Journal of Energy Systems

2023, 7(2)

2602-2052

DOI: 10.30521/jes.1246150

Research Article

Output voltage estimation of a power transformer integrated with three-phase T-type inverter

Seda Kul*
Karamanoglu Mehmetbey University, Engineering Faculty, Karaman, Türkiye, sedakul@kmu.edu.tr
Selami Balci
Karamanoglu Mehmetbey University, Engineering Faculty, Karaman, Türkiye, sbalci@kmu.edu.tr
Suleyman Sungur Tezcan
Gazi University, Engineering Faculty, Ankara, Türkiye, stezcan@gazi.edu.tr

Submitted: 01.02.2023
Accepted: 28.04.2023
Published: 30.06.2023

* *Corresponding Author*

Abstract: The issues related to integrating these systems into the grids continue to gain importance with the increasing use and importance of renewable energy sources. Therefore, the importance of power distribution transformers is increasing. Besides, these power distribution transformers are connected to the grid with power electronics circuits and inverters. Considering the modular inverter structures, ease of maintenance, and connection, three-level T-type inverters are chosen for this study. The secondary output voltage of the power transformer is estimated by using circuit parameters such as the dead time of the inverter circuit, PWM switching frequency, and modulation rate. Based on the finite element analysis analysis according to the selected parameters, 810 data are obtained with time-dependent parametric analysis. The adaptive neuro-fuzzy inference system model is constructed by considering the simulation data to estimate the secondary output of the power transformer of these parameters. In the training phase of the model, 648 randomly selected data from 810 data obtained by ANSYS-Electronics/Simplorer are used. The remaining 162 data are used in the testing process to measure system performance. As a result of the analysis made by ANFIS, the Root Mean Square Error (RMSE) error is found as 2.475%. Since the values obtained in the estimation process of the study are very close to the simulation values, the ANFIS method can be used as an estimation method that will give accurate results during the design phase.

Keywords: *ANFIS, T-type inverter, Parametric analysis, PWM excitation, Transformer*

Cite this paper as: Kul, S, Balci, S, & Tezcan, S. S., Output voltage estimation of a power transformer integrated with three-phase T-type inverter. *Journal of Energy Systems* 2023; *7*(2): 199-211, DOI: 10.30521/jes.1246150

Nomenclature	
ANFIS	Descriptions
SVM	Support Vector Machine
LSTM	Long-Short Term Memory
RMSE	Root Mean Square Error
FL	Fuzzy Logic
MAE	Mean Absolute Error
MSE	Mean Squared Error
FEA	Finite Element Analysis
AC	Alternating Current
DC	Direct Current
MAPE	Mean Absolute Percent Error

1. INTRODUCTION

Renewable energy sources and their use in grids have gained importance in recent years. These systems cannot be connected directly to the grid system. Electronic circuits and transformers are circuit elements that provide these connections. Various converters are used to connect to the grid systems. The task of power transformers is to adjust the inverter outputs to convert the DC electrical energy obtained from renewable energy sources into AC electrical energy at a desired voltage level without loss. There are several types of inverters to be used. These are two-level three-phase inverters and multilevel inverters. Two-level three-phase inverters have a straightforward control system and structure [1]. However, they are not used for high-voltage values. Since the high switching frequency negatively affects the inverters switching loss as well as the overall efficiency. A multilevel inverter is a better alternative, and The conventional topology of inverters is the neutral point clamped inverter. Therefore, high-voltage variable frequency regulation multilevel converters are preferred in high-power applications. The T-type inverter is one of the advanced neutral point-clamped inverter topologies with higher efficiency and a lower number of switching elements compared to conventional neutral point-clamped inverters [2,3].

The three-level T-type inverter has the advantage of having low transmission losses at low switching frequencies compared to other 3-level topologies. Three-level T-type inverter is used instead of a three-phase H-bridge inverter to boost output voltage levels. This type of inverter has a three-phase output and bidirectional switches at the junction of semiconductor materials and two dc capacitors. Therefore, it has the advantages of both two-level and three-level converters due to low switching losses and low part count [4,5]. Based on all this, the design of the three-level T-type inverter and the determination of the parameters should be considered for the system to operate efficiently. In addition, the operating parameters affect each other as well as affect the output obtained as a result of the system. For this reason, the design of inverter systems, especially used in renewable energy applications, has become economically critical, apart from being a solution used only against energy needs. Accordingly, the correct estimation of the output values by considering the basic operating conditions during the design phase of the electronic circuits accelerates the production process. Estimating the output voltage is a complex process due to the nonlinear characteristic of the system. Therefore, advanced software is used to obtain realistic results.

Based on the literature review, one can consider the studies made with Estimation methods, Artificial Neural Networks (ANN), Support Vector Machine (SVM), Fuzzy Logic (FL), Adaptive Neuro-Fuzzy Inference System (ANFIS), extrapolation methods, Dynamic Rating Monitoring (DRM), and many other similar methods have been used for different parameter estimations according to different application areas. For instance, Ref. [6] performed a FEA using a model with equal leakage reactance between each winding using finite element analysis to accurately estimate the leakage reactances between each winding of multi-winding transformers. Since the results obtained with this method could not provide these results in production, two models, vertical and sandwich, were proposed. In Ref. [7], hot spot estimations are made using Dynamic Rating Tracking Algorithm, taking into account the variations and uncertainties in the operating cooling conditions. Estimating parameters such as load and ambient temperature were used to estimate based on a known thermal equivalent circuit. It can also be used to measure the maximum temperature capacity of this system. The performance of the algorithm is compared with a transformer with normal operating data. In [8], genetic programming (GP) based hot spot temperature (HST) estimation was made for traction transformers along the railway line. A GP-HST prediction model based on genetic programming was created for better thermal capacity estimation. According to the estimation set, the MSE, MAE, and R2 values are 1.63%, 0.59 $\circ$C, and 0.9830, respectively. For the estimation of high voltage transformer winding temperature, a hybrid method based on long short-term memory (LSTM) and convolutional neural network (CNN) was used [9]. It was aimed to improve the temperature prediction values obtained with this. In this method, the winding temperature, the temperature of the oils, and various environmental factors affecting the temperature were considered parameters. As a result, it was shown that the method has high estimation accuracy, and thus the hybrid model result is better than the single LSTM result. Total person-hour is one of the important parameters for total production cost in manufacturing. For this reason, GPR, ANFIS, and SVM models were used for person-hour estimation using data from a power transformer company. A total of 395 different data, 316 of them were used for training, and 79 were used as test data sets [10]. The output voltage of a DC/DC converter used in photovoltaic systems was estimated with the help of ANSYS parametric analysis. For this, input voltage, duty ratio, and switching frequency variables are input parameters. By using the output values obtained by parametric analysis, sea predators and the gray wolf optimization techniques were implemented to predict the output parameter. The obtained estimation results were compared with the simulation results, and their accuracy was obtained. As a result, the best output voltage estimate was obtained with a MAPE of 2.701% [11]. Other applications made using ANFIS are; the estimation of core loss in power transformers [12,13], the output voltage of the DC voltage level for fuel cell supplied electric vehicle [14], the Total Harmonic Distortion (THD) value of the output current of a three-level three-phase inverter circuit [15], output voltage in PV systems [16], and the leakage inductance value of the single phase transformer [17].

In this study, three-phase three-level T-Type inverter output voltage obtained by connecting isolation transformer models was modeled by Ansys-Electronics 2019-R3 software with parametric simulation in the range of input parameters to obtain the output voltage at the desired level. Then, the output voltage level estimation according to the input parameters, such as switching frequency, dead time, and modulation speed was tested with ANFIS, and 810 data were received from the parametric simulation. They were used as training and test data in the ANFIS for verification. Therefore, the contributions of the study are listed as follows:

i. Estimation of output voltage value of T-Type inverter based on data set based on parametric simulations based on three variables of power electronics circuit and integrated transformer (PWM frequency, modulation index and transformer leakage inductance).
ii. By using ANSYS-Electronics/Simplorer software, the effect of the transformer integrated as a magnetic circuit element with the inverter circuit on the performance of the power electronic circuit has been carried out.

The performances of the inverter circuits are analyzed depend on the different parameters (PWM frequency, modulation index and transformer leakage inductance) discussed comparatively.

The rest of the study is organized as follows: Section 2 presents material and methods, and parametric analysis and ANFIS methodology have been explained. The result of the simulation and discussion about the estimation of T-type inverter parameters have been examined in Section 3. In Section 4, the conclusions of the study are shared in detail. Thus, a different approach is presented regarding the performance determination of transformer inverter circuits used in grid integration with renewable energy sources.

2. MATERIAL AND METHODS

This section presents parametric simulation studies of power electronics circuits and dataset creation stages. In addition, graphic and numerical data obtained from parametric simulation studies are also included. Then, estimation studies are explained using a parametric dataset and ANFIS.

2.1. The Parametric Analysis of T-Type Converter

Renewable energy sources, uninterruptible power supplies (UPS), motor drives, and electric vehicle and their use in grids have gained importance in recent years. These systems cannot be connected directly to the grid system. Various inverters are used to connect to the grid systems. There are several types of inverters to be used. These are two-level three-phase inverters and multilevel inverters. Two-level three-phase inverters have a straightforward control system and structure. However, they are not used for high-voltage values. Therefore, high-voltage variable frequency regulation multilevel inverters are preferred in high-power applications [18]. Schweizer in [19] first mentioned the T-type converter. Later, due to applications requiring system integration, such as electric vehicles and renewable energy sources, T-type neutral point clamped (T-type NPC) inverters have come to the fore due to their advantages. 3 phase three-level T-type topology is shown in Fig. 1. In this topology, auxiliary switches are used to create a high-side bridge and a low-side bridge to minimize the inductive loop in the switches. Thus, the number of personnel is reduced, and efficiency is increased. Because the T-type inverter has fewer semiconductors compared to conventional inverters, low total harmonic distortion (THD) occurs at low switching frequencies. These are all factors that prevent excessive fluctuation in the output voltage of this system [3,18].

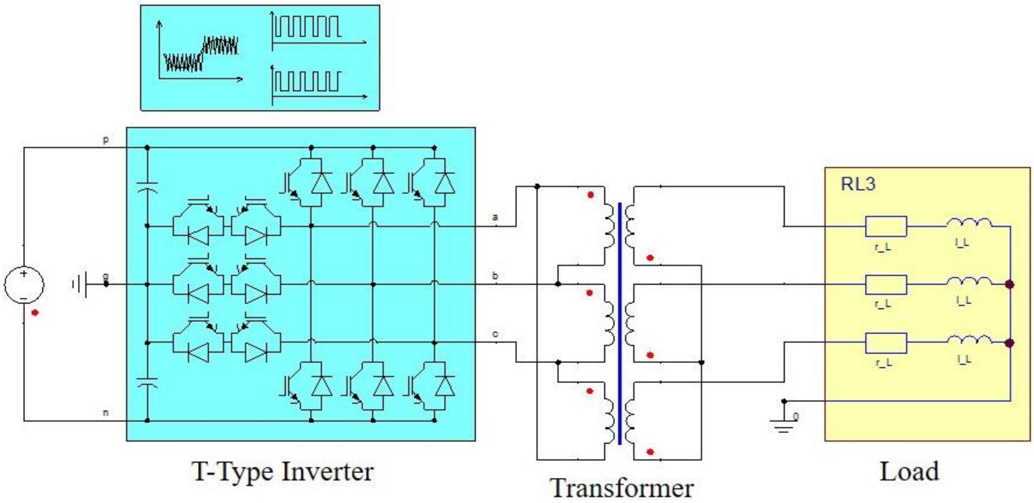


Figure 1. The circuit topology of the transformer with a T-type inverter.

The topology shown in Fig. 1 is the circuit diagram to be used for parametric analysis in this study. Dead time, switching frequency, and modulation speed are determined as three different input variables, and the output voltage is determined as the output variable. As a result of the parametric analysis made depending on these parameters, it is aimed to obtain the output voltage of the isolation transformer whose properties are specified in Table 1. Parametric analyzes were obtained using Ansys-Electronics 2019-R3 Simplorer. The DC input voltage of the circuit is 400 V, and the fundamental switching frequency is 50 Hz. In this circuit, the output values are obtained according to the change of the variable parameters selected from the PWM switching parameters. These variable parameters are the basic parameters in an inverter circuit, as given in Table 2.

Table 1. Specification of the power transformer.

Specifications	Value
V_i	400 V
f_s	50 Hz
Connection type	Δ/Y

In parametric analysis, the modulation rate was 0.05 for the 0.45-0.9 range, PWM. The frequency switching circuit changes in 1 kHz steps for the 1-10 kHz range and 0.1 µs steps for the dead time 0.1-1 µs range. The secondary voltages of all these values were obtained according to the change steps.

Table 2. The variables limit values of the parametric simulation studies.

Parameters	Value	Step Interval
Modulation index	0.45-0.9	0.05
Dead time	0.1-1 µs	0.1 µs
PWM frequency	1-10 kHz	1 kHz

2.2. Adaptive Neural Network Based Fuzzy Inference System (ANFIS)

Fuzzy logic (FL) is weak against environmental factors and has no learning feature against external interventions. Therefore, an Adaptive Network Fuzzy Inference System (ANFIS), which can calculate by incorporating the learning feature of ANN, is used. ANFIS is an inference system derived from the mathematical formulations of artificial intelligence methods, fuzzy logic, and artificial neural networks. Since this system is a hybrid application, it is an artificial intelligence method that can perform parallel computation and learn with artificial neural networks and fuzzy inferential logic, respectively [12]. Briefly, ANN calculates FL parameters used in ANFIS [20]. Fig. 2 shows an ANFIS structure with three inputs and one output with three hidden layers of the Sugeno type. It consists of 5 layers, as in the classical ANFIS model. Nodes in layers have the same property according to the layer they are in. In the first layer, the blur layer, the nodes provide output according to the input values, and the membership function is used [21].

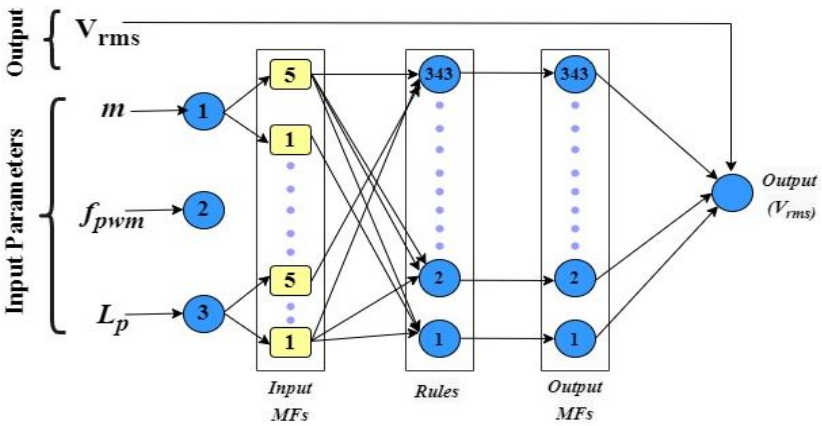


Figure 2. The ANFIS Model Structure

Each node in the rule layer of Sugeno's fuzzy logic inference system contains a rule [22]. These nodes are treated as inputs and also form the input values of the normalization layer. A triangular membership function was used in this application to separate the input values into clusters [22]. The results assigned to the weight value of each rule passed to the defuzzification layer are calculated at each node. These obtained parameters are the result parameters [21]. The last layer is the aggregation layer, which consists of only one node [21]. The success criterion of ANFIS is a function of the error between the output obtained according to the input values used in the parametric analysis and the output value produced by ANFIS against these input values. This study used the root means square error function to obtain the system accuracy. The parameters of the ANFIS model used are given in Table 3. A total of 810 data obtained from parametric analysis were used as data sets. In the training of the ANFIS model, 648 randomly selected data from 810 data obtained by ANSYS/Simplorer were used. The remaining 162 data were used in the testing process to measure system performance. The training data graph obtained from training this data set in ANFIS is as in Fig. 3.

Table 3. ANFIS Model parameters.

Parameters	Value/Type
Input MF type	Triangular membership function (Trimf)
Output MF type	Linear
Input number	3
Output number	1
Number of fuzzy rules	64
Number of MFS	4
Number of epoch	150

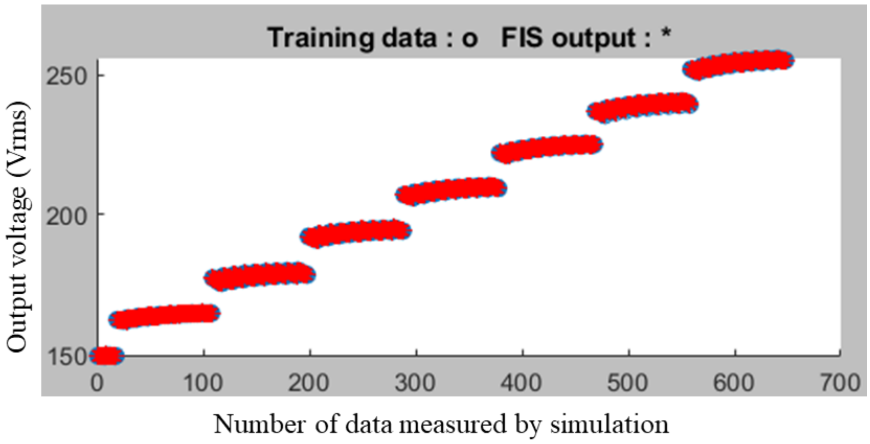
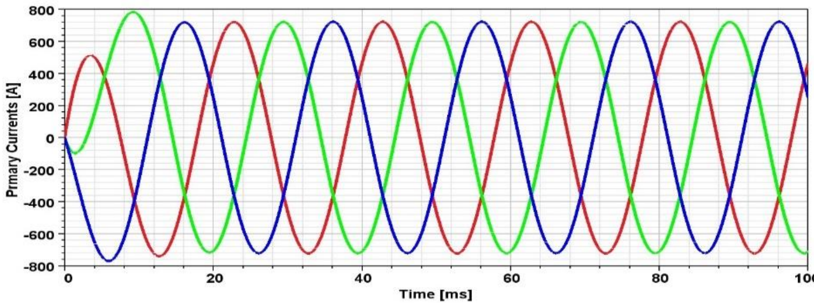


Figure 3. Comparison of ANFIS and simulation data training results

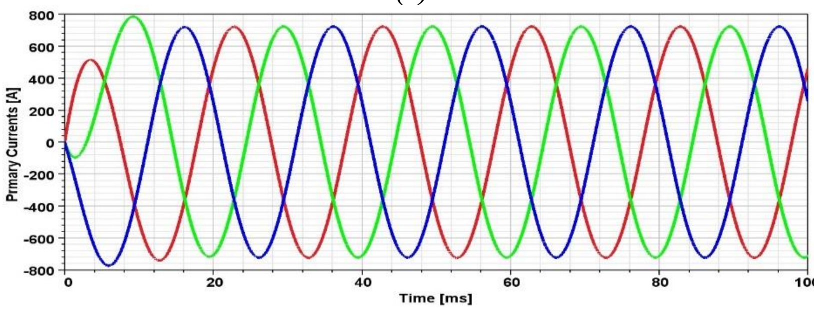
3. RESULT AND DISCUSSION

The switching parameters of the power electronics circuit positively or negatively affect the electromagnetic behavior of the power transformer located at the inverter output. Changes in the PWM frequency values also change the primary current of the transformer amplitude. This situation is given in Figs. 4(a,b,c) for 10 kHz, 5 kHz and 1 kHz PWM frequency values, respectively. When the PWM frequency value increases, it is clearly seen that the amplitude of the current decreases due to the leakage inductance effect of the primary winding of the transformer.

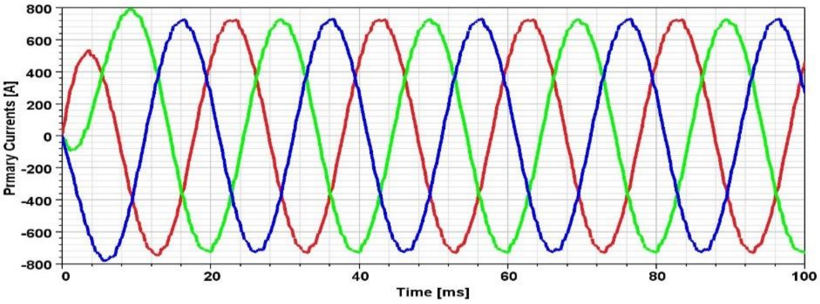
In general, the value of the PWM frequency is important since there is an induction principle according to the primary current waveform at the point of electromagnetic behavior of transformers. Secondary voltage waveforms are given in Figs. 5(a,b,c) for PWM frequency values of 10 kHz, 5 kHz and 1 kHz, respectively. In inverters, the PWM frequency changes the pulse number of the switching signals. As the PWM switching pulse number increases, the inverter output voltage becomes closer to the sinusoidal waveform. Depending on the performance of the power switching element, the PWM frequency also affects the current ripple values of the load and/or transformer at the inverter output voltage as large as possible.



(a)



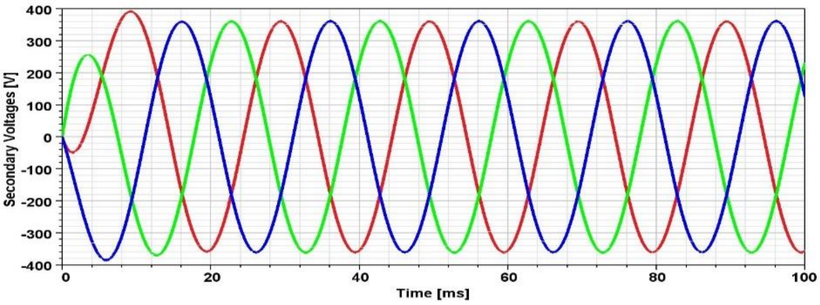
(b)



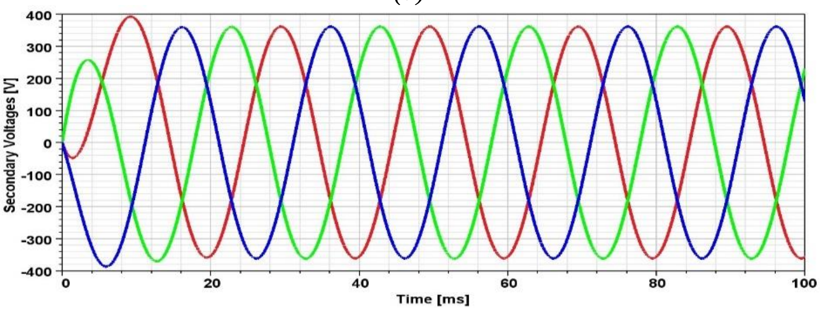
(c)

Figure 4. Primary currents mr=0.85, tdead=0.1 µs of a) fpwm=5 kHz, b) fpwm=10 kHz, c) fpwm=1 kHz.

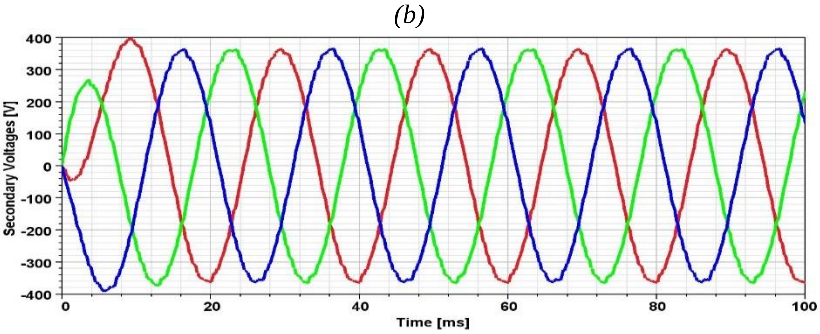
Thus, the current waveform passing through the primary winding of the power transformer at the output of the inverter creates the EMF waveform induced on the secondary side. In this context, while the PWM frequency is 1 kHz, the number of switching pulses for 50 Hz fundamental wave frequency is only 20 in different widths. As the PWM frequency increases, the number of switching pulses naturally increases, and the secondary winding voltage is induced sinusoidally in a more uniform.



(a)



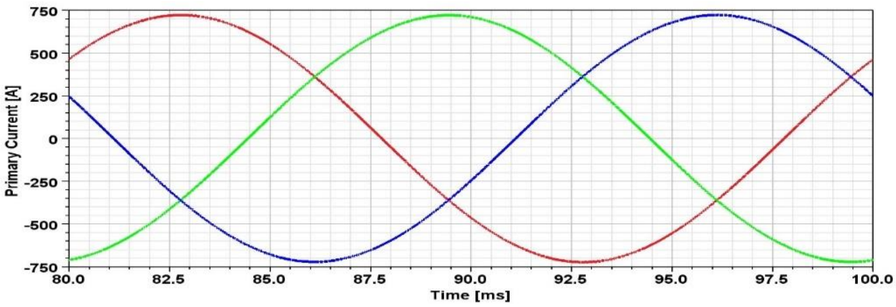
(b)



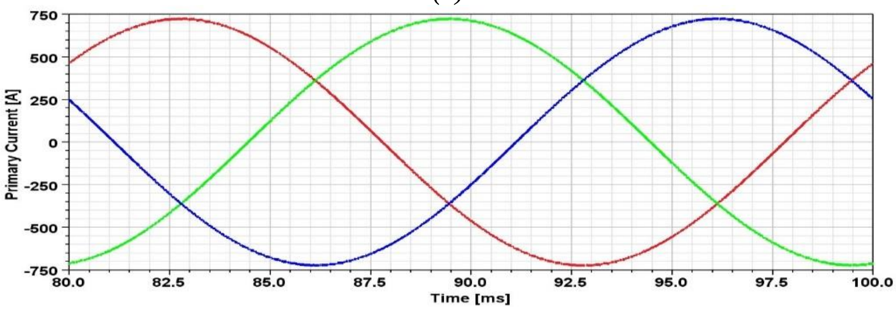
(c)

Figure 5. Secondary voltages m_r=0.85, t_{dead}=0.1 µs of a) f_{pwm}=5 kHz, b) f_{pwm}=10 kHz, c) f_{pwm}=1 kHz.

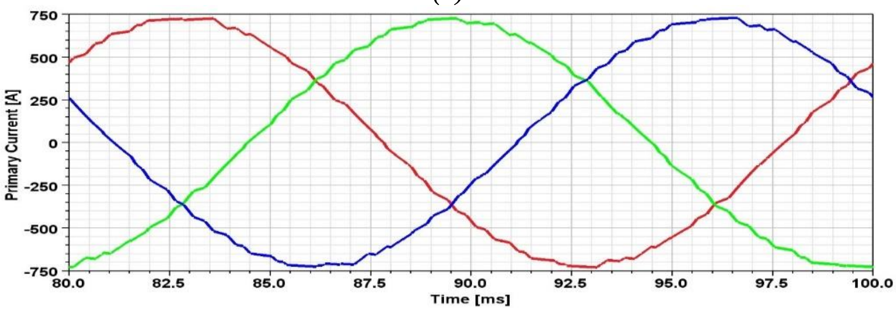
In the current-voltage waveforms obtained by simulation studies, the ripple effect due to the PWM frequency change can be more easily explained as seen in Figs. 6(a,b,c) for the last period. Since the ripple effect also affects the voltage and load current behavior on the load, transformers integrated with the inverter have important contributions to the reduction of harmonic components as well as providing isolation between the inverter and the load making the voltage value adaptive.



(a)



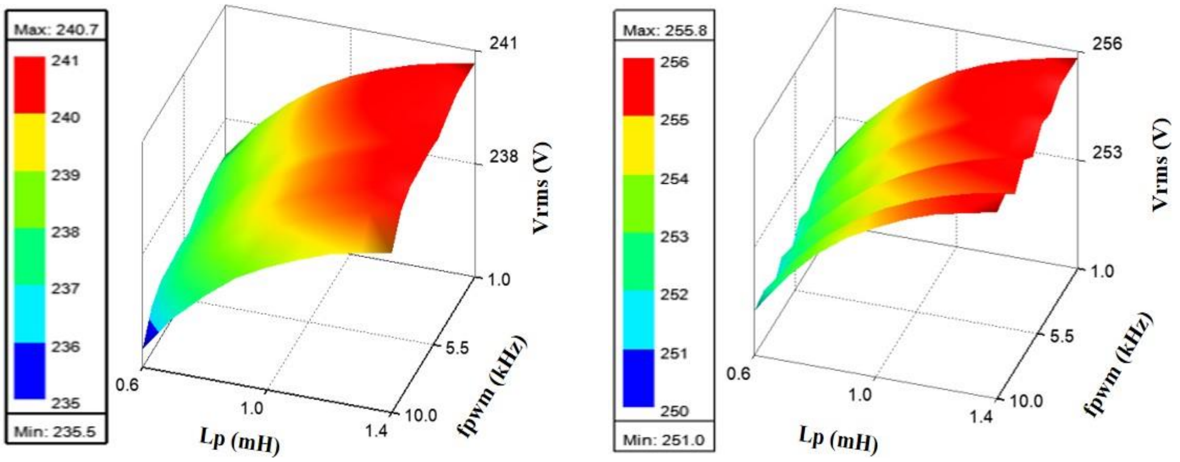
(b)



(c)

Figure 6. Primary current m_r=0.85, t_{dead}=0.1 µs of a) f_{pwm}=10 kHz, b) f_{pwm}=5 kHz, c) f_{pwm}=1 kHz.

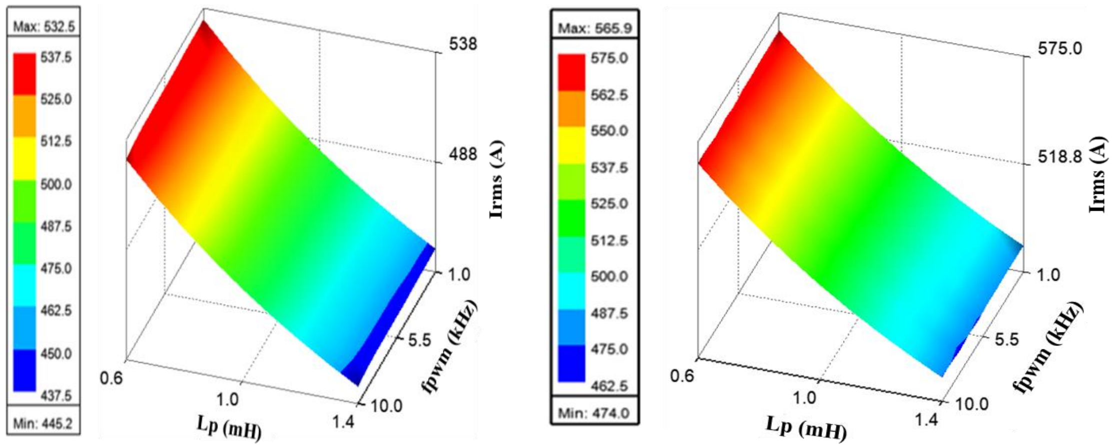
On the other hand, modulation rate (index), one of the PWM switching parameters of the power electronics circuit, directly affects the RMS value of the inverter output. Because the modulation rate is a parameter that determines the peak value of the sinusoidal voltage at the inverter output of the DC bus voltage. Thus, according to the modulation rate change, the *rms* value of the inverter output voltage is also affected, as shown in Figs. 7(a,b,c). These figures demonstrate the nonlinear behavior of the output voltage rms value according to the primary side leakage inductance (L_p) of the transformer power electronics circuit PWM frequency change and modulation ratio with parametric 3D figures.



(a) *(b)*

Figure 7. Output voltages on the surface of PWM frequency and L_p: a) m_r=0.8 b) m_r=0.85.

The values obtained from the parametric simulation studies carried out for the primary current rms value of the transformer are seen in Figs. 8(a,b). As can be seen directly from these figures, leakage inductance (L_p) and PWM frequency values are directly effective parameters in changing the primary current.



(a) *(b)*

Figure 8. Output currents on the surface of PWM frequency and L_p: a) m_r=0.8 and b) m_r=0.85.

In this context, with the data set obtained from parametric simulation studies, a parametric data set was created according to different input variables such as modulation ratio (m), PWM frequency (f_{pwm}), and primary leakage inductance of the transformer (L_p), which are among the power electronics switching variables. Using this dataset, a rule-based example is seen with ANFIS, as seen in Fig. 9. Here, $input1$, $input2$, and $input3$ are input data, respectively. Here, the voltage value obtained when m is 0.85, f_{pwm} is 2kHz and L_p is 0.6 mH is seen as 252 V. When this value is compared with the test value obtained for the same values in the data set, it is seen that the value there is 252.007 V.

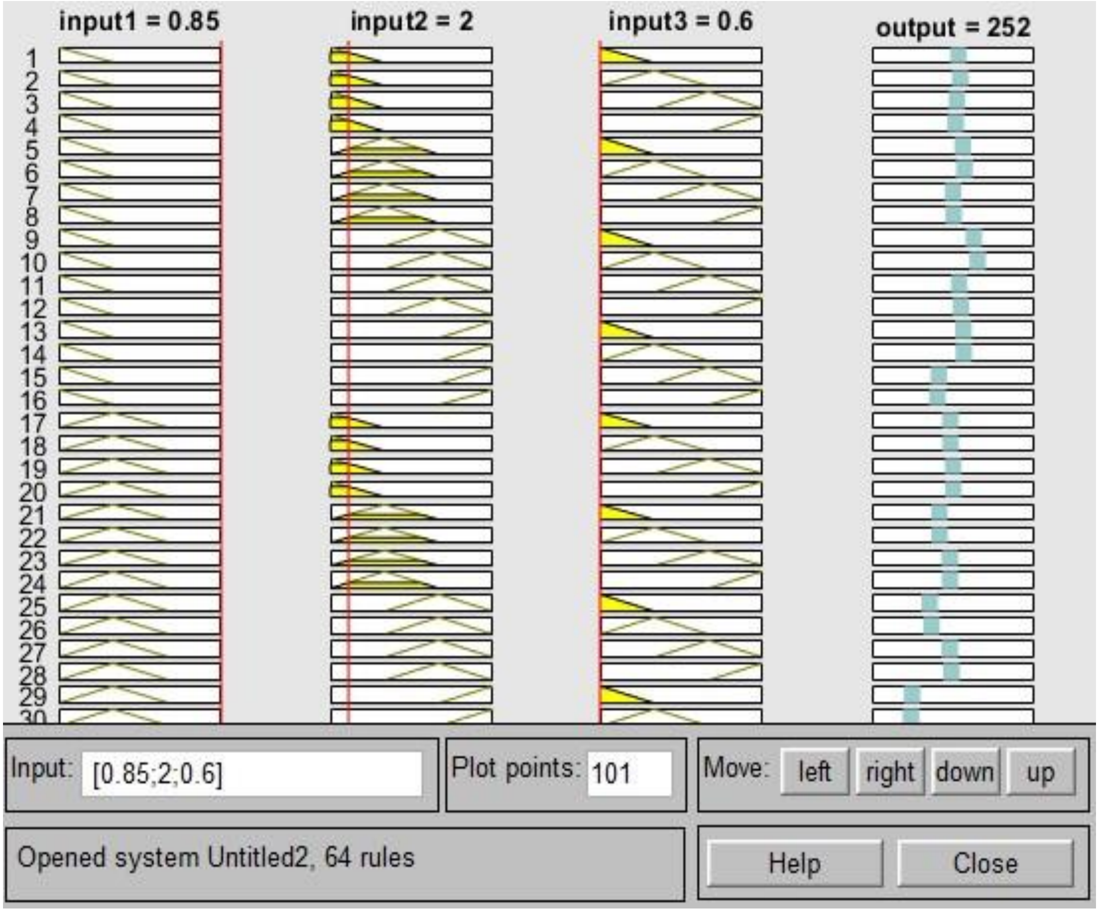


Figure 9. The testing result obtained from the rule-based viewer.

The comparison of the findings obtained in long-term parametric simulation studies with the testing values obtained as a result of estimation with ANFIS is given in Fig. 10. Here, it is clearly seen that the results of very few data differ. This is another situation that shows that the accuracy of the results obtained is high.

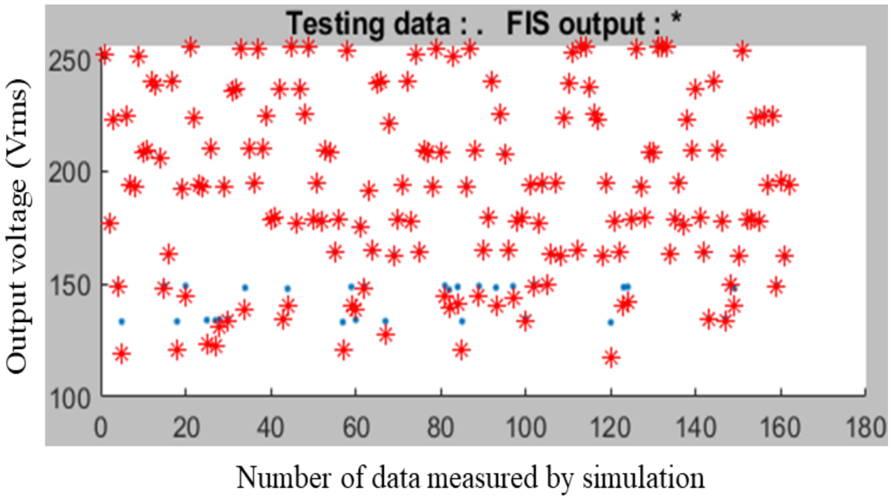


Figure 10. Comparison of ANFIS and simulation data testing results.

In addition, the Root Mean Square Error (RMSE) of the values obtained as a result of the parametric simulation results and the results of testing 162 randomly selected data that have not been used for training before with ANFIS was calculated as 2.475%. 20 data from these values are given in Table 4.

Table 4. Output voltage comparison of simulation test data with ANFIS estimation values.

m	$f_{\mathrm{pwm}}\ (kHz)$	$L_{\mathrm{p}}\ (mH)$	$V_{\mathrm{rms}}\ (Parametric)$	$V_{\mathrm{rms}}\ (ANFIS)$	Error (%)
0.85	2	0.6	252.007	252.0531	0.018274
0.6	1	0.6	177.416	177.398	0.01017
0.75	5	0.8	223.1	223.2241	0.055626
0.5	10	1.2	149.412	149.2451	0.111685
0.45	5	0.8	133.434	119.0735	10.76225
0.75	9	1.1	224.512	224.4999	0.005398
0.65	3	1	194.265	194.365	0.051462
0.65	6	0.8	192.931	192.9223	0.004526
0.85	6	0.6	251.215	251.3996	0.073478
0.7	9	0.9	208.531	208.416	0.055169
0.7	5	1	209.108	209.1937	0.040988
0.8	7	1.1	239.611	239.7335	0.051141
0.8	3	0.7	237.929	237.888	0.017246
0.7	10	0.6	206.1	206.1553	0.02682
0.5	6	1.1	149.262	148.0378	0.820159
0.55	1	0.7	163.177	163.1678	0.005652
0.8	4	1.3	240.317	240.2636	0.022231
0.45	3	0.8	133.475	121.0049	9.34266
0.65	9	0.8	192.66	192.6311	0.015015
0.5	3	1	149.108	144.8872	2.830674
Root Mean Square Error (RMSE) %					*2.475*

According to these data, when the modulation index is 0.85, the transformer leakage inductance value is 0.6 mH, and the PWM frequency is 2 kHz (as seen in the gray lines in Table 4), the rms output voltage value is approximately 252 V, and when the PWM frequency is 6 kHz, the rms output voltage value is about 251 V. The load is kept constant in this dataset analysis approach based on parametrically run simulations. Since the modulation rate and PWM frequency of the PWM switching signals are varified with the transformer leakage inductance, differences occur in the secondary voltage for the same modulation rate and leakage inductance values. This is due to the increase in the PWM switching signal and the corresponding decrease in the primary winding current. With the approach emphasized here, depending on the different switching signals and transformer leakage inductance values, not only the power electronic circuit but also the behavior of the transformer, which is integrated as a magnetic circuit element, determines the behavior of the voltage on the load.

When the modulation rate was selected 0.8 (as seen in the blue lines in Table 4), two different PWM frequencies, 7 kHz and 4 kHz, and two different transformer leakage inductance values of 1.1 mH and 1.3 mH, voltage values of 239 V and 240 V, respectively, were obtained. Here, the PWM frequencies are at different values. However, the transformer leakage inductance values are also different, so the results are very close to each other, with a voltage of approximately 240 V. In general, the leakage inductance value of the transformer depends on the design and does not change unless it is a special design. Therefore, the effect of the electromagnetic behavior of the transformer on the power electronics circuit has been tried to be shown and explained.

4. CONCLUSION

In this study, parameter estimation of a power transformer integrated multi-level T-type inverter circuit frequently used as a grid interface for renewable energy sources is made with ANFIS based on parametric simulations. With the proposed method, transformer leakage inductance values and power electronics circuit switching parameters (PWM frequency and modulation rate) are run with different variations using a parametric solver to create a data set. The output variable for this dataset is the secondary side voltage rms values of the transformer. Then, the obtained data set presents a different approach to parameter estimation from the literature. Thus, the results obtained with parametric 3D graphics and numerical data are presented comparatively. RMSE received 2.475%. Therefore, the proposed approach in this study is to make high-accuracy parameter estimations in a short time with the data set obtained from long-term parametric simulations. This provides useful pre-prototype performance information for power electronics circuit designers in topologies using integrated transformers. In future studies, parameter estimations of transformers with different inverter circuit topologies, properties, and structures can be made. In addition, using different artificial intelligence techniques for parameter estimation, a comparative analysis of the errors in determination can be made with ANFIS.

Acknowledgment

This study was supported by Karamanoglu Mehmetbey University Scientific Research Projects Coordination Unit as project number 04-M-22.

REFERENCES

[1] Gencer, A. Comparison of t-type converter and NPC for the wind turbine based on doubly-fed induction generator. *Balkan Journal of Electrical and Computer Engineering* 2021; *9*: 123-128. DOI: 10.17694/bajece.826624.

[2] Schweizer, M., Kolar, J. W. High efficiency drive system with 3-level T-type inverter. In 14. European conference on power electronics and applications; 30 August-1 September 2011: Institute of Electrical and Electronics Engineers (IEEE), pp. 1-10.

[3] Salem, A, Abido, M. A. T-type multilevel converter topologies: A comprehensive review. *Arabian Journal for Science and Engineering* 2019; *44*: 1713-1735. DOI: 10.1007/s13369-018-3506-6

[4] Pires, V. F, Foito, D, Martins, J. F. Multilevel power converter with a dual T-type three level inverter for energy storage. In: OPTIM 2014 International Conference on Optimization of Electrical and Electronic Equipment; 22-24 May 2014: Institute of Electrical and Electronics Engineers (IEEE), pp. 1091-1096.

[5] Pires, V. F, Foito, D, Sousa, D. M. Conversion structure based on a dual T-type three-level inverter for grid connected photovoltaic applications. In: PEDG 2014 5. International Symposium on Power Electronics for Distributed Generation Systems; 24-27 June 2014: Institute of Electrical and Electronics Engineers (IEEE), pp.1-7.

[6] Pandit, S, Mishra, R. K, Chauhan, G. Estimation and methods of equalizing leakage reactance for multi-winding transformers. In: NPSC 2018 20. National Power Systems Conference; 14-16 December 2018: Institute of Electrical and Electronics Engineers (IEEE), pp. 1-5.

[7] Alvarez, D. L, Rivera, S. R., Mombello, E. E. Transformer thermal capacity estimation and prediction using dynamic rating monitoring. *IEEE Transactions on Power Delivery* 2019; *34*(4): 1695-1705. DOI: 10.1109/TPWRD.2019.2918243

[8] Zhou, L, Wang, J, Wang, L, Yuan, S, Huang, L, Wang, D, Guo, L. A method for hot-spot temperature prediction and thermal capacity estimation for traction transformers in high-speed railway based on genetic programming. *IEEE Transactions on Transportation Electrification* 2019; *5*(4): 1319-1328. DOI: 10.1109/TTE.2019.2948039.

[9] Lin, W, Miao, X, Xiao, S, Jiang, H, Zhuang, S. Research on Winding Temperature Prediction of UHV Transformer Based on Convolutional Long Short-Term Memory Network. In: Chinese Intelligent Systems Conference; 6-8 April 2021: Springer, pp. 109-120.

[10] Işıka, K, Alptekin, S. E. A benchmark comparison of Gaussian process regression, support vector machines, and ANFIS for man-hour prediction in power transformers manufacturing. *Procedia Computer Science* 2022; *207*: 2567-2577. DOI: 10.1016/J.PROCS.2022.09.315.

[11] Colak, M, Balci, S. Parameter Estimation of Photovoltaic System Using Marine Predators Optimization Algorithm-Based Multilayer Perceptron. In: ICRERA 2022 11. International Conference on Renewable Energy Research and Application; 18-21 September 2021: Institute of Electrical and Electronics Engineers (IEEE), pp. 540-545,

[12] Kul, S, Yıldız, B, Tezcan, S. S. Estimation of Core Losses in Three-Phase Dry-Type Transformers Using Adaptive-Network Based Fuzzy Inference Systems (ANFIS). *Electric Power Components and Systems* 2022; *50(* 16-17); 1006-1013. DOI: 10.1080/15325008.2022.2144550

[13] Aslan, B, Balci, S, Kayabasi, A, Yildiz, B. The core loss estimation of a single phase inverter transformer by using adaptive neuro-fuzzy inference system. *Measurement* 2021; *179*: 109427. DOI: 10.1016/j.measurement.2021.109427.

[14] Balci, S, Kayabasi, A, Yildiz, B. ANFIS Based Parameter Estimating of a Two-Phase Interleaved Dual Cascaded DC-DC Boost Converter for Fuel Cell Supplied Electric Vehicles. *Balkan Journal of Electrical and Computer Engineering* 2021; *9*(4): 410-416. DOI: 10.17694/bajece.940791.

[15] Atar, T, Balci, S, Kayabasi, A. The analysis of three level inverter circuit with regard to current harmonic distortion by using ANFIS. *Journal of Energy Systems* 2022; *6*(2): 143-152, DOI: 10.30521/jes.951487.

[16] Balci, S, Kayabasi, A, Yildiz, B. ANFIS based voltage determination for photovoltaic systems according to the specific cell parameters, and a simulation for the non-isolated high gain DC–DC boost converter control regard to voltage fluctuations. *Applied Solar Energy* 2019; *55*: 357-366, DOI: 10.3103/S0003701X19060100.

[17] Aslan, B, Balci, S, Kayabasi, A. ANFIS-based Parameter Estimation of a Single Phase Inverter Circuit with Isolation Transformer. *Kastamonu University Journal of Engineering and Sciences 2022; 8*(2): 135-144, DOI: 10.55385/kastamonujes.1193007

[18] Hizarci, H, Pekperlak, U, Arifoglu, U. Conducted emission suppression using an EMI filter for grid-tied three-phase/level T-type solar inverter. *IEEE Access* 2021; *9*: 67417-67431. DOI:10.1109/ACCESS.2021.3077380

[19] Schweizer, M, Lizama, I, Friedli, T, Kolar, J. W. Comparison of the chip area usage of 2-level and 3-level voltage source converter topologies. In: IECON 2010 36. Annual Conference on IEEE Industrial Electronics Society; 7-10 November 2010: Institute of Electrical and Electronics Engineers (IEEE), pp. 391-396.

[20] Jang, J. S. ANFIS: adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics* 1993; *23*(3): 665-685. DOI: 10.1109/21.256541.

[21] J.S.R. Jang, Fuzzy Modeling Using Generalized Neural Networks and Kalman Filter Algorithm. In: AAAI 1991 9. National Conference on Artificial Intelligence; 14-19 July 1991: AAAI Press, pp. 762-767

[22] Walia, N, Singh, H, Sharma, A. ANFIS: Adaptive neuro-fuzzy inference system-a survey. *International Journal of Computer Applications* 2015; *123*(13): DOI: 10.5120/ijca2015905635