

Research Article

DEEP LEARNING BASED PREDICTION OF POWER QUALITY DISTURBANCES IN DISTRIBUTION NETWORKS**Metin AKDENİZ^{*1}, İlyas ÖZER², Serhat Berat EFE³**¹Bandırma Onyedi Eylül University Dept. of Electrical EngineeringOrcid¹: <https://orcid.org/0000-0002-5336-0128>²Bandırma Onyedi Eylül University Dept. of Computer EngineeringOrcid²: <https://orcid.org/0000-0003-2112-5497>³Bandırma Onyedi Eylül University Dept. of Electrical EngineeringOrcid³: <https://orcid.org/0000-0001-6076-4166>* Corresponding author; metin.akdnz@gmail.com

Abstract: The main objective of this study is to predict harmonic distortions in a power distribution system using real-world active and reactive power data. To achieve this, a Gated Recurrent Unit (GRU)-based artificial intelligence algorithm was employed, which is particularly effective in modeling the dynamic nature of time series. Unlike conventional methods, the GRU model demonstrates successful performance by shortening training duration and increasing prediction accuracy. The prediction results yielded promising error metrics, with mean absolute error (MAE) values of 0.5200, 0.5330, and 0.5771; mean absolute percentage error (MAPE) values of 7.52%, 7.55%, and 7.72%; and root mean square error (RMSE) values of 0.7014, 0.7231, and 0.7848 for the THD_I1, THD_I2, and THD_I3 indices, respectively. These findings indicate that the proposed approach provides a reliable and practical solution for predicting harmonic distortions and can effectively support decision-making mechanisms aimed at enhancing power quality in distribution systems.

Keywords: electric power systems, deep learning, power quality

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1. Introduction

Harmonic distortions in distribution networks are among the most critical issues, arising from the nonlinear load behavior of electrical equipment that causes current and voltage waveforms to deviate from their ideal sinusoidal shape. Such distortions lead to additional losses and voltage drops in key components such as transformers, motors, transmission lines, and power-electronics-based devices, thereby reducing system reliability. With the increasing integration of renewable energy resources, electric vehicles, and Distributed Energy Resources (DER) into distribution networks, the problem has become even more critical. Power-electronic converters act as the main sources of distortion, while the stochastic and time-varying nature of modern load profiles makes harmonic behavior highly dynamic, limiting the effectiveness of conventional methods.

The novelty of this study lies in predicting harmonic distortions in distribution networks using only active and reactive power data, without the need for expensive harmonic measurement devices. The proposed approach provides a low-cost, practical, and scalable solution that can be directly applied in field operations.

The contribution of the study is the development of a GRU-based deep learning model trained with real-world field data, which achieved high prediction accuracy while significantly reducing training time. The model performed particularly well under moderate distortion levels, offering a reliable decision-support tool for distribution networks. In this way, the study introduces a new perspective in deep learning-based harmonic distortion prediction and provides a directly applicable solution for energy distribution companies.

Therefore, the inadequacy of conventional harmonic analysis techniques under dynamic and unpredictable conditions has increased the importance of Artificial Intelligence (AI) and MACHINE LEARNING (ML)-based methods, as in the proposed GRU model. In this context, numerous AI-based studies have been developed in the literature for the prediction of harmonic distortions.

For instance, probabilistic prediction approaches have been proposed to accommodate the temporal uncertainty of DER and varying electrical loads [1]. Artificial neural networks have shown promise in estimating harmonics originating from grid-connected Photovoltaic (PV) inverters [2]. Additional studies have examined the impact of harmonic currents from nonlinear loads on low-voltage networks [3] and implemented deep learning frameworks for prediction voltage harmonics in wind power facilities [4]. Moreover, the influence of emerging harmonic sources on grid stability and power quality has become a focus of comprehensive investigations [5]. This growing body of literature highlights the need for intelligent, data-driven techniques that can robustly model and predict harmonic distortions under complex operating conditions.

Recent advancements in harmonic distortion prediction for PV, wind, and hybrid energy systems have increasingly employed specialized and hybrid architectures such as CNN-LSTM, LSTM-ANFIS, ANN-GMDH, CNN-GRU, DTW-LSTM, RF, LSTM, GRU, ANN, XGBoost, CatBoost [6-14]. These developments reflect a broader trend toward applying machine learning to power quality analysis across various domains, including IoT-enabled platforms [10], railway electrification systems [8], marine microgrids [15], and large-scale distribution grids using smart meter data [16].

Beyond data-driven prediction, real-time power quality enhancement is gaining increasing importance, and innovative approaches such as intelligent filtering and nonlinear autoregressive neural networks have been proposed in this context [17, 18]. More recently, methods such as forecasting voltage harmonic distortion in residential low-voltage networks using smart meter data and hybrid Fourier–neural network models have emerged; these developments highlight the ongoing shift from traditional deterministic models toward adaptive AI-supported solutions [19, 20].

Drawing inspiration from these trends, this study proposes an artificial intelligence-based harmonic distortion prediction model employing GRU neural networks. By leveraging readily available active and reactive power measurements in distribution networks, the proposed approach eliminates the need for dedicated harmonic sensors. This framework aims to deliver cost-effective and reliable power quality monitoring while supporting the development of decision-making systems in medium-voltage grids.

2. Methodology

Total Harmonic Distortion (THD) is a quantitative measure of the distortion in a signal caused by harmonic components. It expresses the extent to which these harmonic elements contribute to the overall waveform distortion in relation to the fundamental frequency. For current signals, the THD value can be calculated using Equation (1).

$$THD_I = \frac{\sqrt{\sum_{n=2}^{\infty} I_n^2}}{I_1} \times 100\% \quad (1)$$

Harmonic detection is a fundamental component in effectively addressing power quality issues. Moreover, the dynamic structure of power systems causes harmonic levels to vary continuously over time. Therefore, regular monitoring of harmonics within the electrical grid is of critical importance. However, deploying devices such as analyzers, harmonic meters, or power quality analyzers at every busbar point in the transmission system is not always feasible due to high implementation costs.

Typically, harmonic calculations in such instruments rely on the Fast Fourier Transform (FFT) method. In contrast, this study proposes an Artificial Neural Network (ANN)-based model that estimates harmonic distortion directly from active and reactive power data, eliminating the need for FFT-based computation. Accordingly, a GRU-based Recurrent Neural Network (RNN) is introduced.

The GRU is a powerful neural network architecture commonly employed for time series analysis and sequential data processing tasks. By utilizing update and reset gates, GRU networks can selectively retain or discard previous information, enhancing their ability to capture long-term dependencies. Its lightweight structure requires relatively low computational resources, enabling fast and efficient training. GRUs have demonstrated successful applications across various domains, including natural language processing, financial prediction, and electrical system analysis.

The main purpose of this research is to prevent future failures stemming from harmonic distortions. While existing studies in the literature typically predict current harmonics based on present current measurements, this study instead forecasts the THD values for each phase current using active and reactive power data as inputs. This approach enables a more accessible and indirect estimation of harmonic levels within power systems.

3. Experimental Application

In this study, a GRU-based artificial neural network model was developed to predict total harmonic distortion values (THD_I1, THD_I2, THD_I3) across three phases using active and reactive power data. GRU's capability to learn long-term dependencies in temporal data allows it to mitigate the vanishing gradient problem commonly encountered in classical RNN architectures, resulting in more stable learning.

The dataset used in the study was collected from the Fider-5 line connected to the Tatvan Transformer Center (TM), via an ENTES-branded MPR63 power and energy analyzer. The measurements, spanning from July 1, 2023 to April 24, 2024, include active and reactive power values as well as total harmonic distortion ratios of current and voltage for each phase. A total of 58,340 data points were obtained in 5-minute intervals through Entbus Pro software, and imported into the analysis environment with corresponding timestamps.

As model inputs, time series features — such as "hour" and "day" — along with active and reactive power values were used. The target outputs were the harmonic distortion values for each phase. During the preprocessing phase on the real measurement data recorded at a 5-minute resolution, missing values were removed, numerical transformations were applied, and Min-Max normalization was performed. For each input, sequential arrays of 24 time steps were created to capture temporal dependencies. Dense layers were added after the GRU layer to improve representation of nonlinear relationships within the data.

Training of the model incorporated callback functions such as EarlyStopping and LearningRateScheduler to ensure balanced learning and avoid overfitting. Prediction results were reconstructed from test data and evaluated using common error metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The predicted THD values were compared to the actual measurements, and results were also presented graphically to showcase the model's overall performance.

The model was initially trained using randomly assigned weights. Due to the intuitive nature of deep learning techniques, different initializations may lead to different outcomes. Accordingly, various configurations involving the number of GRU units and dense layer architectures were tested to identify the most effective prediction performance.

Figure 1 illustrates the evolution of training and validation losses throughout the learning process of the GRU-based RNN model, which forms the basis of this study. The model is designed to forecast harmonic distortions (THD_I1, THD_I2, THD_I3) using Active Power (Watt) and Reactive Power (VAR) inputs. The X-axis corresponds to the number of training epochs (iterations over the dataset), while the Y-axis represents the MSE, indicating the prediction error. Initially, the error rates were relatively high but decreased as the number of training epochs increased, enabling the model to better learn the dataset. Around the 10th epoch, a balance between training and validation losses indicates that the model can generalize without entering overfitting. Moreover, the similarity between the training and validation loss curves suggests successful learning across both datasets. Overall, the learning curve observed during training is encouraging, and the lack of major fluctuations in the validation loss may point to the model's strong generalization capability.



Figure 1. Training and validation losses.

Evaluation metrics serve as essential instruments for gauging the performance of intelligent predictive models. In light of the diverse array of available metrics, this study adopts MSE, RMSE, MAE and MAPE to quantify predictive accuracy. These metrics are extensively utilized in time series forecasting literature to facilitate comparative analyses of prediction error. The prediction results were analyzed using the MSE, MAPE, MAE, and RMSE, as described in (2), (3), (4) and (5), respectively.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (4)$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i} \quad (5)$$

In these equations; n is the number of observations, y_i is the actual value, $\hat{y}_i$ is the predicted value and $|\dots|$ is the absolute value.

Training and evaluation processes were performed on a computer equipped with an AMD Ryzen 7 7435HS processor and 16 GB of RAM. The model development utilized Python version 3.10 and the

Visual Studio Code editor. The neural network was implemented using the Keras API within the TensorFlow library. Table 2 presents the resulting error metrics, including MAE, MAPE, MSE, and RMSE.

Table 2. Resulting error metrics.

Error metrics	THD_I1	THD_I2	THD_I3
MAE	0.5200	0.5330	0.5771
MAPE (%)	7.52	7.55	7.72
MSE	0.4920	0.5228	0.6159
RMSE	0.7014	0.7231	0.7848

In order to strengthen the contribution of this study, the forecasting results were compared with those reported in a recent LSTM-based study [21]. While the reference study achieved MAE = 0.81, MAPE = 10.24%, and RMSE = 0.94, our GRU-based approach significantly reduced the errors to MAE = 0.543, MAPE = 7.60%, and RMSE = 0.736 on average across three harmonic indices. This comparison demonstrates that the proposed GRU model provides more accurate and robust forecasting performance than similar models in the literature.

Graphs obtained are given in Figures 2, Figure 3 and Figure 4.

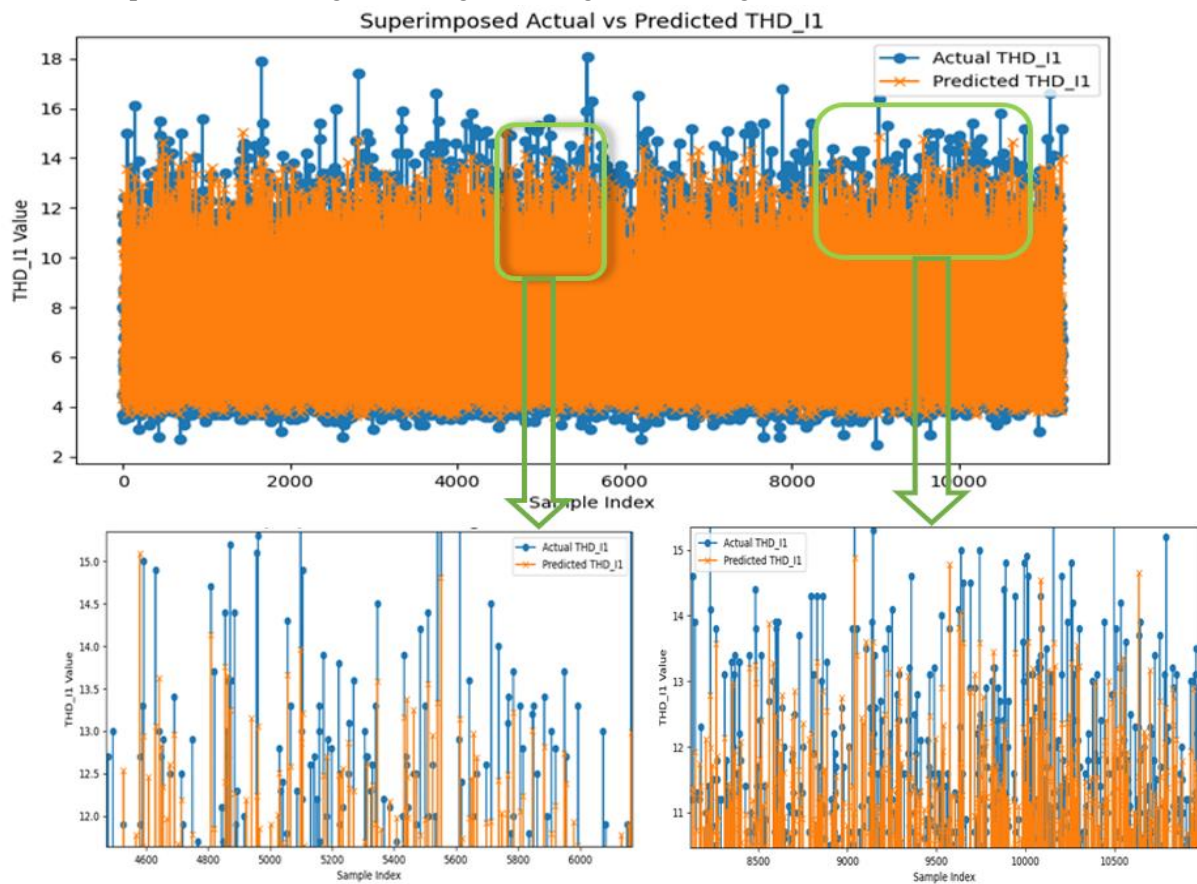


Figure 2. Results for Line 1

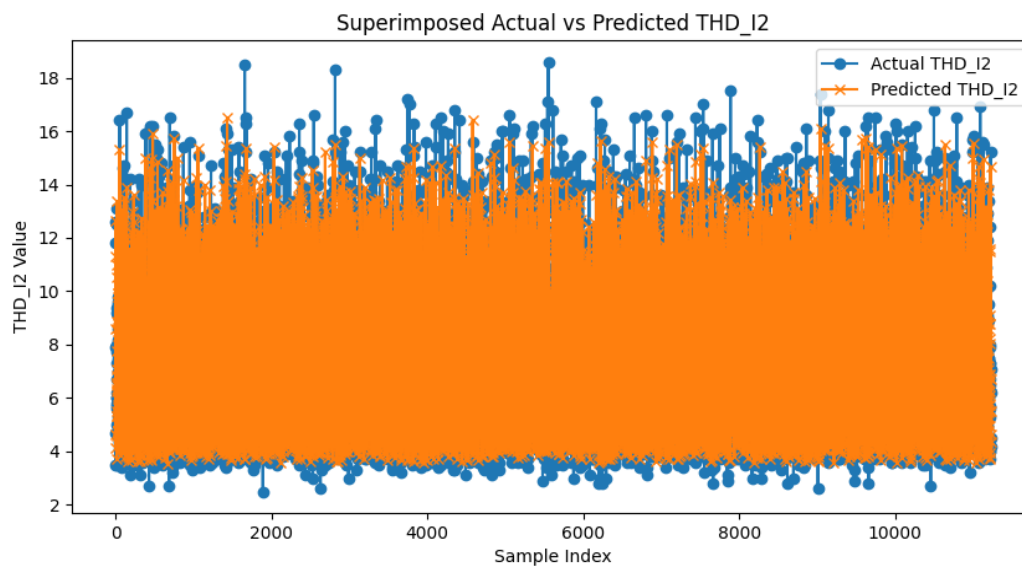


Figure 3. Results for Line 2

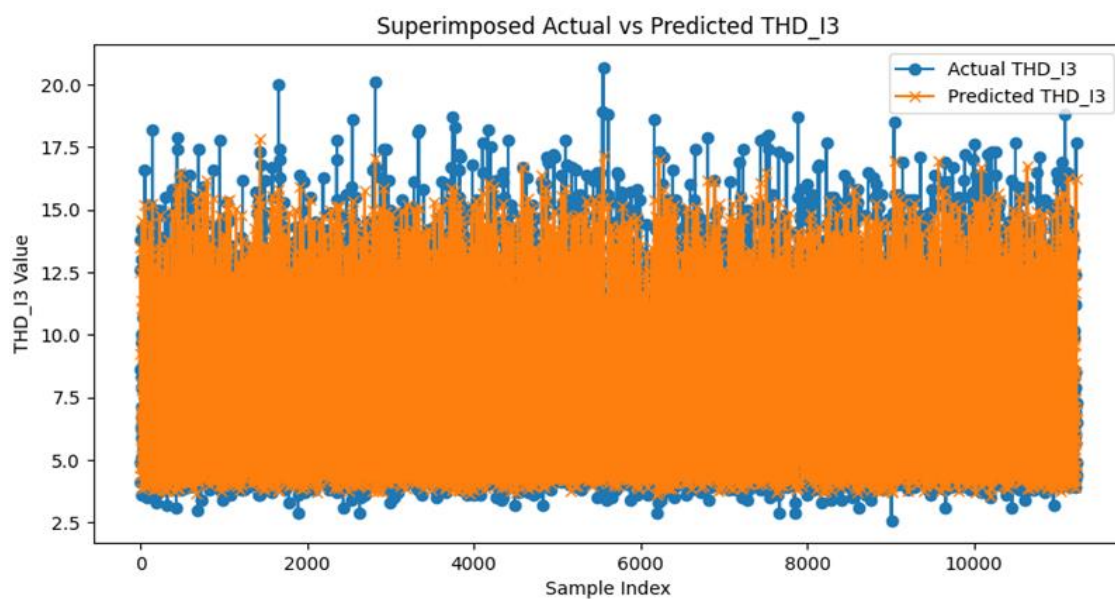


Figure 4. Results for Line 3

The graph generated for THD_I1 illustrates the model's performance by comparing actual and predicted values. On the horizontal axis are the sample indices, while the vertical axis shows the THD_I1 values. Blue dots represent the measured (actual) data, and orange crosses depict the model's predictions. A key observation is the close alignment between predicted and actual values, indicating that the model has accurately learned the THD_I1 behavior and delivers high predictive performance.

In particular, for moderate distortion levels (approximately between 10 and 14), the model's forecasts exhibit a striking resemblance to the actual values, reflecting high accuracy. Since the majority of the data points fall within this range, the model's success in this segment is especially meaningful. However, minor deviations can be observed at the extremes—specifically for THD_I1 values exceeding 16 or falling below 4. These slight discrepancies indicate that the model's sensitivity to outlier values is somewhat reduced. To address this limitation, future studies should focus on constructing more balanced

and comprehensive datasets that include extreme THD values. In addition, applying data augmentation techniques or generating synthetic data to better represent outliers could enhance the model's generalization capability.

The large volume of test samples (exceeding 10,000) and the consistent accuracy achieved across this extensive dataset indicate that the model has strong generalization capabilities. As such, the graph clearly demonstrates that the proposed GRU-based model produces highly accurate and reliable results in forecasting THD_I1. Similar observations and conclusions apply equally to the prediction graphs for THD_I2 and THD_I3.

4. Results and Discussion

In modern power distribution systems, power quality—especially regarding harmonic distortion—has become increasingly critical. This study moves beyond traditional measurement and analysis techniques by estimating harmonic distortion levels (THD_I1, THD_I2, THD_I3) for all three phases using only active and reactive power data. The GRU (Gated Recurrent Unit)-based artificial neural network model employed for this purpose demonstrates high predictive accuracy thanks to its ability to learn complex patterns in time series data.

The error metrics used throughout the model's training and evaluation phases—MAE, MAPE, MSE, and RMSE—clearly quantify the performance of the proposed method. These values show that the model generalizes successfully not only to the training dataset but also to the test data. Despite the temporal variability of THD values, the model's sensitivity and adaptability to sudden load changes in the system are reflected in its highly accurate predictions. Its exceptional performance in the mid-range distortion zone, where the majority of data points are concentrated, indicates that the method has substantial practical applicability.

Moreover, reducing dependency on harmonic measurement instruments and enabling distortion prediction purely from existing power measurements presents a major cost and operational advantage for system operators. The GRU architecture's low computational load and fast learning capabilities also render the method suitable for integration into real-time monitoring and decision-support systems in distribution networks.

In conclusion, this study provides a reliable and applicable AI-based solution for estimating harmonic distortion from active and reactive power data. The findings offer meaningful contributions to ensuring energy quality continuity, advancing preventive maintenance strategies, and enhancing grid reliability.

Ethical statement

No ethical documentation is required.

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Conflict of interest

This study has no conflict of interest.

Authors' Contributions

All authors contribute equally. All authors read and approved the final manuscript.

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