is particularly suitable for the non-linear properties of PV system harmonics, strikes a balance between quick convergence and accurate gradient updates.

# 3. Results

Based on data obtained from the power analyzer, the Total Harmonic Distortion(THD) varied from a minimum of 9.12% to a maximum of 32.45%. The ANN, trained using this dataset achieved a prediction accuracy of 83%, which is considered satisfactory given the limited volume of data.

Table 3 shows that, The ANN model performs well, as evidenced by the low Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values for all predicted harmonic components. In particular, a high degree of accuracy with minimal deviation from actual values is indicated by the small error in THD prediction (RMSE = 0.039, MAE = 0.029). Similarly, the model performs well in estimating both the fundamental and 3rd harmonic components, with no significant outliers or large prediction errors.

As shown in scatter plots Figure 8, Figure 9 and Figure 10, the predicted values of THD, fundamental harmonic and 3rd harmonic shows as strong correlation with actual

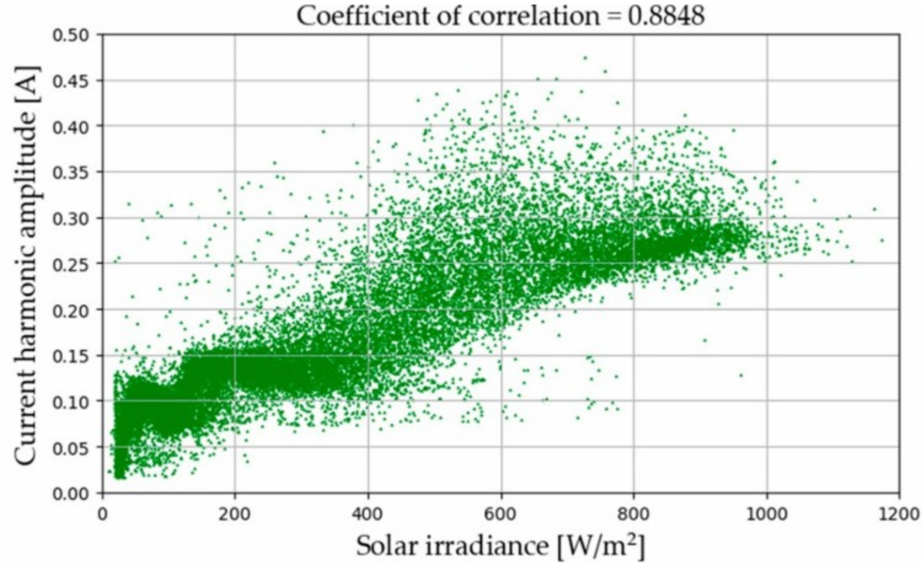


Figure 4. Current harmonic amplitudes in relation to solar irradiance

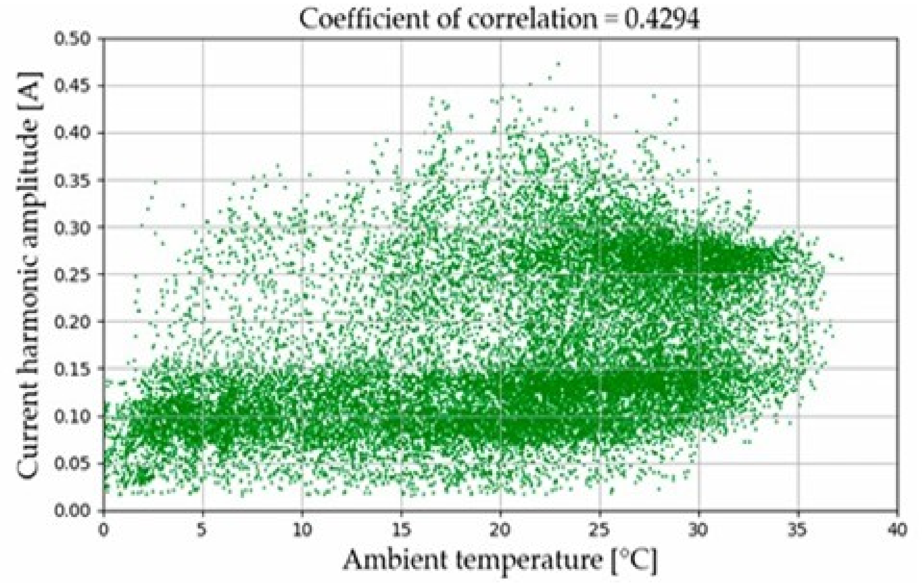


Figure 5. Current harmonic amplitudes in relation to ambient temperature

Table 3. Performance metrics for harmonic distortion variables

| Variable | RMSE | MAE |
|---|---|---|
| THD (%) | 0.039 | 0.029 |
| 1st Harmonic (p.u.) | 0.082 | 0.064 |
| 3rd Harmonic (p.u.) | 0.070 | 0.056 |

values. The close alignment of predicted and observed data points suggests that the model operated within an acceptable error margin and is effective model in estimating harmonic components under varying conditions.

Furthermore, for validation of actual vs. predicted values, a regression line and confidence interval are added to convey how well the model is predicting. Figure 11 shows the actual vs. predicted THD plot; here the regression line visually assesses the alignment between predicted and actual values, providing a clearer interpretation of model performance. The actual and predicted values of THD have a strong linear connection, as indicated by the regression lines. A 95% confidence band (gray shaded area) around the regression line has been added to represent the uncertainty in the model's predictions. The narrow width of these bands across most of the data range implies low variance and high reliability.

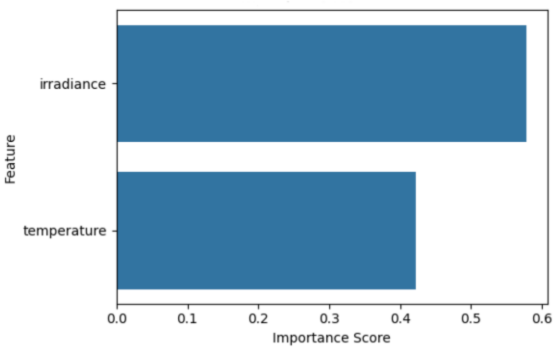


Figure 6. Feature Importance for THD% prediction

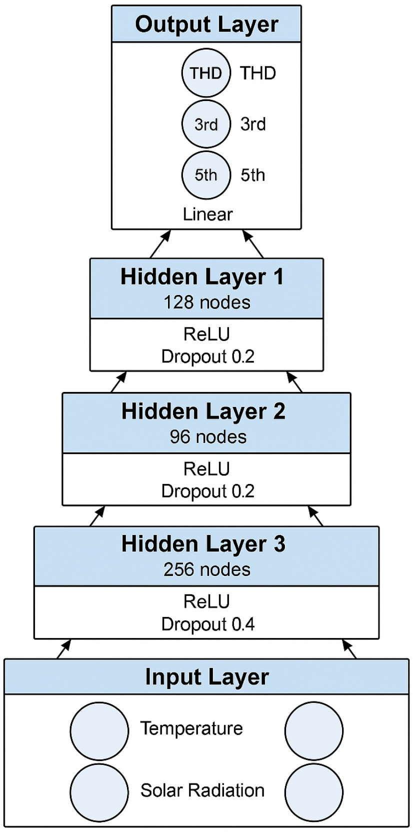


Figure 7. Model architecture layout for harmonic prediction

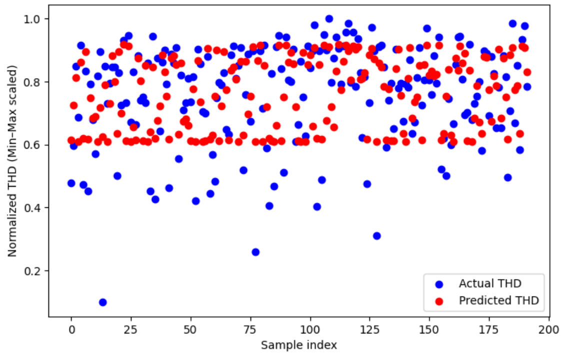


Figure 8. Actual Vs Predicted THD

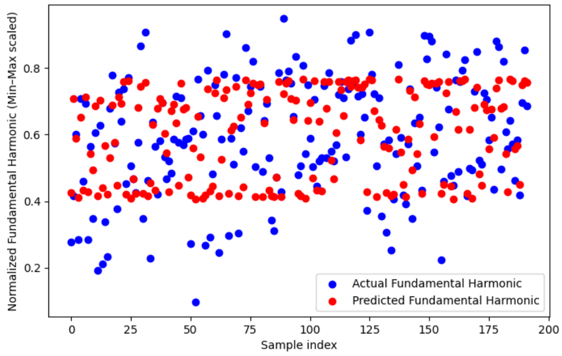


Figure 9. Actual Vs Predicted Fundamental Harmonic

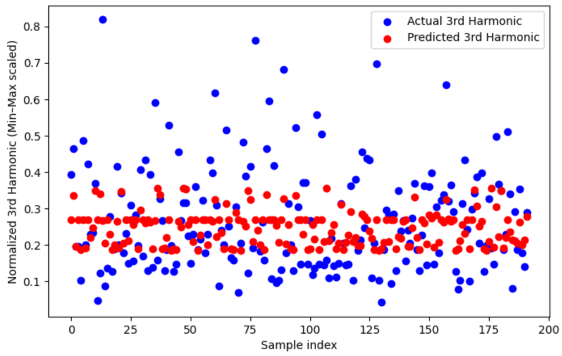


Figure 10. Actual Vs Predicted 3rd Harmonic

## 4. Discussion and Conclusion

In this paper, a novel method for predicting current harmonics is presented. The proposed method uses an artificial neural network to predict the THD, fundamental, and 3rd current harmonics. This model requires only solar irradiance and ambient temperature as input-the minimum parameters needed to predict harmonic components.

Trained on a dataset from a 5kW PV system, this model and architecture are suitable for small-scale industrial applications with fixed loads, making them practical for filter design. In real deployment, the trained ANN can run online and provide predicted THD/harmonic levels as an additional input to the shunt active power filter control scheme, allowing the filter to adapt its compensation settings proactively and reduce delay-related degradation. With more varied datasets, the model can be trained more effectively, improving its adaptability and increasing accuracy beyond the current 83%. Once optimized, this approach could significantly reduce the limitations of traditional filters, thereby enhancing energy efficiency, system protection, and stability.

However, the model has some limitations. Its

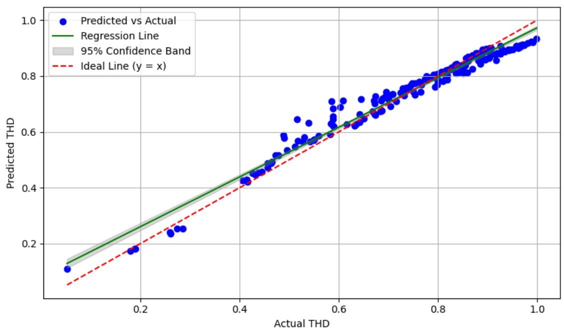


Figure 11. Actual Vs Predicted THD including regression line and confidence interval

performance under dynamic load conditions or during grid disturbances remains unvalidated, as the training data focused on fixed-load scenarios. Additionally, if trained on irrelevant or inaccurate data such as noisy measurements or timestamp-misaligned solar irradiance and ambient temperature values which do not correspond to the real-time harmonic/THD records, it may produce incorrect predictions. Data quality and security are also critical concerns. By addressing these challenges through proper data selection, accuracy validation, and secure training practices, this ANN-based model can overcome the drawbacks of traditional filters.

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