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Research Article

HARMONIC PREDICTION FOR ELECTRIC VEHICLES IN DIFFERENT CHARGING CONDITIONS

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Abstract: *The rapid adoption of electric vehicles (EVs) has introduced new challenges to power distribution networks, with harmonics generated during EV charging emerging as a critical issue affecting power quality. This paper proposes a machine learning-based approach to predict harmonic levels under varying EV charging conditions. By leveraging a real-world dataset containing measurements of charging currents and their associated harmonic amplitudes, the study ensures a comprehensive and practical analysis of harmonic behavior. The Nonlinear Autoregressive Exogenous (NARX) model, a time-series forecasting method well-suited for nonlinear systems, is utilized to accurately predict harmonic levels for various charging currents. Separate predictions for harmonics at the 3rd, 5th, 7th, 9th, 11th, and 13th levels are performed to highlight the model's effectiveness across a range of frequencies.*

The results demonstrate that the proposed approach achieves satisfactory prediction performance, as evidenced by low mean squared error (MSE) values across training, validation, and testing datasets. This study's key contributions include the development of a predictive framework for harmonic estimation, the application of a robust AI model to nonlinear harmonic data, and insights into the implications of harmonic distortion for grid stability and EV component performance. By providing an accurate and proactive method for harmonic prediction, this research contributes to the design of more efficient and reliable EV charging infrastructures, ensuring smooth integration of EVs into modern power grids. Future work will focus on enhancing model performance with larger datasets and exploring additional applications of predictive analytics for power quality management.

Keywords*: harmonic prediction, machine learning, electric vehicles, power quality, NARX model*

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1. Introduction

The increase in the number of electric vehicles (EVs) in recent years has led to an increase in the number of charging stations for these vehicles. EVs have a detrimental impact on energy quality when they are being charged. EV harmonics are a major factor in the development, functioning, and integration of EV systems. Charging infrastructure can be defined as the major harmonic source for EVs. Chargers (onboard or offboard) draw power in non-linear ways, creating harmonics in the supply grid, where fast chargers, can introduce significant harmonics due to high-power operations [1–3].

In particular of this study, impacts of harmonics of charging states can be mentioned in two main titles as effects on EVs and distribution grid. On the EV side, harmonics can cause overheating in electrical components like motors and cables, increased energy losses due to harmonic-induced eddy currents and additional stress on components and possible resonant conditions in the electrical system, leading to damage. On the other side, high total harmonic distortion (THD) can interfere with other equipment connected to the grid, increase losses in transformers, transmission lines, and other power infrastructure and can lead to voltage waveform distortions, affecting the stability of the grid [4–7].

With the growing global emphasis on lowering carbon footprints, electric vehicles (EVs) have emerged as a viable alternative to traditional automobiles. However, the increasing integration of EVs creates substantial issues to power distribution networks, owing to the harmonics produced during the charging process. Harmonics not only affect power quality, but they also cause operational inefficiencies in the grid and EV components. To successfully detect and prevent harmonic distortions, creative solutions based on sophisticated technologies such as artificial intelligence (AI) are required [8–13].

The inspiration for this research derives from the limitations of existing harmonic prediction models, which frequently use synthetic datasets or fail to account for the nonlinear dynamics of charging currents. This work seeks to overcome the gap by using a real-world dataset and the Nonlinear Autoregressive Exogenous (NARX) model. The main contributions are as follows: (1) a thorough examination of harmonic levels under various charging settings; (2) the creation and validation of an AI-powered model for reliable harmonic prediction; and (3) insights into the effects of harmonics on grid performance and EV components.

In this study, harmonics that occur during charging electric vehicles are examined and artificial intelligence-based prediction algorithm was performed by using a real measurement-based dataset. Results were discussed by using the graphs and numerical values.

2. Power Quality

The term "harmonics" describes waveforms of voltage or current at frequencies that are multiples of the fundamental frequency, such as 50 Hz or 60 Hz as shown in Figure 1. Power quality, dependability, and efficiency may all be impacted by these aberrations [14,15].

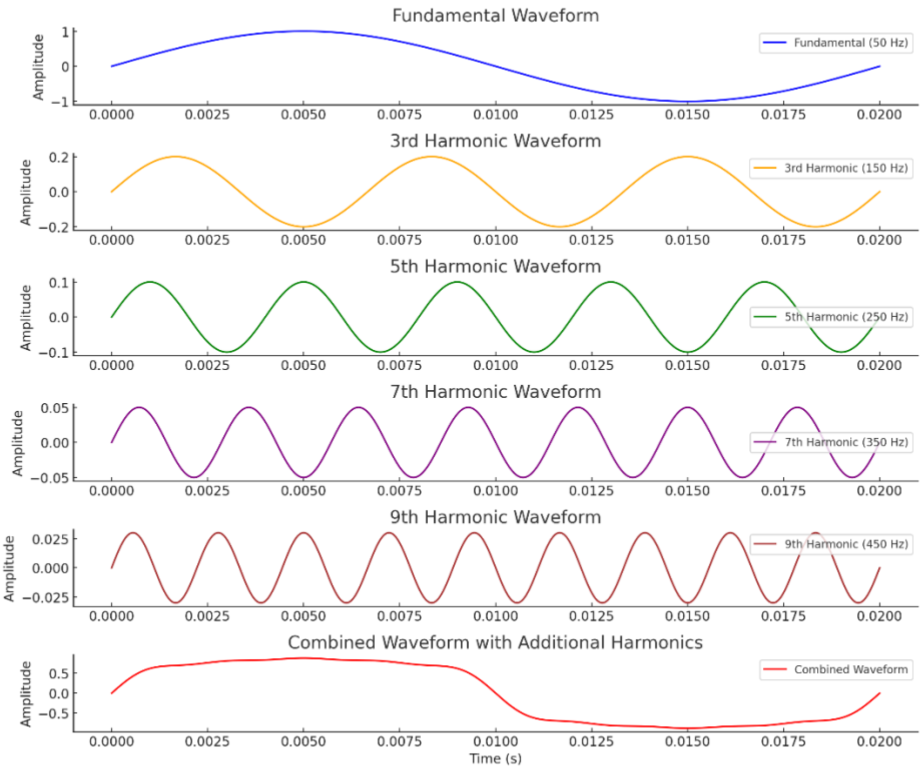

Figure 1. Harmonic waveforms for 50 Hz frequency.

THD measures the distortion of current or voltage compared to the ideal waveform. It represents the relative signal energy at frequencies greater than the fundamental frequency. The THD for current and voltage harmonics can be calculated as

$$THD_I = \frac{1}{I_1}\sqrt{\left(\sum_{n=2}^{\infty} I_n^{\ 2}\right)} \tag{1}$$

$$THD_V = \frac{1}{U_1}\sqrt{\left(\sum_{n=2}^{\infty} U_n^{\ 2}\right)} \tag{2}$$

THD_I must be below 5% according to IEEE 519-2014, where THD_V must be below 8% (for voltages up to 1 kV).

To mitigate the impact of harmonics on power systems various approaches can be applied as installing harmonic filters to reduce harmonic currents and voltages, using power factor correction capacitors to improve power factor, selecting and designing equipment with lower harmonic emissions and conducting harmonic studies and monitoring to assess the impact of harmonics to take appropriate corrective actions [16,17]. These mitigation techniques are for occurred harmonics. Through the rapid developments in AI technologies, harmonics can also be determined before they occur [18–20].

3. Methodology

According to the main aim of study, charging currents with the harmonic levels of Renault Zoe ZE50 car were used for prediction. The open-access dataset was obtained from [8,21]. In this study, the Nonlinear Autoregressive Exogenous (NARX) Model, which is a time-series model for forecasting and modeling systems in which a variable's future values are determined by both its own past values and the past values of an external input (exogenous variable) used [22,23]. This approach is very effective in systems with nonlinear dynamics.

The NARX model can be expressed as follows;

$$y(t) = f\,(y(t-1), y(t-2), \ldots, y(t-n_y), u(t-1), u(t-2), \ldots, u(t-n_u)) + h(t) \tag{3}$$

In the equation (3); y(t) is the output (dependent variable) at time t, u(t) is the external input (exogenous variable) at time t, n_y is the number of past output terms (lagged values) to consider, n_u is the number of past input terms to consider, h(t) is a noise term accounting for model inaccuracies or random disturbances and f (·) is the nonlinear function that relates the inputs and outputs.

NARX model have three main key components. Autoregressive component refers to the dependence of y(t) on its own past values (y(t−1), y(t−2), …). Exogenous input is the influence of another variable u(t) on y(t). This is what distinguishes the model from purely autoregressive models. The function f (·) is nonlinear, capturing complex relationships that linear models cannot. The nonlinear function f (·) is usually unknown and must be estimated from data by using approaches as artificial neural networks (ANNs), polynomial models, kernel methods and piecewise linear approximations.
The implementation of NARX model is summarized in the flowchart given in Figure 2.

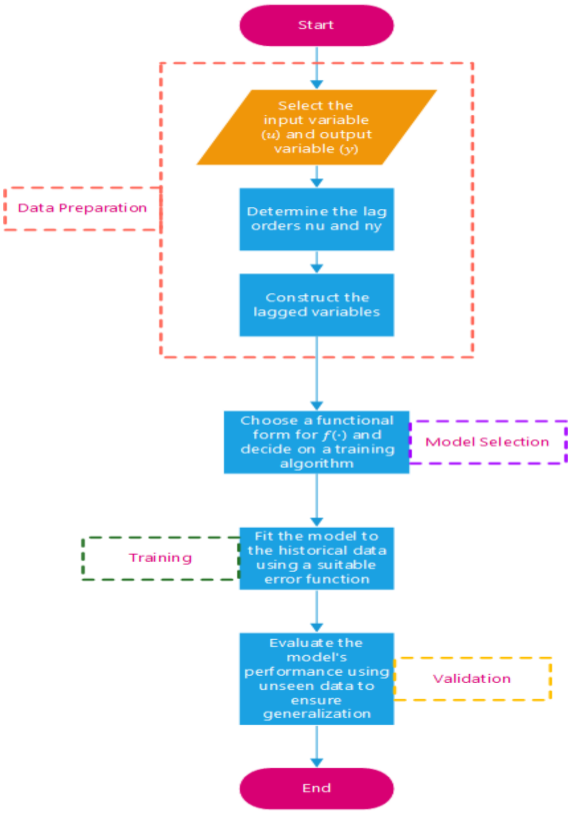

Figure 2. NARX Model Flowchart.

NARX model have advantages as capturing complex dynamics due to its nonlinear nature including external factors, making it more flexible than pure autoregressive models and can be tailoring to a wide range of applications. This is the main reason for the selection of such model for data processing in this paper.

Dataset used for the study is consist of charging currents and harmonic amplitudes. Charging voltage increases with 1 A steps starting from 6 A to 30 A. It is observed that there is a nonlinearity characteristic in this increment. Graphical representation of 5th harmonic is given in Figure 3 for a better understanding.

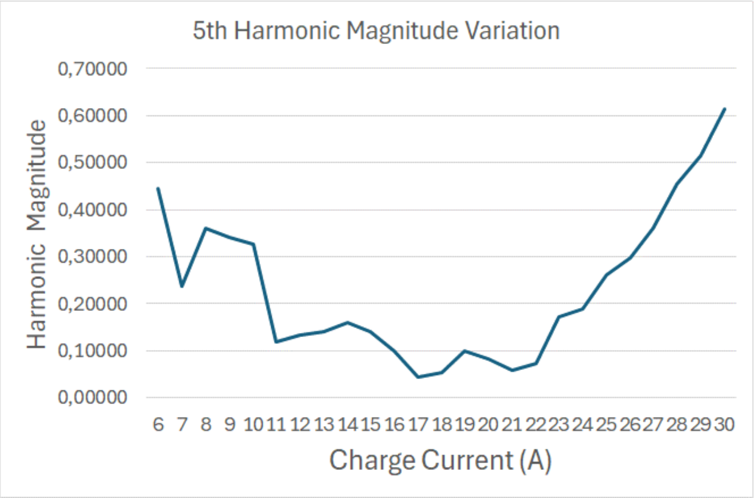

Figure 3. 5th harmonic variation with charging current.

It can be observed from Figure 3 that the change is nonlinear, that the data is appropriate for using NARX model.

4. Results and Discussion

Harmonic levels of 3, 5, 7, 9, 11 and 13 are used for prediction. 70% of data is used for training, where 15% is for validation and 15% is for testing. Since this partitioning is the most widely used and accepted structure in the literature in estimation studies, it is used in this way in order to make an accurate comparison with the literature. Layer size for the model is 20 for all experiments. Prediction results and mean squared error (MSE) graphs for the 5th and 7th harmonics were given in Figure 4 and Figure 5 respectively.

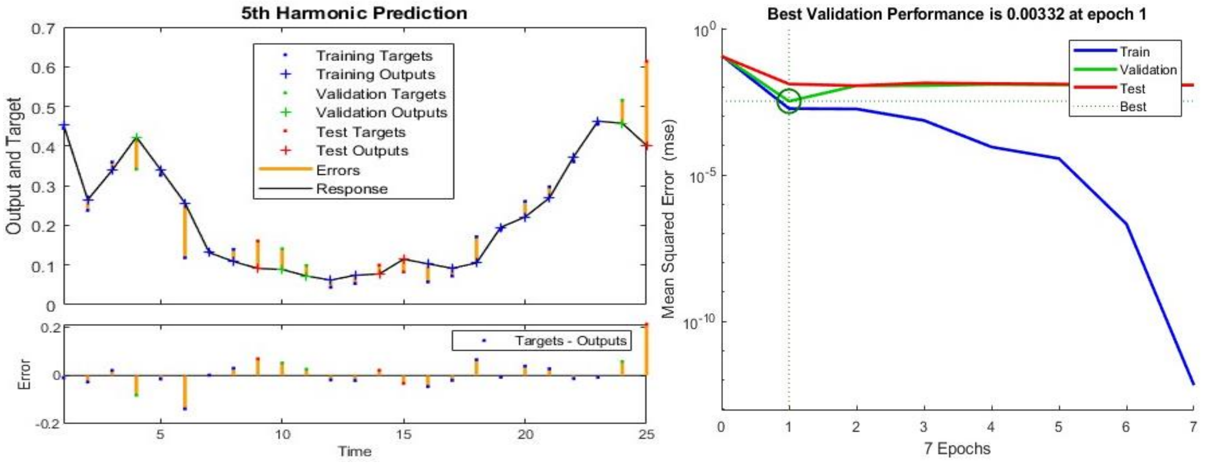

Figure 4. Prediction results and MSE graph for the 5th harmonic.

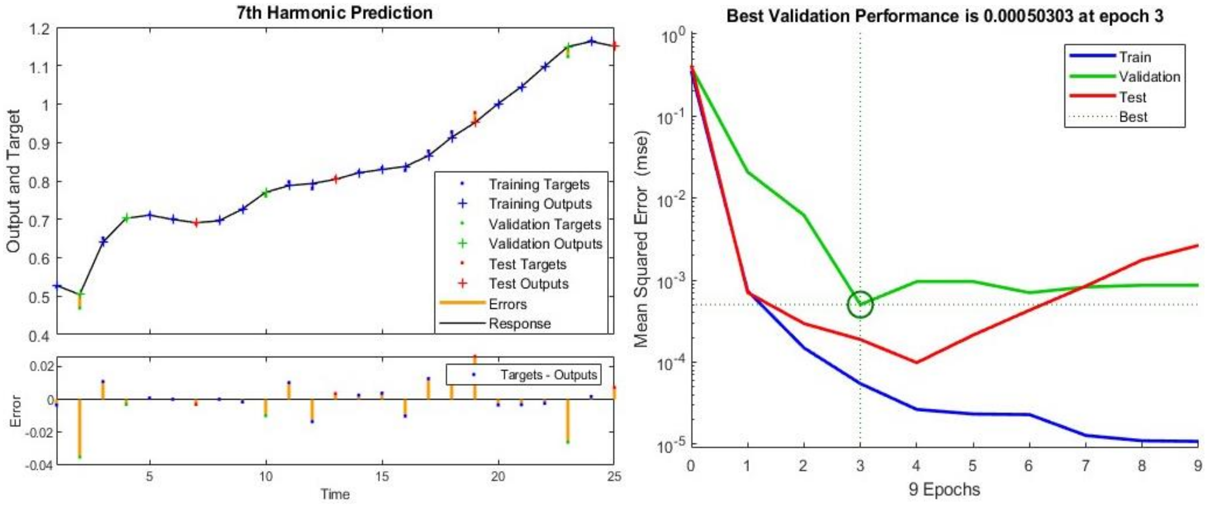

Figure 5. Prediction results and MSE graph for the 7th harmonic.

MSE values for training, validation and test at other harmonic levels were summarize in Table 1.

Table 1. MSE values for harmonic levels.

Harmonic Level	Training	Validation	Test
3rd harmonic	$1.0074e^{-04}$	$3.6123e^{-04}$	$6.1454e^{-04}$
9th harmonic	$2.2149e^{-06}$	$9.0681e^{-05}$	$6.2117e^{-05}$
11th harmonic	$2.1942e^{-04}$	$7.7579e^{-04}$	0.0028
13th harmonic	$1.0660e^{-04}$	$2.6452e^{-04}$	$5.0978e^{-04}$

It is clear from the values given in Table 1 that training and test performance is satisfactory, as the MSE values are convergence to zero.

5. Conclusion

Harmonics management is critical as EV adoption grows, especially to ensure smooth integration with the grid and prolong the lifespan of EV components. Advanced technologies and thoughtful design will continue to address these challenges. As mentioned in this paper, prediction of harmonics is a crucial study for power system protection and satisfying the energy quality. An effective AI model for time series prediction, NARX, was used and results show that prediction performance is appropriate for each harmonic level. It should be noted that the study was performed with limited data, so as can be referenced in literature, large dataset can suggest more robust results and performance can be improved.

Ethical statement

Ethics committee decision is not required for this study.

Acknowledgment

No acknowledgment provided.

Conflict of interest

This study has no conflict of interest.

Authors' Contributions

S.B.E. carried out all stages of the article. Author read and approved the final manuscript.

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