AN APPROACH FOR MULTIMODEL REPRESENTATION OF PROCESS: A CASE STUDY OF BOOST CONVERTER

Hichem Bennasr[1], Faouzi M'Sahli[2]

[1] Higher Institute of Technological Studies of Sfax, Department of Electrical Engineering – Tunisia
[2]National Engineering School of Monastir, Department of Electrical Engineering – Tunisia.

Abstract. *In this paper, we will present a new concept for multimodel representation of complex nonlinear systems. This approach is conducted via a construction of a model's library based on Fuzzy k-means algorithms and a new scheme for mutimodel construction of nonlinear process. This novel strategy is developed focusing on the use of a neural network for validity computation. The recommended approach is compared with the classical one based on his implementation on a boost converter. The proposed approach seems to enhance the accuracy and precision of modeling compared to traditional methods.*

Keywords*: multimodel, validity, neural network, boost converter.*

1. INTRODUCTION

As the system becomes more complex, so does the model.. For some systems, simple linear stationary models are sufficient to present them. But unfortunately, in real life, systems are often quite complex. Complexity can take many forms, such as high non-linearity, non-stationarity, a wide operating range, and changes in system parameters or external disturbances. For this type of system, simple (linear stationary) models prove insufficient, and the use of more complex models (non-linear and non-stationary, or even high-dimensional) obviously provides a better approximation of the behavior of the process in question, but is difficult to implement, especially when it comes to control design [1]. It is also sometimes difficult, if not impossible, to design a single global representative model that can account for all the complexity of the system.

One practical possibility is therefore to use a combination of local approaches, introducing the notion of multimodel representation. In this context, the solution is either to study the system locally to define a model for each situation, or, if a model has already been defined, to linearize it around one or more operating points. In this way, the models obtained are simpler than the initial global model, which facilitates the task of control process.

Several researchers have explored the multimodel approach, proposing various methods that consider the diverse physical aspects of complex processes [2-5]

The multi-model approach is a powerful technique used in the modeling and control of complex systems. The idea is to represent the system by several simple models. Each model represents the process in a particular area of its operation space. These models which can be of different structures and parameters are exploited to study locally some properties and control performances [6-10].

The multimodel approach's most intriguing concept lies in its capacity to approximate a nonlinear system by weighing local models using a validity degree. This validity degree essentially defines the operational scope of each sub-model and its impact on the overall model. Just as crucial as constructing the model itself, calculating validity is among the pivotal considerations in the multimodel approach.The normalized validity of a local model is a numeric value ranging from 0 to 1, assessing how effectively each local model describes the global system. A value of 1 indicates perfect representation of the system in that region, while a value of 0 signifies complete inadequacy. These coefficients significantly influence the accuracy or control of the global model, underscoring the importance placed on validity calculation by researchers. Consequently, various methods for validity estimation have been proposed in the literature [11-17]. Among these methods, the residue approach is prominently recognized for computing validities, typically formulated through geometric distance calculations [18].

The residues approach, widely employed [19-24], calculates residues as the discrepancy between the actual output and the outputs of sub-models. Despite this method being used to determine the validities of base models in multimodel approaches, performance often significantly declines across various complex system scenarios [13-14]

Lately, a specific validity is accorded to the structure of cluster repartition was considered of a great importance [15-16].The latest work doesn't make in evidence that the process is usually noisy due to the sensors or the influence of external factors which can affect the structure of clusters distribution. So, a new strategy of validity calculation is presented to quantify the limits of each sub-model. To formalize the selection of the appropriate models for the task at hand, a new method is presented to overcome this difficulty by using both two types of validity for each sub-model in the model's base [17].

This paper is organized as follows. Section 2 introduces the principle of multimodal representation, addressing the associated problems the research points and the conventional solution. The proposed remedy to these issues through a new multimodal representation scheme is presented in Section 3. Simulation results validating the proposed concept and experimental results on a Boost converter are presented before concluding this paper.

2. PRINCIPLE OF MULTIMODEL REPRESENTATION

The multimodel approach involves defining a set of models that together constitute the model base.. Each of these models represents the process in a particular domain of its operating space. So, instead of considering a global model that covers different situations and is probably more complex, an alternative is to use local models for each situation and a law for switching from one model to another. In this way, we obtain a model that is much simpler to manipulate, while retaining the ability to provide sufficiently precise predictions within the activation domain of each model. Also, each of these models is not a faithful representation of the process, and in general is even false, except in exceptional cases when the system is governed by the corresponding local behavior [3]. The aim of the multimodel approach is to reduce the complexity of a system by studying it under certain conditions, thus simplifying control design. There are two possible scenarios for implementing this approach:

- either it's a "black box" system, where only input/output measurements are available, due to the difficulty or impossibility of developing a mathematical model that can reproduce the system in its operating space. In this case, the multi-model approach is a powerful and effective way of overcoming the difficulties involved in modeling this kind of complex system;

- or a non-linear mathematical model (knowledge model) is available, which can be used to deduce the model base.

In this paper, our focus is on investigating "black box" SISO systems, where only input/output measurements are available due to the inability to define or construct a mathematical model. Figure 1 depicts the typical representation of a process using a multimodel approach. This approach assesses how each model contributes to describing the system's behavior.

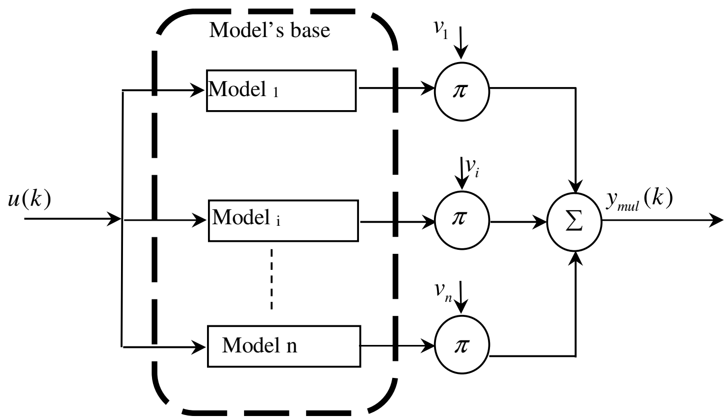

Fig. 1 The classical Multimodel representation

The overall structure of the multimodel approach is provided in Figure 1 where it is formed via 3 units: the models library unit, the selection unit and the output unit [12, 17, 18]. The model library unit contain the different submodel that can be determined with different structure of classification or partition of the overall data given from the process. The Decision unit is responsible in the computing of the validity of each submodels and can demonstrate the contribution of the local models's in the construction of the overall process [11,21].

For two decades, the classic structure of multimodal representation of complex systems has been retained, and most research has focused on two points: how to define the number of models in the library, and secondly, what is the adequate validity for each model in order to achieve good modeling performance. So, most research addresses these two points, covered by several papers: either focusing on defining validity, or exploring alternative approaches to find the optimal number of models while ensuring accuracy of fitting.

In this paper, we focus on the two points mentioned earlier. Indeed, we propose a new structure for multimodal representation by using a neural network that allows adjusting the validity of each model while improving modeling accuracy compared to traditional approaches. This situation arises where the number of neurons in the hidden layer determines the number of models in the library.

Referring to the literature, the residue approach is the main known approach dealing with the validities' computation. This residue is expressed as the distance between the system's outputs y and the considered local output y_i given by:

$$r_i = |y - y_i|, i = 1, \cdots, N_m \tag{1}$$

Tthe output system is expressed by:

$$y_{mul} = \sum_{i=1}^{N_m} v_i \, y_i \tag{2}$$

Where v_i is the validity of the local model given as follow:

$$v_i(k) = \frac{(1-(r_i(k))/1+\sum_{i=1}^{N_m} r_i(k))}{N_m - 1}, i = 1, \dots, N_m \quad (3)$$

Subject to:

$$\sum_{i=1}^{N_m} v_i(k) = 1 \quad (4)$$

Where:

N_m : Number of model in the base,

3. PROPOSED SOLUTION FOR CONVENTIONAL MULTIMODEL

The classic multi-model structure representation remains constrained by two aspects. The first concerns the search for the optimal number of sub-models, and the second involves calculating the validity of each model. Several research works demonstrate contributions regarding multi-model representation. In this context, we propose a structure different from the classical one, allowing, through a neural network, to limit the number of sub-models on one hand and to improve the validity calculation of each sub-model on the other hand. The structure is presented in Figure 2. The solution consists on a set of models $M = \{M_1, M_2, \dots, M_n\}$ which are obtained by Fuzzy k-means algorithm. Originally defined by Dunn [30] and later refined by Bezedek [31], Fuzzy k-means is one of the most widely used clustering methods. With a predefined number of cluter (k) and the number of observation (N), This approach aims to identify fuzzy clusters by calculating cluster centers C_j and assigning data x_i points to these centers, and thus is done by minimizing a specific objective function given by:

$$J_m = \sum_{j=1}^{K}\sum_{i=1}^{N} \mu_{ij}^m \left\| x_i - c_j \right\|^2, 1 \le m \le \infty; \quad (5)$$

μ_{ij} degree of membership of x_i to cluster j , $\sum_{j=1}^{K} \mu_{ij} = 1$;

For each model is assigned a set of correspondent validity computation $V = \{v_1, v_2, \dots, v_n\}$

We are seeking to minimize the difference of each sub-model, taking into account its validity, with respect to the desired output of the global model. Therefore, minimizing this difference involves optimizing the validity of each sub-model to achieve minimal error. In essence, the goal is to adjust the weights or contributions of each sub-model so that their combined output closely approximates the desired output, using their respective validity as a guide for this optimization. In this work, the neural network is represented by a feedforward structure consisting of three hidden neurons with a hyperbolic tangent transfer function, and an output layer with a linear transfer function. During the optimization process, the weight parameters are encapsulated in the parameter vector θ = {w1, w2}. These parameters are randomly chosen and uniformly distributed between -0.5 and 0.5. The input and output are normalized such that their mean values are zero and their standard deviations are 1. The Levenberg-Marquardt method was chosen for optimization due to its robustness and fast convergence properties. It is based on nonlinear minimization techniques which aim to :

$$\underset{\theta_i}{Min}\left(\sum_{j=1}^{N_m} (f_{NN}(\theta_i)(v_i y_i - y)^2 - y\right). \quad (6)$$

The parameters of the neural network are determined according to an iterative procedure governed by:

$$\theta_{k+1} = \theta_k - (J_k^T J_k + \mu I)^{-1} J_k E_k \quad (7)$$

Here, J_i denotes the Jacobian matrix comprising the first derivatives of the network errors with respect to the weights, and E represents the error vector of the network. The Jacobian matrix J_i is computed using standard backpropagation techniques. The optimization process is facilitated by an online recursive least squares procedure.

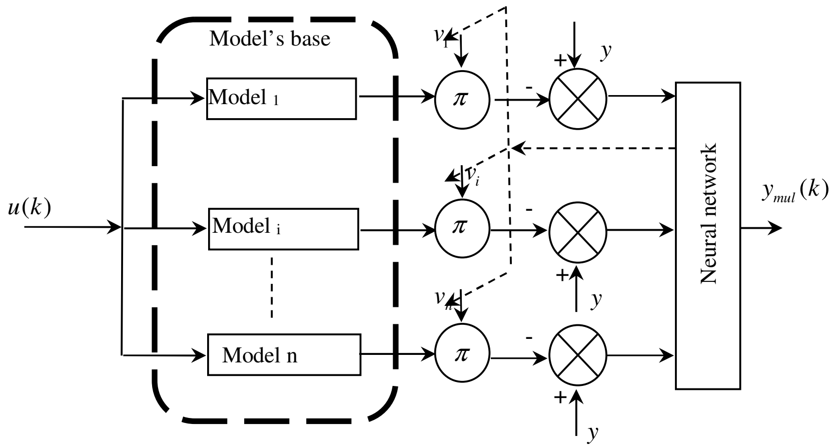

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Fig. 2 Multimodel representation :new concept

4. SIMULATION AND EXPERIMENTAL RESULTS

In this section, to evaluate the effectiveness and efficiency of the proposed method, simulations are conducted via three representative dynamical system identification examples. These simulations analyze the identification results using two primary performance metrics. One of these metrics is the Variance Accounted For (VAF), which quantifies the percentage of variance explained between two signals using the formul
Where:

$$VAF = 100\left[1 - \frac{\mathrm{var}(y - \hat{y})}{\mathrm{var}(y)}\right]$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y - \hat{y})^2 \tag{8}$$

Where:

y : The process output and $\hat{y}$ is the estimated process output.

4.1. Dynamic system modelling

The modeling aspect is illustrated by the dynamics of the system studied in this section. A nonlinear dynamical system is studied with the corresponding dynamical equation given by [28] as follow:

$$y(k) = 0.72y(k-1) + 0.025y(k-1)u(k-1) + 0.01u^2(k-2) + 0.3u(k-3)$$
$$u(k) = \begin{cases} \sin(\pi k/25) & 0 \le k \le 250 \\ 1 & 250 \le k \le 500 \\ -1 & 500 \le k \le 750 \\ 0.3\sin(\pi k/25) + 0.1\sin(\pi k/32) + 0.6\sin(\pi k/10) & 500 \le k \le 1000 \end{cases} \tag{9}$$

The simultaion results demonstrate the validity of the neural network using three submodels as well as the output results compared to the actual values. This example shows the suitabiity of the modeling approach, highlighting a VAF of value 99.8819 and an MSE of a value 1.76410^{-4}

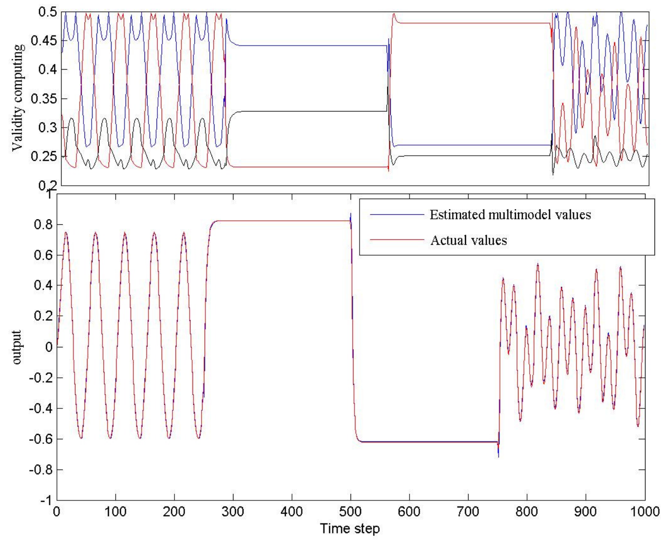

Fig. 3 Multimodel representation :Dynamic system case study

4.2. Biological reactor model base construction example

To emphasize the significance and contributions of our new modeling approach, we compare our results with those presented in [32] and [33] using the same bio-reactor system. The biological reactor, a notable example of a nonlinear system, has been extensively studied for modeling and control in various works [34-36]. The discrete model is described by the folowing equation :

$$
\begin{aligned}
x_{k+1}^{(1)} &= x_k^{(1)} + 0.5\frac{x_k^{(1)}x_k^{(2)}}{x_k^{(1)}x_k^{(2)}} - 0.5u_k x_k^{(1)}, \\
x_{k+1}^{(2)} &= x_k^{(2)} - 0.5\frac{x_k^{(1)}x_k^{(2)}}{x_k^{(1)}x_k^{(2)}} - 0.5u_k x_k^{(2)} + 0.05u_k, \\
y_k &= x_k^{(1)},
\end{aligned}
\tag{10}
$$

The system's output y represents the microorganism concentration, and the control input u denotes the output flow rate. Our task involves using multimodeling in this new configuration to validate the acquired model for simulating the bioreactor. We employed two types of experimental data: firstly, 2416 data points were collected to identify the number of models and the structure of each submodel. In this setup, the system described by Equation (34) was excited with a 4-second-long stair signal with random amplitudes between $0 \le u \le 0.7$. Secondly, 602 training points were used to validate our modeling strategy. Our approach resulted in the design of a new multimodel structure with only 3 linear models, compared to 9 models obtained in [25] and 10 models in [33, 36]. The smaller database size underscores our approach's ability to achieve satisfactory representation with fewer models for the same system under study. From the results obtained, the multimodel constructed with 3 submodels demonstrated the best performance with an MSE of 2.720×10^{-7}compared to the 10 models yielding an MSE of 3.1774×10^{-4} in [36]. In figure 3 we present the three validity computation for each model and respectively the neural network validity

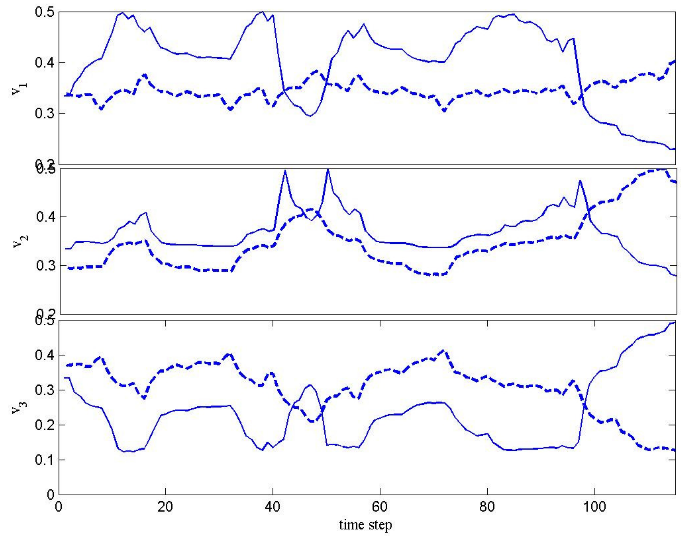

Fig. 4. Validity computation: Simple validity (dotted line), Neural network validity (dashed line) :Bioreactor system

The modeling results for a specific input are shown in Figure 4, demonstrating the ability of the proposed approach to accurately represent the system model

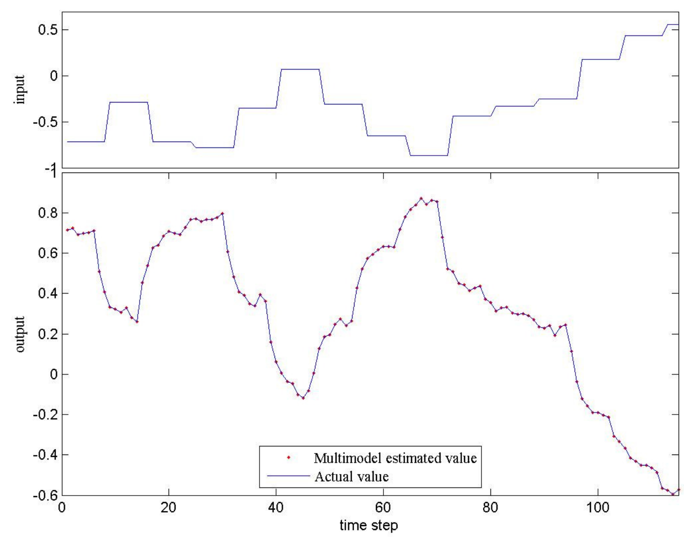

Fig. 5. Multimodel Biorector modeling

4.3. Boost converter study Model base construction

The Boost converter process involves the following setup: A block diagram depicts the signal controlling the power transistor switching via the MOSFET driver (Fig 4). The boost converter's output connects to the microcontroller's analog-to-digital converter (ADC) input. Key characteristics of the system to be identified include a supply voltage VDC=12V, output voltage Vout=24V, switching frequency of 80 kHz, load resistance Rch=, and a duty cycle D0=0.5. To establish a multimodel for the Boost converter, we generated experimental datasets using an amplitude-modulated pseudo-random binary signal (APRBS) as the excitation signal.

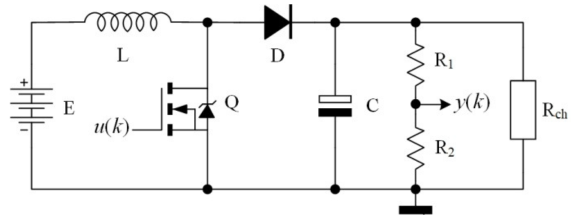

Fig. 6.Boost Converter bloc diagram

By setting three neurons in the hidden layer of the neural network, the number of sub-models is limited to three. The evolution of each validity—both simple and optimized using the neural network—is recorded in Figure 5. The structure of each model is given by:

$$y(k) = -\sum_{i=1}^{n_a} a_i y(k-i) + \sum_{j=1}^{n_b} b_j u(k-j) + c_i \tag{11}$$

Where a_i and b_j are the parameters of the i^{th} model

Based on the set of 900 experimentally collected values (Fig 7), the online optimization procedures for validity for each model are shown in figure 8. The modeling results of the Boost converter using three models, adhering to equation 11, demonstrate good performance compared to current values Fig 9. A comparison is thus made, summarized in Table 1, between the newly adopted approach and the conventional procedure, showing the ability of this approach to model nonlinear systems with good accuracy.

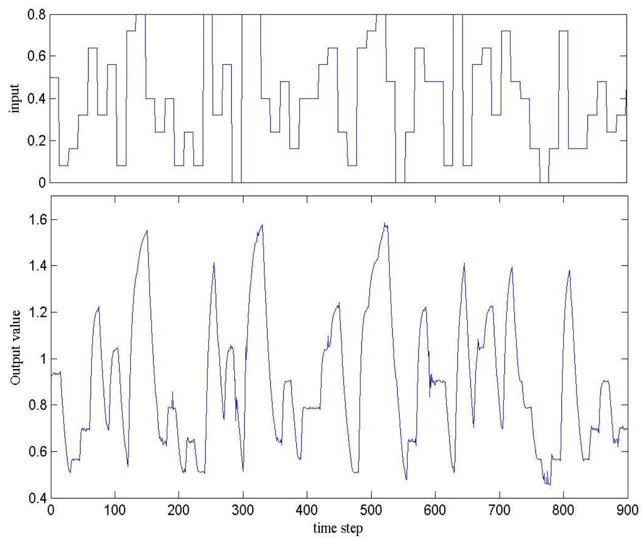

Fig. 7.Boost Converter Input/output data

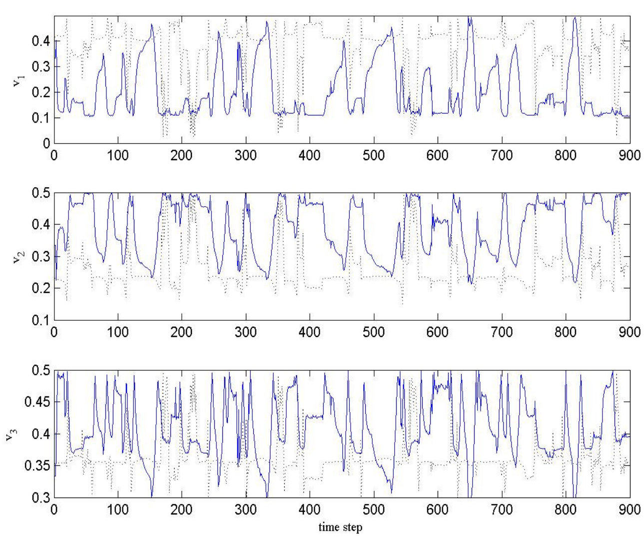

Fig. 8. Validity computation: Simple validity (dotted line), Neural network validity(dashed line) :Boost converter case study.

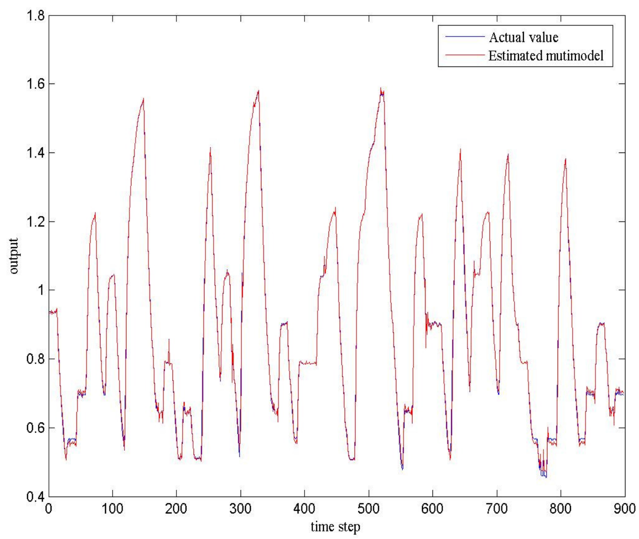

Fig. 9.Multimodel Boost Converter results

Table 1*. Performance comparison*

	MSE	VAF
Conventional Case	0.0107	83.2311
New approach	1.1510^{-4}	99.8199

5. CONCLUSION

In This paper, the validity computations of the multi-model structure are optimized using neural network. The weight coefficients of the optimal network are learned using the Levenberg-Marquardt algorithm, which are effectively implemented to identify a nonlinear dynamical system of a boost converter. The proposed multi-model structure shows very satisfactory results for nonlinear modeling while using the minimum number of sub-models

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