Study on the Impact of Fuzzy PI and Artificial Neural Network on a Hybrid Indirect Matrix Converter with a Flying Capacitor Inverter Control in Active Power Filtering Application

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Abstract: This paper investigates the implementation and comparative performance of a Fuzzy PI controller and an Artificial Neural Network (ANN)-based controller applied to a Hybrid Indirect Matrix Converter (HIMC) and to a Flying Capacitor Inverter (FCI) with its output RL filter, for active power filtering applications. The main objective is to achieve an accurate reference current tracking under DC voltage perturbations. A RLC circuit and a three-phase full-wave converter are employed for generating a fluctuating DC input voltage for the inverter. The FCI is designed to produce a compensating current equal in magnitude and opposite in phase to the harmonic components, while its semiconductor switches must withstand the applied voltage stress. The inverter's dynamic response, governed by the semiconductor switching behavior, is inversely related to the supported voltage. In order to analyze and validate both control strategies, simulations were carried out in the MATLAB/Simulink environment using the Simscape and SimPowerSystems toolboxes. The results confirmed that both controllers effectively improved the filtering performance, with the neural controller providing a higher accuracy and the fuzzy PI controller enabling a simpler implementation.

Keywords: Flying Capacitor Inverter (FCI), Hybrid Indirect Matrix Converter (HIMC), Fuzzy PI Controller, Artificial Neural Network (ANN), Active Power Filter, Total Harmonic Distortion (THD), Intelligent Control, Harmonic Compensation.

1. Introduction

Electrical energy is a prominent energy source because it is easy to transport through environmentally friendly methods such as hydraulic, wind, and solar power (green energy). High-voltage electricity networks facilitate its efficient transmission over long distances. For minimizing the risks and reducing the dangers of unstable, fluctuating, and harmonic energy, it's important to use methods like active filtering (Mikkili & Panda, 2015; Maza-Ortega et al., 2017; Azri & Rahim, 2011).

Active Power filtering, which employs various devices based on advanced power electronics -such as matrix converters and multicellular inverters—aims to enhance power quality by reducing the harmonic distortion, thereby improving the efficiency and reliability of the electric grid (Carrere, 1996; Gang, 2024). The quality of the power grid (PG) is affected by harmonic currents caused by non-linear loads. One effective solution to this issue is the use of Active Power Filters (APFs). The APFs consist of a transformer connected to an AC–DC converter. The converter supplies a two-capacitor filter, known as a Flying Capacitor Inverter (FCI), along with a RL filter (Yang et al., 2024; Wang et al., 2017).

This study focuses on reference current tracking for the Flying Capacitor Inverter (FCI) and its output RL filter, also under disturbances in the FCI input DC voltage. To achieve this, a three-phase full-wave converter, a transformer, and a third-order RLC filter (Azri & Rahim, 2011) are used for supplying the inverter with a perturbed DC input voltage (Krause et al., 2025; Iyer et al., 2025).

The FCI is required to generate a compensating current equal in magnitude and opposite in phase to the harmonic components, while its semiconductor switches must withstand the applied voltage. The dynamic behavior of the switches represents the inverter's time response, which is inversely related to the supported voltage (Maza-Ortega et al., 2017).

For enhancing the filtering quality, an output passive filter placed between the inverter and the

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PG, which is designed to prevent the propagation of harmonics produced by the FCI into the PG.

The FCI, which belongs to the serial multicellular inverter family, has a design that reduces the voltage applied to the switches. This allows the use of fast dynamic switches for both medium and high voltages. Also, the harmonics in this inverter are in the range of f_nN (where f_n is the carrier frequency and N is the number of cells) and are evenly phased. This helps reduce the constraints on the output filter. In this situation, a simple RL filter can achieve the goal of passive filtering (Carrere, 1996; Iyer et al., 2025; Petric et al., 2022).

The phase-locked loop (PLL) (Forghani & Afsharnia, 2007) is the technique most frequently used for identifying harmonics. Other techniques include wavelet analysis (Kamwa, Grondin & McNabb, 1996), the instantaneous power theory (Alali, 2002), Kalman filtering (KF) (Kamwa, Grondin & McNabb, 1996; Guffon, 2000), the fast Fourier transform (FFT) (Nakajima & Masada, 1989; Dzonde Naoussi, 2011) and artificial neural networks (ANNs) (Qasim, Kanjiya & Khadkikar, 2014; Djaffar, 2005). This paper is organized as follows: Section 2 describes the components of the filtering system, while Section 3 details the parameter computation for the fuzzy PI controller. Further on, Section 4 presents the control approach based on artificial neural networks and Section 5 compares the simulation results for both control strategies. Finally, Section 6 concludes this paper and outlines possible future research directions.

2. Active Power Filter

2.1. Full Structure

The current filtering process is as follows. The way the inverter works is by measuring the current, using a technique called neural identification, and using a method called STRPWM (Space-Vector Time Ratio Pulse Width Modulation) to create signals for the inverter and keep the voltages of the flying capacitors constant (Qasim, Kanjiya & Khadkikar, 2014). The power part includes a three-phase rectifier, a filter called FCMI, an output RL filter, and a transformer with its filter.

Figure 1 shows these two parts and the perturbed grid, indicating where the two sections are located.

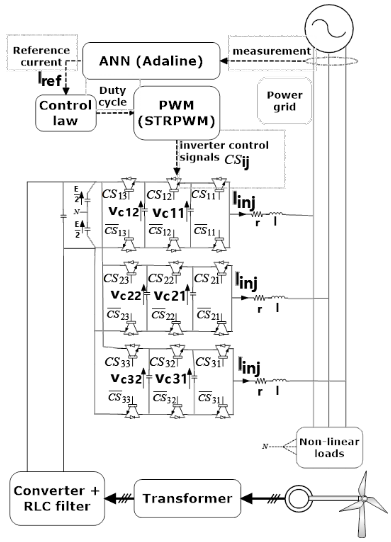


Figure 1. The two parts of the current filtering process and the perturbed grid

3. Structure and Concept of a Fuzzy System

Fuzzification, rules, an inference engine, and defuzzification are the fundamental components of a fuzzy control system. Instead of explicitly describing the control action as a function of the prior control and error variables, as in the case of classical controllers, fuzzy control uses linguistic variables to specify a set of control rules. After that, a process called “aggregation” is employed to combine the numerous rules consequences that each distinct rule produces into a single fuzzy set that indicates the possible courses of action for control (Zadeh, 1965). In order to extract a single precise control value from a rule consequence, an appropriate mechanism must be developed - this process is known as defuzzification. The points below provide further information about creating a fuzzy controller:

- Selecting the linguistic variables (such as the error and the error derivative) and the linguistic values (Negative, Positive, Zero, Small, Big, Negative Big, etc.);
- Choosing the membership functions (Triangular, Trapezoidal, Linear Z-shaped, Linear S-shaped, Gaussian, and Bell-shaped curves) which convert the input and output values between crisp values (precise numerical inputs and outputs) and fuzzy values;
- Developing the rule base, which defines the degree of membership of the linguistic variables with regard to the membership functions;

- Fuzzification: converting the crisp inputs into fuzzy values by means of the membership functions;
- Inference: performing rule evaluation and combining the results;
- Defuzzification: converting the fuzzy values into a crisp output value using different methods, which may produce results that are not necessarily identical, such as the Random Choice of Maxima, First of Maxima, Last of Maxima, Middle of Maxima, Middle of Support, Center of Gravity, Center of Sums, Basic Defuzzification Distributions, Indexed Center of Gravity, and Semi-Linear Defuzzification.

The defuzzification methods can be categorized based on their mathematical properties or mathematical transparency (Zadeh, 1965; Zadeh, 1975; Mamdani & Assilian, 1975).

3.1. Fuzzy PI Control

In order to ensure that $I_{inj}(t)$ tracks $I_{ref}(t)$ and minimizes the error e, a fuzzy PI controller is employed (Figure 2).

3.2. Typesetting and Structure

This controller is derived from a fuzzy PD controller, to the output of which an integral action is added to form a PI controller. As shown in Figure 2, the inputs of the controller are the error and its derivative:

$$e(t) = I_{ref}(t) - I_{inj}(t) \quad (1)$$

$$\triangle e(t) = e_{k+1}(t) - e_k(t) \quad (2)$$

The controller output u is weighted by Ku, while the two inputs are weighted by Ke and KΔe, respectively. As shown in Figure 3, three triangular input membership functions are selected: a linear S-shaped membership function, along with a linear Z-shaped membership function at the positive and negative ends, which overlap with their neighboring functions at a membership value of 0.5.

A set of 25 rules (Table 1) is processed by the Sugeno inference system (Sugeno & Nishida, 1985), which uses a singleton output membership function. It employs a product operation for implication and a summation for aggregation. As it uses a weighted average or sum (in the analysed case) of a few points, the defuzzification process for the Sugeno system is more efficient than for the Mamdani system, which computes the centroid of a two-dimensional area (Hirota, 1993). Nine constant membership defuzzification functions are implemented for speeding up the controller operation.

Table 1. Rules table

Δe \ e	PB	PS	ZE	NB	NS
PB	PB	PB	PB	PS	ZE
PS	PB	PB	PS	ZE	NS
ZE	PB	PS	ZE	NS	NB
NB	PS	ZE	NS	NB	NB
NS	ZE	NS	NB	NB	NB

The weight parameters Ke, KΔe, and Ku are calculated using both Particle Swarm Optimization (PSO) and the Genetic Algorithm

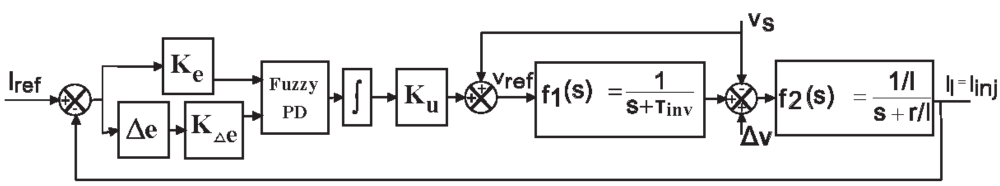


Figure 2. Fuzzy PI control loop

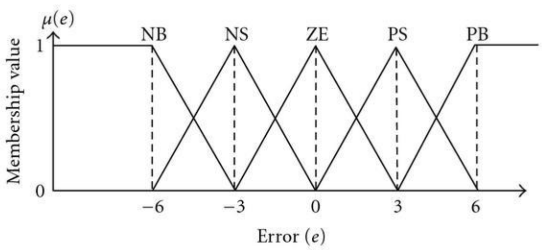


Figure 3. Membership functions

(GA) optimization method in MATLAB (Optimtool). The target function (TF) to be optimized is the square root of the fuzzy PI controller response error.

$$TF = \sqrt{e^2} \quad (3)$$

4. Artificial Neural Network Control

In order to configure a neural controller, it is necessary to determine certain variables.

The number of input neurons corresponds to the number of input vector variables used for solving the given problem. However, there is no systematic approach for determining this number. This parameter must be considered during the model construction process. Ideally, a small number of input neurons should be selected (McCulloch & Pitts, 1943).

An important factor in the implementation of a neural network controller is the number of hidden neurons and hidden layers. The hidden layer neurons utilize the data model to perform a sophisticated non-linear mapping between the input and output variables (Rumelhart, Hinton & Williams, 1986).

Most researchers use only one hidden layer in their neural networks. It is not recommended to have an excessive number of hidden neurons, as this can have a detrimental effect on both the learning time and the generalization ability of the network.

For determining the optimal number of hidden neurons, experiments and tests were conducted, and the configuration that produced the smallest error was selected. Furthermore, to implement an application, it is first necessary to express the problem as a mapping between two spaces, then construct a representative learning dataset, and finally, based on experience, choose the network model and its parameters. It is also necessary to define the performance evaluation criteria (the construction of the test dataset), preprocessing, and data encoding for the network (Rumelhart, McClelland, & Corporate PDP Research Group, 1986; Yamada, & Yabuta, 1992; Lewis, 1996).

The four main stages of designing a neural network are as follows:

4.1 Sample Selection

This step helps the designer determine the most appropriate type of network for solving the given problem. The way how the sample is presented determines the type of network to be chosen , the number of input and output cells, and the manner in which learning, testing, and validation are conducted (Ameur, Ameur & Benalia, 2021).

4.2. Network Structure Development

The structure of the network depends on the type of samples and, of course, on the application itself, since some structures are better suited to specific problems (Bakeer et al., 2022).

4.3. Learning

Learning is the penultimate phase in developing a neural network. It first involves calculating the optimal weights of the various connections using a portion of the samples. The most commonly used method is backpropagation. Care must be taken to avoid overtraining the neural network. (Wang et al., 2022).

4.4. Validation

Once the network has been trained,tests must be carried out to verify its performance: this is the validation step. The simplest method is to keep some of the samples used in the learning phase for validation purposes.

4.5. Controller Application

The goal is to replace the PI current controller in the inverter and the RL filter control diagram with a neural controller. The latter must exhibit a response similar to that of the PI controller in terms of the relationship between the reference voltage and the current error.

The topology is selected to give the neural controller a greater degree of freedom: five layers, including the input and output layers, arranged in a feedforward configuration. The activation functions of the input and three hidden layers are hyperbolic tangent sigmoid (tansig), as this function centers the data and facilitates learning in subsequent layers.

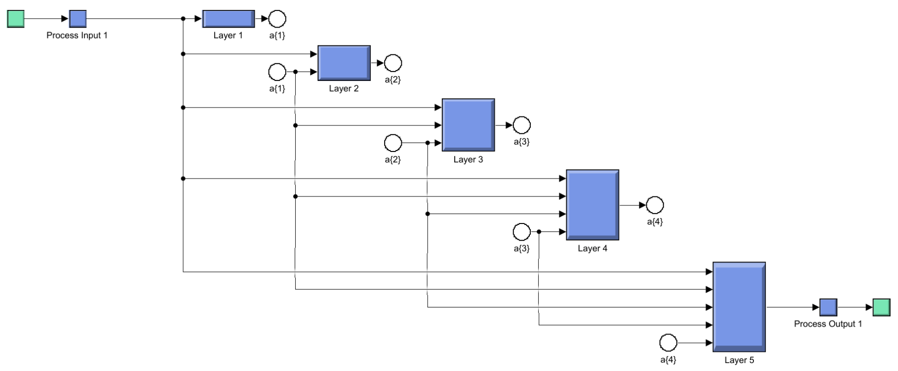


Figure 4. Block diagram of the ANN controller

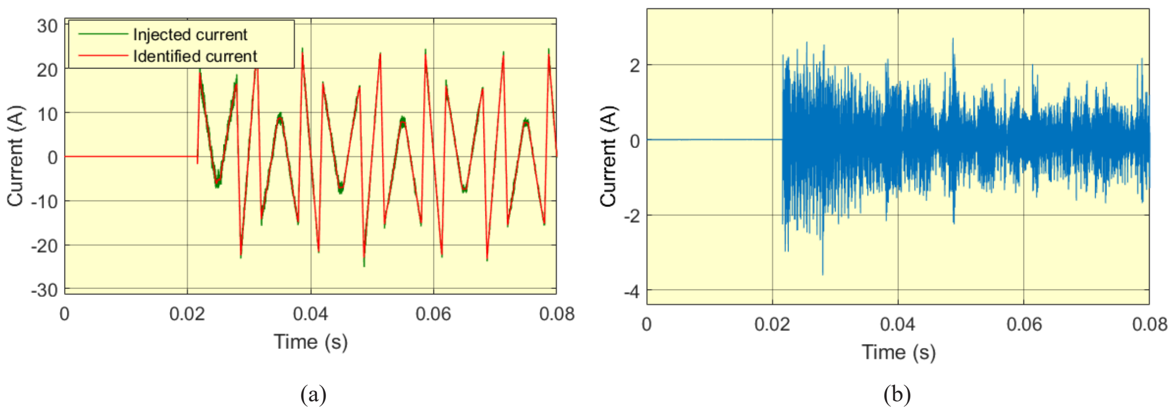


Figure 5. (a) Reference tracking; (b) Tracking error while using the Fuzzy PI controller

For the output layer, a linear activation function is selected. Network training is performed using the Levenberg–Marquardt backpropagation learning algorithm, chosen for its rapid convergence (McCulloch & Pitts, 1943), while performance is measured by the Mean Squared Error (MSE). The network weights are initialized randomly in this case.

5. Simulation Results

The simulation parameters are presented in Table 2.

Table 2. Simulation Parameters

Parameters	Value
Adaline learning parameter µ (correction factor)	1
Carrier frequency fc	12 khz
Simulation period	1-7s
Transformer	
Output filter r,l	10Ω, 0.5mh
Flying capacitors	470µf
DC capacitor	470µf
Number of cells	N=3
Δφ (Phase margin) desired	50

The results for the ADALINE (Adaptive Linear Neuron) artificial neural network (ANN) identification technique are presented in (Ren et al., 2022; Pan et al., 2023). The filtering process starts at t = 0.022 s. Figure 5(a) shows the accurate reference tracking, while the ripple can be observed based on the tracking error shown in Figure 5(b).

Figure 6 shows the grid current during the filtering process. After t = 0.022 s, a smooth sinusoidal waveform is obtained.

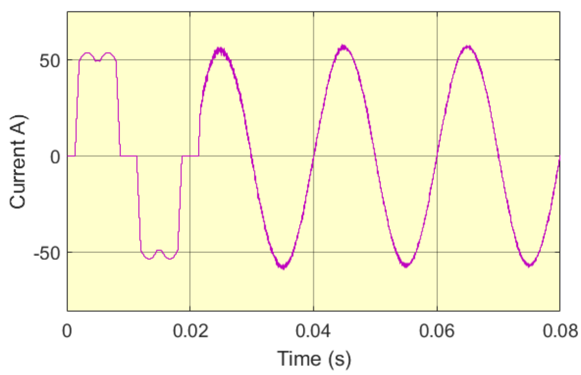
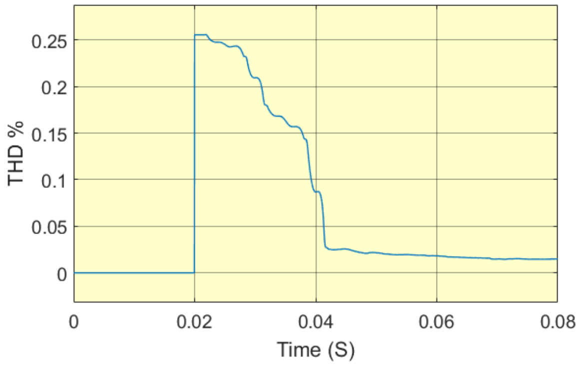
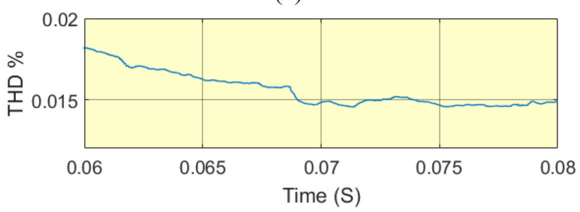


Figure 6: Grid current while using the Fuzzy PI controller

Figure 7 illustrates the evolution of the Total Harmonic Distortion (THD) before and after filtering. Thus, the THD is reduced from over 26% to approximately 1.5%. Figure 8 shows the flying capacitor inverter voltages while using the Fuzzy PI controller, which exhibit uniform fluctuations within a range of ±20 V.



(a)



(b)

Figure 7. (a) THD; (b) Zoomed caption for THD while using the Fuzzy PI controller

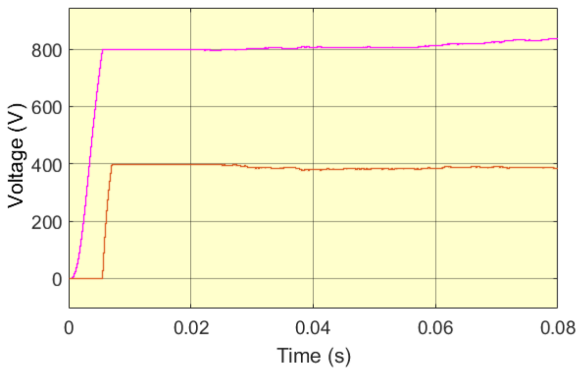


Figure 8. Flying capacitor inverter voltages while using the Fuzzy PI controller

The grid current is presented in Figure 9:

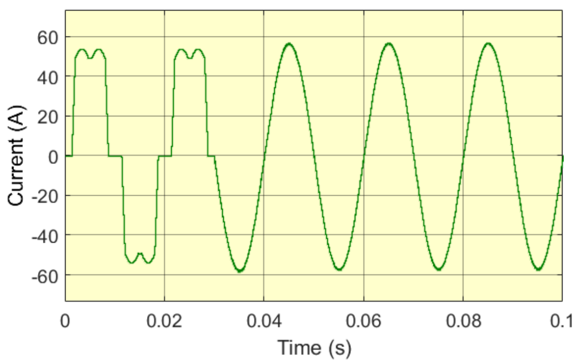
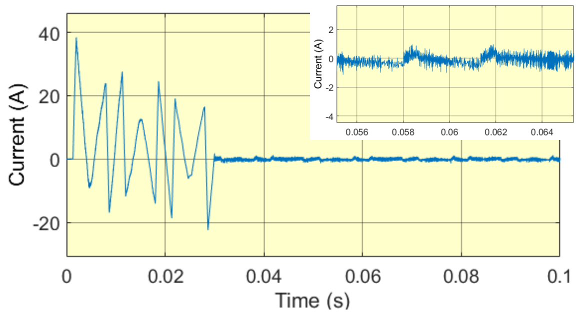
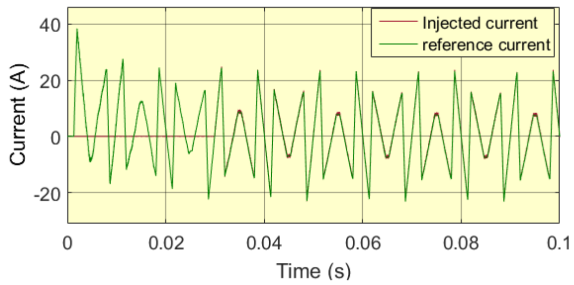


Figure 9. Grid current while using the neural controller

The filtration process starts at t=0.03s as shown in Figure 10 after the voltage of all the capacitances of the flying capacitor is stabilized,. Figure 10(a) illustrates the tracking error with a zoomed caption and Figure 10(b) illustrates the reference current and the injected current, the ripple of the injected current and the error value were very satisfied.



(a)



(b)

Figure 10. Tracking error and reference tracking while using the neural controller

The variation of the flying capacitor inverter voltages during the filtration process is maintained within an accepted range of ±10V, as shown in Figure 11.

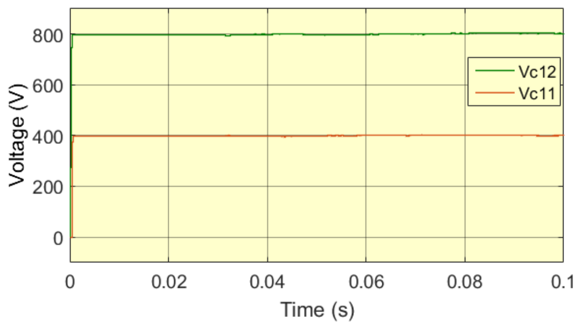


Figure 11. Flying capacitor inverter voltages while using the neural controller

The THD (total harmonic distortion) value decreased from about 26% before filtration to less than 0.8% after filtration as shown in Figure 12. This is also evident from the grid current's sinusoidal form and the controller's low frequency rippling. Figure 13 shows the THD results for the Neural Network Controller (NNC) and the Fuzzy PI controller and the difference between them.

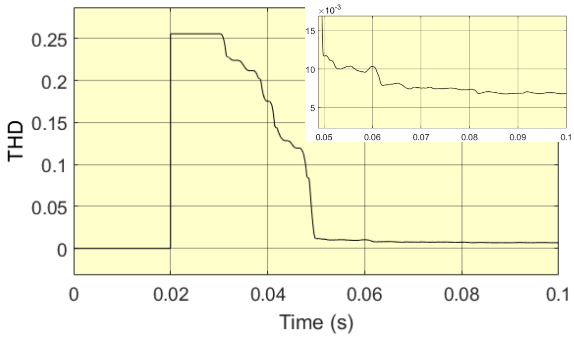


Figure 12. THD with a zoomed caption while using the neural controller

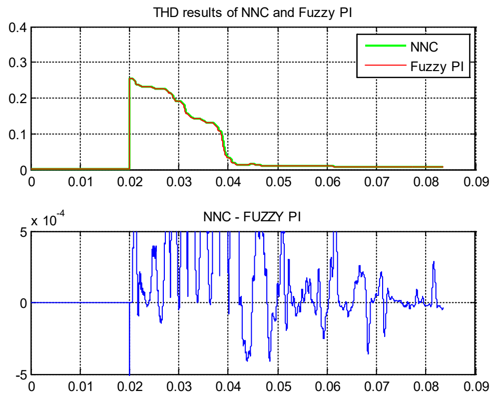


Figure 13. THD results for the Neural Network Controller (NNC) and Fuzzy PI controller

6. Conclusion

This paper presents a synthesis method or a fuzzy PI controller, along with introducing a tuning method for a neural controller. The latter gives promising results, with a THD value lower than that obtained by the fuzzy PI controller. However, in terms of synthesis, the fuzzy PI controller has fewer conditions and requires a shorter computation time for gain adjustment than the neural controller, which has more conditions and needs a longer training time.

Unlike the conventional automatic methods, the controllers based on fuzzy logic do not require an analytical model of the task to be solved. Indeed, they are not based on the physical equations of the system to be controlled but on the knowledge and experience of operators and domain experts. In fact, in the simplest cases, their development is carried out through a knowledge extraction phase, that is, through a dialogue with experts or questionnaires. At the end of this phase, the human operators' reasoning is described, more or less accurately, in the fuzzy controller's "If–Then" rules.

Neural networks are a practical solution for solving several problems. Their use has proved effective in processes that require interaction with the environment. Moreover, information processing in neural networks is performed in parallel and in a distributed manner, which reduces the computational time. These characteristics make them more efficient than the traditional solutions.

The use of neural networks instead of the conventional techniques for controlling complex systems may be justified by their ease of implementation (requiring little preliminary mathematical analysis), their universal approximation capability, their ability to treat a process like a black box, and their capacity to operate with minimal information about the system. The use of neural networks in active filtering applications is therefore of considerable interest.

The exploitation of neural networks in perturbation identification provides fast and accurate results, which serve as references for the controllers. In addition, a stable state of the flying capacitor inverter voltages is achieved by using the STRPWM method, while also taking advantage of the TCFCI's natural stabilization. The efficiency of both controllers throughout the filtering process is demonstrated by the results obtained by using MATLAB and the Simscape/ SimPowerSystems toolboxes.

Finally, some perspectives emerge for enhancing and optimizing the control of active filters:

- For analytical synthesis methods, the aim is to achieve the same objectives in discrete time, in order to obtain more accurate methods that would improve controller performance;
- Designing a controller with the objective of compensating for inverter-generated fluctuations, while ensuring reference tracking by the implemented identification technique, to take advantage of its predictive capabilities;
- Integrating the inverter control into the identification techniques based on the online identification of the harmonic development function(s);
- Applying the optimization methods to the RST controller and introducing constraints for reducing the tracking fluctuations.

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