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MODELING NONLINEAR INDUCTOR, RESISTOR, AND BUCK CONVERTER USING NARX NEURAL NETWORK

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ABSTRACT

This study investigates the methodology of using the capability of Artificial Neural Networks (ANNs) as an alternative approach for modeling nonlinear inductors, nonlinear resistors, and power electronic circuits in electrical power systems. While traditional physical modeling approaches face challenges due to the complex dynamic behavior of these elements and power electronic circuits. In comparison, physical models offer accuracy but require extensive time and detailed parameter knowledge. In contrast, the ANN-based methodology is considered a powerful and efficient solution for enabling approximation of any nonlinear component, simple implementation, and fast computations. The research explores diverse ANN architectures (nonlinear autoregressive network with exogenous inputs (NARX), A feedforward neural network (FNN), and A recurrent neural network (RNN)) to model nonlinear inductor, resistors, diode, and a Buck converter. The investigation demonstrates the effectiveness and versatility of ANN-based modeling in predicting and optimizing nonlinear behavior for the nonlinear components.

KEYWORDS

Nonlinear inductor, nonlinear resistor, Buck converter, Artificial Neural Networks.

1. INTRODUCTION

Nonlinear inductors, nonlinear resistors, and power electronic circuits are commonly used in electrical power systems and show complex dynamic behavior that is challenging to capture using traditional modeling approaches. A physical model, also known as the traditional approach, is a good model for linear electrical circuits, subcircuits, devices, or elements since all the detailed parameters of the physical systems are known. This kind of modeling offers many benefits, including accuracy, safety, education, high predictability for the impacts of a system (Meijer, 1988), receiving virtual feedback from the model, and a well-behaved model (Meijer, 1996). However, there are some major disadvantages of physical modeling, such as being time-consuming, it could take years to model a new device, and it is challenging to know all the detailed parameters of the physical systems or components. Additionally, buck converters, widely used in DC-DC power conversion applications, involve nonlinearities and interactions between different components, further complicating the modeling process. Therefore, describing the complete behavior of a complex and extensive system with consideration for different operating regimes becomes impractical to represent in a single equation (Andrejević and Litovski, 2003). These reasons led to the exploration of another approach for modeling. The Artificial Neural Network (ANN) approach is a more and more successful substitute for traditional approaches like numerical modeling, which may be computationally expensive; analytical models, which may be challenging to obtain for new devices; or experimental models, whose range and accuracy may be constrained. Additionally, the ANN technique does not need a complete understanding of the element, device physics, structure, control algorithm, or systems in the modeling. The artificial neural network model requires a capture measuring input as a signal stimulation and output as a target. This kind of modeling has a lot of significant advantages for instance, any nonlinear component, device, or system may be approximated modeling using this comprehensive model. In addition, it has a straightforward structure in which dedicated hardware is possible. Since it has a parallel-distributed structure, it gets another advantage of performing fast computations. ANN could model multi-variable systems (Murray-Smith et al., 1992). Furthermore, ANN effectively links a device or measurement data and a circuit simulation. Recently, ANN has been considered a powerful tool for modeling and optimizing challenging situations (Hammouda et al., 2008; Abbood and Benigni, 2018). Many studies study the use of ANN in predicting transistor DC (Wang and Zhang, 1997; Zhang and Gupta, 2000), small (Zhang et al., 2003), and large signal behaviors (Zaabab et al., 1995; Shirakawa et al., 1997; Shirakawa et al., 1998) behaviors in specific semiconductor devices.

The aim of this study is to examine the performance of a model for a non-linear inductor, Diode, resistor, and DC-DC buck converter, using an NARX neural network model, with the delays and non-linearities. The efficacy of the proposed models is assessed through the analysis of both average and maximum estimated errors, utilizing various forms of artificial neural networks. A comparison of the results of the proposed models with those of experimental and simulated results has also been presented.

The rest of the paper is organized as follows: Section 2 focuses on related works, and Section 3 discusses the modeling approach using the ANN model. Sections 4 and 5 are utilized for modeling nonlinear inductors and nonlinear resistors, respectively. Section 6 presents a model for a buck converter. Finally, section 7 recaps the presented research work.

2. RELATED WORKS

Artificial neural networks (ANN) have recently been recognized as a powerful modeling, optimization, and control tool. Also, ANNs are an alternative method for modeling electrical devices or (sub) circuits. In 1992, the first attempt to use ANNs for modeling electric devices was made by employing a feedforward Neural Network for modeling a MOS transistor (Litovski et al., 1992), and the ANN showed a good result, leading to many researchers interested in this technology. In 1998, active and passive microwave components were modeled using Feedforward Artificial Neural Networks (Wang et al., 1998). Moreover, Artificial Neural Networks (ANN) is examined for channel estimation in Generalized Frequency Division Multiplexing (GFDM) systems. Their findings revealed that ANN surpassed traditional techniques like Least Squares (LS) and Normalized Least Mean Square (NLMS) in reducing Bit Error Rate (BER), employing advanced training methods like Bayesian Regularization and Levenberg-Marquardt algorithms (Ali and Hreshee, 2023). Artificial Neural Networks (ANNs) have been shown to be successful in addressing intricate geotechnical issues, such as the forecasting of soil recompression parameters, as illustrated in (Al-Taie and Al-Bayati, 2021).

However, modeling dynamic behavior and some complex physical dependencies of an electromagnetic circuit were presented using ANN. The ANN model showed a fast and accurate simulation of an electromagnetic system. A problem of dynamic load modeling is presented, and the analysis and comparison between a multilayer feedforward ANN and a conventional difference equation (DE) approach are presented. The ANN showed the ability to handle that problem (Lindorfer and Bulucea, 1993).

Meanwhile, the empirical modeling of operational power plant dynamics and long-term electric load forecasting is studied in (Parlos and Patton, 1992). The recurrent multilayer perceptron and the ANNS are employed, and the results showed improved forecasting accuracy. After that many researchers employed ANNs in the area, not just in the modeling; for instance, in control, many types of ANNs are used. However, we employed NARX (Nonlinear autoregressive with external input) networks to model some electrical elements, for instance, nonlinear indicators, resistor capacitors, diodes, and buck converters.

3. MODELING METHODOLOGY BASED ON NEURAL NETWORKS

Neural networks, particularly the Nonlinear auto-regressive with exogenous inputs (NARX) neural network, are the foundation of the modeling approach used in this paper. Neural networks represent computational frameworks that are inspired by the human brain. Interconnected units known as neurons are mainly components of Neural network models, which are systematically arranged in multiple layers (Serikov et al., 2021). Therefore, the nonlinear dynamics of components and complex systems, such as nonlinear electrical components and circuits, are modeled by the NARX neural network due to their ability to capture the nonlinear dynamics of complex systems (Avdeev et al., 2021). A comprehensive study that explores practical applications of neural networks and classifies artificial neural networks (ANNs) is offered by Abiodun et al (2018), which shows the ANN applications and contributions in various disciplines such as including technology, computing, medicine, engineering, medicine, and business etc. We modelled nonlinear electrical components and circuits by utilizing ability of NARX neural network to capture the nonlinear dynamics of complex systems. The proposal modeling process contains five steps as shown in. Fig. 1.

1. Verify ANN's inputs and outputs.
2. Form the range and distribution of input and output.
3. Data Generation.
4. Neural Network Architecture.
5. Learning algorithms.

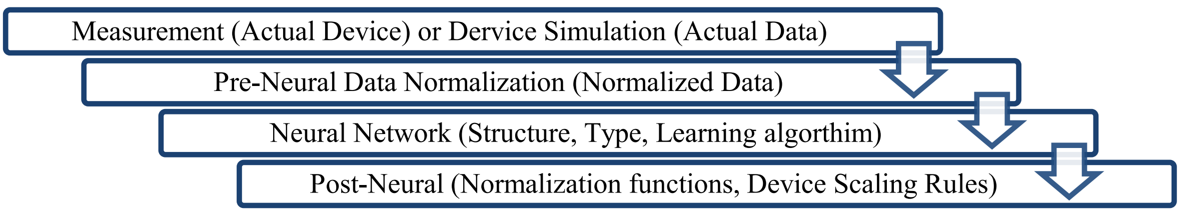

Fig.1. Flowchart for modeling methodology

3.1. ANN Inputs and Outputs:

Identifying appropriate inputs and outputs is the initial stage in getting an artificial neural network (ANN) model ready for a component, device, or system. The variables chosen will depend on the intended model accuracy as their selection can impact the model. Therefore, power, voltage, current, frequency, and other factors determine the input and output values.

Hence, assessing all crucial factors that impact the ultimate outcomes is crucial (Cheng and Low, 2023).

3.2. Data Range and Sample Distribution:

Use The ANN model development is influenced by the range of input data and distribution of samples that contain operational conditions. In this case, it becomes extremely important to include a wide variety of operating conditions to produce a precise system model for forecasting its behavior; otherwise, restricted or biased ranges may cause errors in predictions. An even distribution of samples through the range of inputs is important for avoiding model over-fitting or under-fitting. To develop an ANN model that can generalize well and give accurate future forecasts on unseen points, a balanced sampling distribution at the training stage should be used. Finally, when creating an artificial neural network (ANN) model, the scale and distribution of data to capture all complexities exhibited within the system under study should be taken into account.

3.3. Data Generation

In training an ANN model, data collection from real-time measurements or simulation software is performed using programs. This data can still be used to train and test the ANN model even when both sources have errors or noise. Determining how many input-output data samples are needed to make a good ANN model is not clear; however, it is recommended that the training samples have to be equal to or greater than the number of trainable weights in the network. In our study, the data generation is experimental, and other data were collected from simulations.

3.4. Neural Network Architecture, Parameters

The structure of an artificial neural network is a critical stage, which determines the effectiveness and the ability of the ANN to model nonlinear components and complex systems. Therefore, the number of hidden layers, neurons in each layer, and as well as the appropriate type of activation functions (linear and nonlinear) utilized in each layer form the structure of an artificial neural network. Various problems are solved by various kinds of ANNs, which means they each need their unique solution and structure. Due to the capture of NARX neural networks (nonlinear auto-regressive with exogenous inputs) to catch the dynamic behavior of nonlinear systems, in our study, NARX neural networks (nonlinear auto-regressive with exogenous inputs) are employed with a different structure.

Different types of ANNs solve different problems and therefore require unique solutions and structures. Therefore, the optimal number of layers and neurons per layer, plus effective modeling activation functions, is still a challenging issue for researchers.

3.5. Learning Algorithms

Different training algorithms, such as Levenberg-Marquardt, Bayesian regularization, and the scaled Conjugate Gradient algorithm, have been proposed, each with distinct advantages and limitations that link them to the speed and efficiency of these. Choosing a proper learning algorithm for training artificial neural networks (ANNs) is crucial. Moreover, it can be difficult to compare the speed and effectiveness of various algorithms since their performance depends on the specific nature of the problem being addressed as well as the structure of the ANN, such as its type (feedforward neural network or recurrent neural network), number of layers, nodes per layer, presence of bias, etc. As a result, these factors significantly affect how training takes place. However, it is hard to find an ideal learning algorithm for our particular ANN, given both its constraints and requirements for this domain problem. Consequently, researchers can use a tradeoff analysis on different learning algorithms to ensure that effective and efficient MATLAB-trained ANNs are produced, so that they can guide them in making decisions like this one.

4. MODELING OF NONLINEAR INDUCTOR

In the past few years, electrical engineering has shown great interest in nonlinear inductors because of their broad range of applications in power electronics and RF systems. These inductors exhibit intricate non-linear characteristics, making it crucial to model them correctly for optimizing circuit designs and system performances. However, traditional methods of modeling nonlinear inductors pose mathematical formulation challenges that limit their usability and accuracy. However, there have been significant advances made through artificial intelligence (AI) and machine learning techniques that allow for alternative approaches to modeling using neural networks (Oliveri et al., 2022).

The nonlinear behavior of an inductor with a magnetic core arises from the magnetic saturation effect, deviating from the linear relationship between magnetic flux (ϕ) and magnetomotive force ($\phi = \mu HA$), where related to the magnetic field strength (H) the core's permeability (μ) and A is the cross-sectional area of the core. Flux is related to field strength and permeability, and as the inductor enters saturation, permeability decreases, resulting in a nonlinear relationship between field and flux. This behavior can be modeled using a nonlinear function derived from the inductor's B-H curve. Inductance ($L(i) = di/d\phi$) in saturation effect becomes a function of current, decreasing as current increases. Therefore Voltage-Current relationship becomes nonlinear as shown in Eq .1 Experimental inductor is used to capture nonlinear characteristics, and the neural network model approximates this relationship.

$$v(t) = \frac{d\phi}{di} = \frac{d}{di}\,(L(i) \cdot i) \qquad \text{Eq. (1)}$$

Experimental data collection is the first crucial step in the process, occurring outside the framework of the Neural Network. This study employs prior work (Davidson et al., 2017), which involved the use of a Real-Time Simulator (RTS) with Opal RT (vl1.0.8.13) and MATLAB/Simulink (R2011b) to facilitate input/output capabilities and amplifiers for the systematic variation of the input voltage applied to the circuit to capture diverse operational scenarios. To emulate the nonlinear behavior of a nonlinear inductor, an experimental circuit configuration comprising a resistor (R = 5.4 Ω) and an inductor (L = 4.47 mH) is utilized to collect experimental data, as shown in Fig. 2. The input voltage applied to the circuit is represented by a random signal, as depicted in Fig. 3. Concurrently, the output current response of the inductor is recorded, as shown in Fig. 4 (Test 1). Furthermore, another input voltage applied to the circuit is represented by a sinusoidal signal (50V, 60Hz-Test 2) and (50V, 500Hz-Test 3).

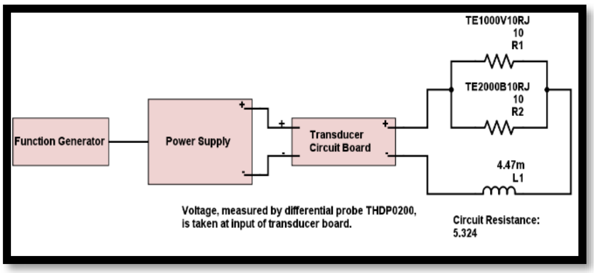

Fig.2. Circuit for the measurement of input voltage and the output current for an inductor and a resistor

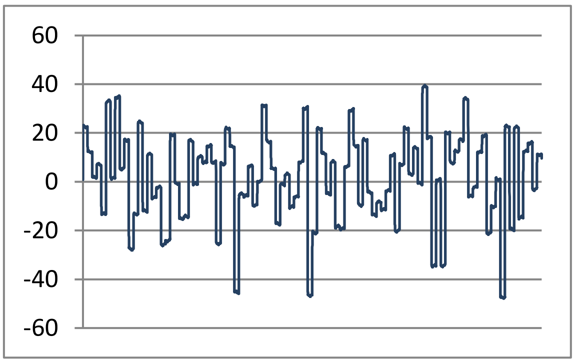

Fig.3 Input Random Voltage Applied to the Inductor

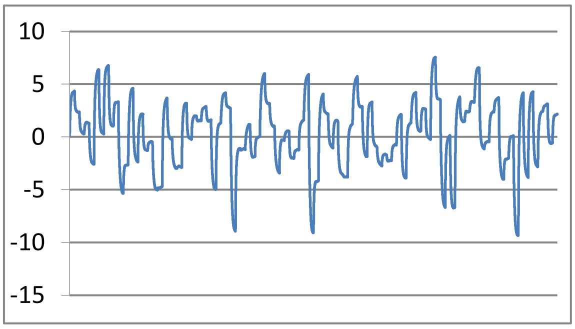

Fig.4 Output Current Response of the Inductor to Applied Random Voltage

Then, the most critical part of developing a model for nonlinear inductors using ANN is the type and configuration of ANNs. In the case of modeling nonlinear inductors, the NARX neural network is well-suited for capturing the dynamic behavior of nonlinear inductors by choosing a single hidden layer and a nonlinear activation function (hyperbolic tangent Activation Function). Therefore, four artificial neural networks (ANNs) are developed and trained using four different datasets. Firstly, the NARX model is trained using a random input signal (Test 1), and its performance is assessed, providing a very tiny error, while the second ANN model is trained based on the sinusoidal input voltage (50V, 60Hz-Test 2), yielding a suitable inaccuracy. Moreover, the third ANN is trained using experimental data with different sinusoidal input signals (30V, 50Hz to 60Hz, 500Hz), while the fourth ANN is trained with a sinusoidal input signal (40V, 60Hz) with a performance of (Performance = 0.0619).

Several tests are conducted using different input voltages to evaluate the performance of the ANNs. In Test 1, a random signal is applied as the input to the ANNs, and the output responses of both the transfer function model and the ANNs are shown in Fig. 5. The ANNs successfully capture the behavior of the nonlinear inductor-resistor system, as their outputs closely match those of the transfer function model.

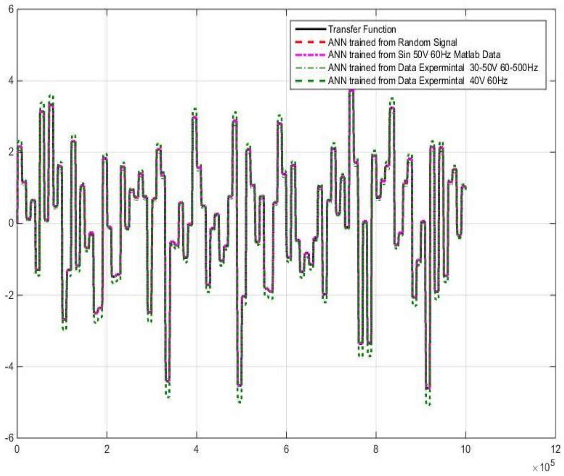

Fig.5 Output signals of the transfer function of the inductor-resistor and ANNs when the input signal is random.

Test 2 applies a sinusoidal signal of 50V and 60Hz as the input to the ANNs, which are then compared with the transfer function model and their output responses. Through this, it can be seen that again, these ANN models have an excellent agreement with the transfer functions model, confirming thus their capability for accurately representing system dynamics. A replication of Test 2 is carried out in Test 3, but at a higher frequency of 500Hz while preserving the same magnitude value of 50V. By doing so, Fig.6 demonstrates that these artificial neural network models can indeed capture and predict the behavior of the system accurately based on their output responses from both artificial neural networks and transfer function models. Such results show that trained ANNs effectively describe non-linearities within an inductor-resistor system in this case.

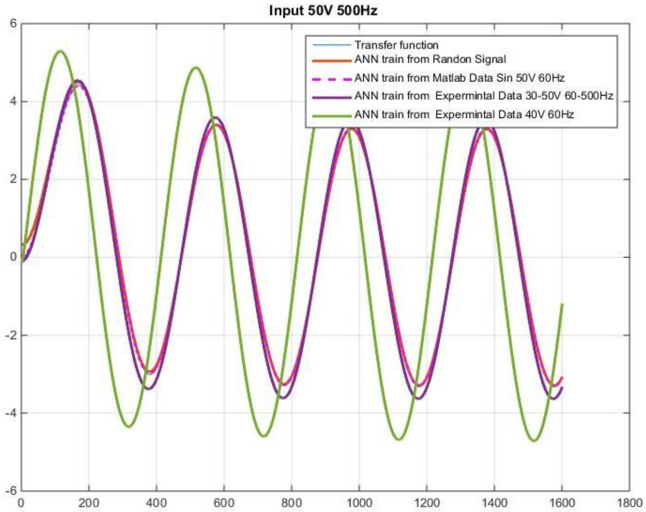

Fig.6. The linear inductor-resistor transfer function's outputs, as well as those of ANNs when the input signal is a sinusoidal signal whose amplitude is 50 volts with a frequency 500 Hertz

From the above, we note that ANNs successfully learn from and capture complex nonlinear relationships as they exist within this system. The use of different input signals and also having ANN outputs matching experiment data always provides evidence for reliability and effectiveness within an ANN-based modeling approach for nonlinear inductors. These findings advance the understanding and modeling capabilities of nonlinear electrical components, enabling improved circuit designs and control strategies.

5. MODELING OF NONLINEAR RESISTOR

Mercury, sodium, and fluorescent luminaires with ballasts are identified as the primary harmonic sources in low-voltage (LV) system lighting fixtures. In addition, laboratory measurements show that the terminal equation of the mercury lamp luminaire cannot be expressed as a linear function v=Ri but has to be a nonlinear function (Acarkan and Kılıç, n.d.). Thus

$$f(i,v)= 0 \qquad \text{Eq. (2)}$$

Therefore, modeling, studying and and analyzing nonlinear electrical resistors is very essential as such may be present in cases of nonlinear luminaries. The linear resistor models, which are represented by the equation $v = Ri$, do not precisely express the non-linear behaviors of lamps fitted with mercury, sodium, or fluorescent lamps with ballasts.

Increasing power losses and poor power quality, and harmonic distortion in LV Systems are presented due to the behavior of mercury lights, sodium lights, and fluorescent bulbs that have non-linear characteristics. Therefore, in our study, developing the correct model for the terminal equation of a Mercury lamp luminaire is seen as a non-linear function f(i,v)=0.

Three distinct nonlinear resistance scenarios ($I(t)=V^3(t)$, $I(t)=V^5(t)$, $I(t)= Id(e^{40v}-1)$-Diode equation) are utilized to study the nonlinearity, where simulation experiments are performed to collect data from the terminal equations. Figs. 7,8, and 9 show the data collected that was evaluated to identify nonlinear behavior and used to develop the appropriate nonlinear resistor model.

A feedforward neural network (FNN), which simplifies architecture and efficiently captures the input-output relationship, is utilized to model the behavior of a nonlinear resistor, with an efficient design that maintains computational speed without sacrificing the accuracy of the resistor's input-output depiction. The developed models simulate the complex characteristics exhibited by the luminaires and present a more realistic representation of the nonlinear behavior compared to traditional linear models. The developed model is evaluated by comparing its predictions with the simulation experiments that were collected for each case, as shown in Figs. 7, 8 and 9.

The developed models contribute to studying and analyzing the impact of nonlinear electrical elements, specifically nonlinear resistors in lighting fixtures. These models aim to accurately model resistance nonlinearity, which contributes to improving power quality and enhancing system performance in LV systems. Further research directions may include an extension of the modeling approach to other nonlinear resistors and exploring advanced control strategies toward mitigating harmonics in electrical systems.

Case 1: $I(t)=V^3(t)$

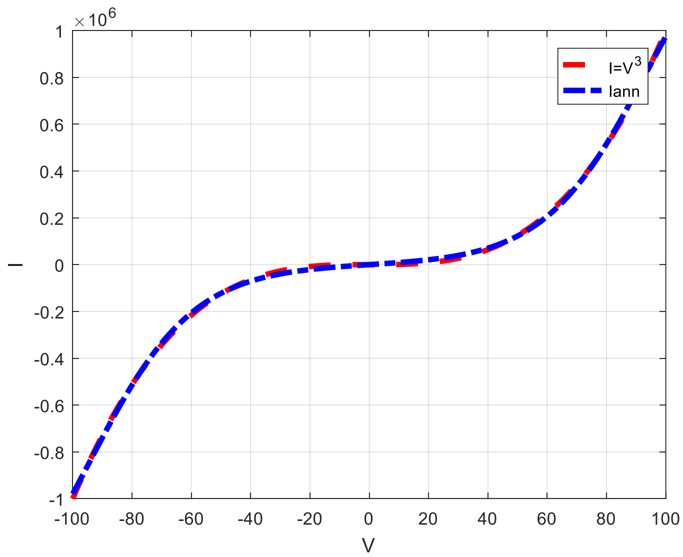

Fig.7. I $_{Analytical}$ ($i(t)= v^3(t)$) and I$_{ANN}$

Case 2: $I(t)= V^5(t)$

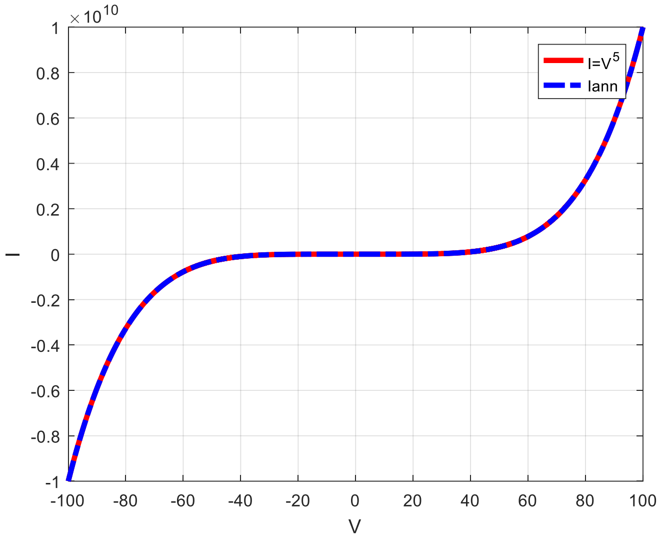

Fig.8. I $_{\text{Analytical}}$ (i(t)=V^5(t)) and I$_{\text{ANN}}$

Case 3(Diode): $I(t) = Id(e^{(\frac{v}{0.025})} - 1)$

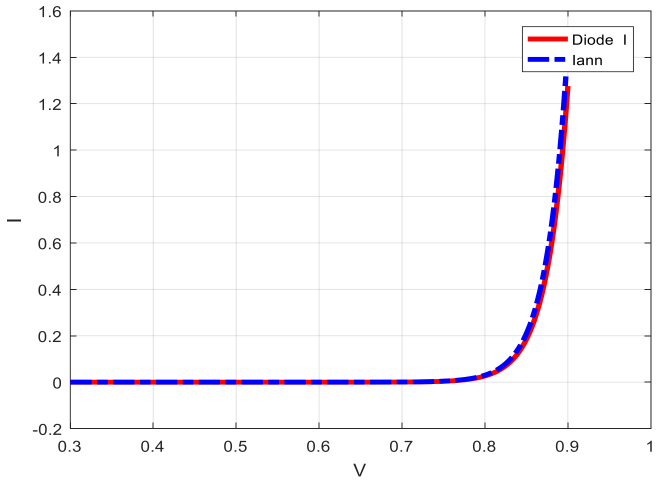

Fig.9. I $_{\text{Analytical}}$ and I$_{\text{ANN}}$ (Diode)

6. MODELING OF BUCK CONVERTER

Buck converters represent one of the most common switching topologies for step-down conversions of voltage, such as regulators, chargers, and power supplies (Mohan et al., 2002). Due to their widespread utility, Precise modeling of the buck converter has been proposed for designing and optimizing control strategies to ensure effective and reliable operations (Erickson and Maksimović, 2001). However, a very complicated and time-consuming reqrired in the analytical models to involve nonlinearities or switching dynamics (Lee and Lee, 2005).

Therefore, Artificial Neural Networks (ANNs) have become an important tool for modeling complex systems and optimization problems in recent times. In this section, ANN-based models were formulated and implemented for buck converters. Two case studies that provide the input-output relationship of a buck converter are investigated. The first case used MATLAB

Simulink, having physical components; however, ideal elements were used to perform the second simulation. The third case study illustrates a novel configuration consisting of neural network components integrated by training with data acquired from physical element simulations shown in Fig. 10. Typically, collected data includes input voltage as well as output load current.

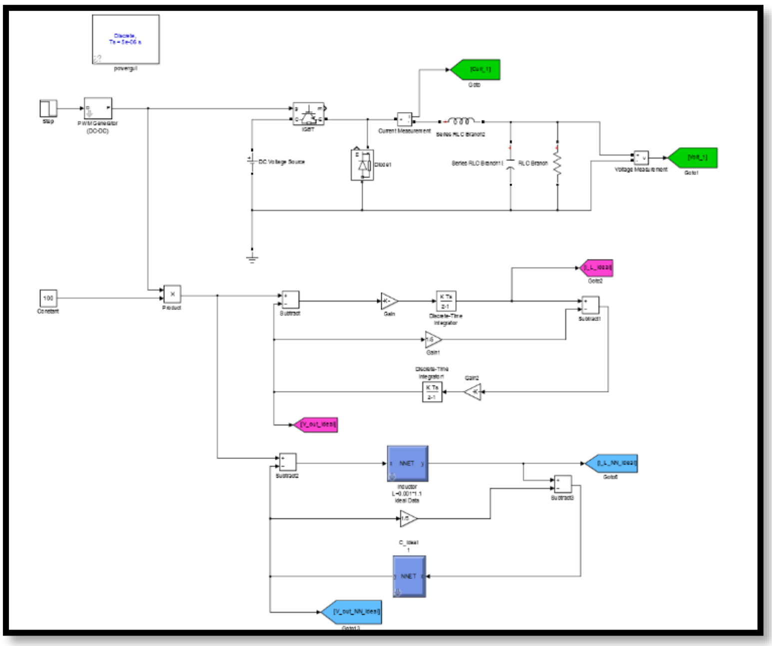

Fig.10. Buck Converter Models

After data collection, an appropriate ANN architecture is created. A recurrent neural network (RNN) structure was implemented to adapt sequential data and capture the converter's time-dependent dynamics. For instance, the number of layers, neurons in each layer, and activation nonlinear functions are chosen based on the buck converter's complexity and the model's required accuracy. The phases of training, validation, and testing were executed employing a data partitioning strategy of 70:15:15. Hyperparameter optimization was performed during the validation phase, while the evaluation of performance took place on data that had not been previously encountered in the testing phase.

ANN adjusts its weights and biases during training to minimize errors between predicted output and actual output. The training process continues until satisfactory accuracy has been achieved on the validation set by the ANNs. After being trained and validated, it can be used in various applications where for instance it gives an accurate estimation of the output voltage of a buck converter. Moreover, ANN-based models may develop and optimize control schemes such as pulse width modulation (PWM) control for buck converters designed to satisfy specific performance objectives.

Fig. 11 shows the current signals produced by phasic, ideal, and Neural Network Buck converter. The first and second circuits are done with phasic elements and ideal elements respectively for the buck converter. However, this is not the case for circuit three which is designed and constructed using a neural network.

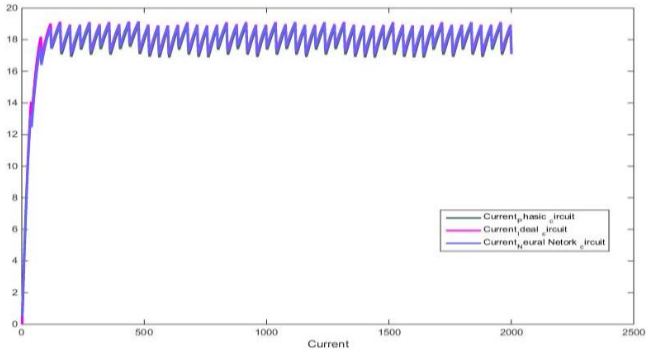

Fig.11 The currents response for Buck converters and Output of ANN

The above case studies illustrate how neural networks may be used to model and simulate buck converters to indicate their effectiveness in capturing complex nonlinear phenomena as well as dynamics. A possible alternative that has possible benefits of improved efficiency, flexibility, and other attributes compares the neural network-based Buck Converter to conventional techniques. The ANN-based modeling method also aids in the development of more dependable and efficient buck converter systems for various practical applications.

7. CONCLUSIONS

In this study, the benefit of utilizing Neural Networks (NN) which are artificial for modeling highly non-linear power systems is established. Definite physical modeling techniques are dependable as well as safe, but they are time-consuming and require complete data that might not always be readily available. On the other hand, ANN provides a strong, flexible alternative to conventional options limitations. Nonlinear inductors, resistors, and buck converters have been successfully simulated. The findings demonstrate that ANN-based models can accurately depict the complex dynamic behavior of nonlinear inductors, resistors, and power electronic circuits. Besides, the ANN's ability to approximate any nonlinear element or device gives it an edge over other techniques when dealing with complicated modeling issues.

In future years, further research into ANN-based modeling approaches will lead to more accurate approximations of complicated nonlinear electrical systems that are also more efficient. This ever-improving ANN technology is expected to play a critical role in dealing with issues caused by non-linear components and power electronic circuits, thereby enhancing a better understanding and management of electrical power systems.

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