Design of optimal robust adaptive Neuro-Fuzzy inference controller using sliding mode approach for application to DC-DC converter

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Abstract. The present paper is a systematic and simple approach to design adaptive neuro-fuzzy inference system (ANFIS) controller; application to bucks DC/DC converter system. The design of neuro-fuzzy inference controller is based on enhancement of the performances of the sliding mode controller, in particular, the robustness and system time fast response. The Sliding Mode Control (SMC) theory associated to DC/DC Converters has been used in recent years in many applications and offer estimated performances to DC/DC converter control. The paper describes a new approach to design ANFIS controller based on sliding mode data studied in the previous article, the strategy proposed harness the advantages of the ATSMC and PID-SMVC strategy and eliminate the imperfections of the sliding mode strategy. The simulation results of both systems using ANFIS and sliding mode are shown as well as compared to signify better of the two. The advantages of the design proposed are illustrated by the simulation results.

Keywords: Adaptive Neuro-Fuzzy inference system, Buck DC/DC converter, Sliding mode,

1. Introduction
Nonlinear control methods have significantly developed in terms of theory and practice. Numerous methods and approaches exist for the analysis and design of nonlinear control systems. Important theoretical developments have been obtained in the fields of nonlinear robust control methods such as sliding mode control or intelligent control. The Sliding Mode Controller (SMC) has attracted the interests of many researchers due to its fast response and robustness against disturbance, noise, and uncertainty. The main reason for choosing this controller is its acceptable control performance for a wide range of operating conditions. Also, two main challenges to control, namely stability, and robustness can be effectively solved using this method [1]-[2]. In conventional SMC, the sliding surface is usually a linear surface that only guarantees the asymptotic stability. Thus, error dynamics cannot converge to zero in finite time. By tuning the parameters of SMC, faster error convergence can be achieved. However, this increases the control gain and thereby leads to a chattering phenomenon on the sliding surface that may damage the system [3].

The other interesting nonlinear control methods based on intelligent control theory known as ANFIS are a class of adaptive networks that incorporate both neural networks and fuzzy logic principles. Neural networks are supervised learning algorithms which utilize a historical dataset for the prediction of future values. In fuzzy logic, the control signal is generated from firing the rule base.
This rule base is drawn on historical data and is random in nature. This implies that the controller’s output is also random which may prevent optimal results. The use of ANFIS can make the selection of the rule base more adaptive to the situation. In this technique, the rule base is selected utilizing the neural network techniques via the back propagation algorithm. To enhance its applicability and performance, the properties of fuzzy logic, i.e. approximating a non-linear system by setting IF-THEN rules is inherited in this modeling technique. This integrated approach, makes ANFIS to be a universal estimator [4].

The goal behind the design is to propose a DC/DC buck converter control method based on ANFIS strategy, where this controller offers to the user the opportunity to handle the parameters of the membership functions based on data collected. The training capacity of the ANFIS is behind the idea to use the data collected from the SMC method described in [5]. To proof the performances of the design proposed based on SMC described in [4]-[5]; a comparison was done with other SMC strategy recognized by their performances. The advantage of the ATSMC introduced in [6]-[7] is to adjust the hysteresis width regarding the changes in input voltage and the sliding coefficient regarding the step load changes. The PID-SMVC strategy described in [8]-[9] is based on the model of the buck converter with bilinear terms. The performances results of the SMC proposed offered a compromise between the ATSMC and PID-SMVC. So the objective of this study is to design ANFIS controller with the best characteristics of the both methods (ATSMC and PID-SMVC) regarding the faster time response and the robustness all based on SMC method results as training data.

2. Adaptive Fuzzy-Logic inference system Strategy

2.1 ANFIS Architecture

ANFIS appertain to a family of the hybrid system ‘neuro-fuzzy networks’ mix the properties of both fuzzy logic and neural networks. The ANFIS architecture as defined has a function similar to the model of Takagi–Sugeno fuzzy inference system [10]-[11]. The system is supposed with one output \( f \) and two inputs \( x \) and \( y \). As shown below, for Takagi–Sugeno model two rules were used in the method of “If-Then”:

\[
\mu_i(x) = \begin{cases} 
1 & \text{if } x \in A \text{ implying full membership} \\
0 & \text{if } x \notin A \text{ implying non membership} 
\end{cases} \quad (1)
\]

ANFIS architecture is an adaptive network that uses supervised learning on learning algorithm, which has a function similar to the model of Takagi–Sugeno fuzzy inference system [12]-[13]. Figure.1 shows the architecture of ANFIS structure. For simplicity, assume that there are two inputs \( x \) and \( y \), and one output \( f \). Two rules were used in the method of “If-Then” for Takagi–Sugeno model, as follows:

Rule 1 = If \( x \) is \( A_1 \) and \( y \) is \( B_1 \) Then \( f_1 = p_1x + q_1x + r_1 \) \quad (2)

Rule 2 = If \( x \) is \( A_2 \) and \( y \) is \( B_2 \) Then \( f_2 = p_2x + q_2x + r_2 \) \quad (3)

Where \( A_1, A_2 \) and \( B_1, B_2 \) are the membership functions of each input \( x \) and \( y \) (part of the premises), while \( p_1, q_1, r_1 \) and \( p_2, q_2, r_2 \) are linear parameters in part-Then (consequent part) of Takagi–Sugeno
fuzzy inference model. Referring to Figure 1, ANFIS architecture has five layers. The first and fourth layers contain an adaptive node, while the other layers contain a fixed node.

In order to assure that the controlled system operates properly the existing condition and stability must be verified. These are the summarized controller design steps; but also the system modeling could be considered as a design step.

![Figure 1. Architecture of ANFIS Structure](image1)

3. Adaptive Fuzzy-Logic inference system Controller Design

3.1 System Modeling

To illustrate the underlying principle, the state space description of the buck converter under sliding mode voltage control, where the control parameters are the output voltage error dynamic and capacitor current, is first discussed in [3]. Figure 2 shows the schematic diagram of the ANFIS control of a buck converter.

![Figure 2. Synoptic diagram of the ANFIS controller of a buck converter](image2)
In this case, the control signal $u$ is a nonlinear function as a function of the capacitor current $I_c$, the error $e$ and its derivative $de$.

$$u = f(I_c, k \cdot e, de)$$  \hspace{1cm} (4)

Where $V_i$, $V_o$, $I_c$, $C$, $L$, and $R_L$ are the input voltage, output voltage, capacitor current, capacitance, inductance, and load resistance respectively. The coefficient $k$ ensures stability and sets the desired dynamic and static performance.

### 3.2 ANFIS Controller Structure

The generic scheme of the ANFIS controller proposed is illustrated by the Figure.3.

![Figure 3: Structure of an ANFIS regulator with proportional controller](image)

Using the current in the capacitor $I_c(t)$ and the output voltage $V_o(t)$ error as state variables, the state space equation involving the simple model with integral action to avoid static error voltage in steady state is:

$$\begin{align*}
    e &= V_{ref} - V_o \\
    de &= \frac{d(V_{ref} - V_o)}{dt} \\
    dI_c &= -\frac{1}{R_i C} I_c - \frac{1}{L} V_o + \frac{1}{L} V_{ref} u
\end{align*}$$  \hspace{1cm} (5)

Where $V_{ref}$ is reference voltage and $u$ the control input.

### 4. Structure of ANFIS System

Adaptive Network based Fuzzy Inference System ANFIS is implemented as a Sugeno fuzzy inference system. ANFIS system allows the user to choose or modify the parameters of the membership functions based on the data. The parameters are adjusted automatically by the neuro
adaptive learning techniques like back propagation algorithm or hybrid method (which is a combination of back propagation and least squares method). These techniques allow the fuzzy inference system to learn information about the dataset. During the learning process, the parameters of the membership functions will be changed. Sugeno systems are more compact and computationally efficient representation than a Mamdani system.

4.1 ANFIS Model

The structure of the neuro-fuzzy model adopted here has three inputs and one output as illustrated in Figure.4. The first input is the capacitor current, the second input is the output voltage error and the third input is the derivative of the output voltage error. The outputs illustrate the ANFIS control ($u$) of the DC-DC converter switch. These inputs are represented by two fuzzy membership functions for the first input and three membership functions for each second and third input, resulting in a total of 18 fuzzy rules. The system has a single output representing the stabilizing signal.

![ANFIS model with three inputs and one output](image1)

**Figure.4.** ANFIS model with three inputs and one output

Structure of the Sugeno model is designed in such a way that the input is mapped to input membership function, the input membership function is mapped to rule, then the rule is mapped to output membership function and then the output membership function is mapped to the output. Thus the system takes five layers.

Each node in the first layer generates a membership grade. Each node in the second layer calculates the firing strength of the rule. Each node in the third layer calculates the ratio of the $i^{th}$ rule’s firing strength to the total of all firing strength [16]-[17]-[18]. Each node in the fourth layer is an adaptive node which maps to the output membership functions. The node in the fifth layer gives the overall output. The ANFIS structure is shown in Figure.5.

![Neuronal structure of the ANFIS](image2)

**Figure.5.** Neuronal structure of the ANFIS
The input membership functions for each of the three inputs are depicted in Figure 6.

![Graphs showing input membership functions for Ic, e, and de](image)

**Figure 6.** Input membership functions (a) $I_c$, (b) $e$ and (c) $de$

The collected data is used to train ANFIS with the objective of automatically generating the fuzzy rules that match a corresponding output for each given pair of inputs [14]-[15]. Since this fuzzy model is of the Sugeno type, unlike the Mamdani model, the output is crisp rather than fuzzy.
Therefore, there will be an output value for each of the 18 fuzzy rules generated by the ANFIS structure instead of fuzzy output membership functions. However, the fuzzy decision surface is concisely represented here in a three-dimensional space to examine the degree of nonlinearity that this fuzzy stabilizer is capable of capturing. This fuzzy decision surface, shown from Figure 7a and 7b, plots the fuzzy output versus the two inputs.

![Surface plots](image)

**Figure 7.** Surface plot of $u$ (a) as a function of $e$ and $de$, (b) $u$ as a function of $e$ and $I_c$, and (c) as a function of $de$ and $I_c$.

### 4.2 ANFIS Training

It is a learning process of the developed model. The model is trained till the results are obtained with minimum error. To design an ANFIS system for real world problems, it is essential to select the parameters for the training process [19]-[20]. It is essential to have proper training and testing data sets. If the datasets are not selected properly, then the testing data set will not validate the model. If the testing data set is completely different from the training dataset, then the model cannot capture any of the features of the testing data. Then, the minimum testing error can be achieved in the first epoch. For the proper data set, the testing error decreases with the training proceeding until a jump point. Over fitting occurs when the training passes that point. The optimization methods are used to learn about the training data.

Training the ANFIS system with the training data set is shown in the Figure 1. The training error is the difference between the training data output value, and the output of the fuzzy inference system corresponding to the same training data input value, (the one associated with that training data output.
value. The training error records the root mean squared error of the training data set at each epoch. The ANFIS Editor GUI plots the training error versus epochs curve as the system is trained. Testing the trained FIS is shown in Figure 8a. The FIS testing with the training data is shown in Figure 8b; the average testing error for the training data set is 0.04062.

Figure 8. (a) Training error and (b) Testing the FIS with Training data set

Traditionally, the rule table of a fuzzy controller is often designed by in-depth knowledge of the system. It is then tuned using trial and error method. Extensive tuning requires a significant amount of time. On the other hand, the proposed design method determines the rule base of an ANFIS controller based on the principle of sliding mode control. The rule extraction method first determines the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule’s consequent equations. The table (I,II) below shows the inference configurations selected and tested:

<table>
<thead>
<tr>
<th>TABLE I</th>
<th>INFERENCE TABLE: CASE OF IC NORMAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>ε</td>
<td>INF</td>
</tr>
<tr>
<td>de</td>
<td>0</td>
</tr>
<tr>
<td>AVR</td>
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</tr>
<tr>
<td>SUP</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE II</th>
<th>INFERENCE TABLE: CASE OF IC LIMIT</th>
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<tr>
<td>ε</td>
<td>INF</td>
</tr>
<tr>
<td>de</td>
<td>0</td>
</tr>
<tr>
<td>AVR</td>
<td>-114.3</td>
</tr>
<tr>
<td>SUP</td>
<td>-0.02264</td>
</tr>
</tbody>
</table>
5. Simulation results

In order to demonstrate the performance of the proposed SMC strategy, simulation results of the proposed sliding mode controller are provided to validate the theoretical design and are conducted on the buck converter described below. Simulations are carried out using Simulink of Matlab. The parameters of the system are $V_i=40V$, $V_o=28V$, $V_{ref}=2.8V$, $L=125mH$, $C=250\mu F$, $R_L=15\Omega$, and $f_s=100kHz$. They are chosen to comply with the design restrictions and have been fine tuned to respond to the desired regulation and dynamic response.

A figure below shows the simulated start-up and transient response of the output voltage, output current and the inductor current obtained by ANFIS strategy and compared to sliding mode, himself was compared to adaptive terminal sliding mode control (ATSMC) and PID-SMVC strategy, described respectively in [5].

**Figure 9.** Time responses and transient response of output voltage $V_o$, for a variation of the load $R$ from $15\Omega$ to $5\Omega$ at time $0.05s$

**Figure 10.** Time responses and transient response of inductor current $I_L$, for a variation of the load $R$ from $15\Omega$ to $5\Omega$ at time $0.05s$
Figure 11. (a) $V_o$ output voltage time responses and transient response, with the presence of a short perturbation in the input voltage $V_i$ and (b) $V_o$ transient response due to a step change in input voltage $V_i$ at time $t=0.05s$
The controller performances are studied using a load resistance step change from 15Ω to 5Ω for constant switching frequency of 130 kHz. The transient responses are due to a $R_L$ step change from 15Ω to 5Ω at $t=0.05s$. From the Figure.9, it is obvious that the reference is successfully tracked by the output voltage in all cases, the controller acts very fast in correcting the output voltage. The time response and the transient response of the ANFIS (0.2ms) are faster and stable than the SMC strategy (1.8ms) [5]. The inductor current overshoot is higher in the case of the ANFIS than the SMC strategy as shown in Figure 10. The transient responses due to a step change in $V_i$ as well are studied, it is obvious from the Figure.11.a that the time response of the $V_o$ obtained by ANFIS strategy is faster and stable than that obtained by the SMC strategy. The transient responses due to drop voltage in $V_i$ in Figure.11.b, show that the ANFIS strategy offer a stable response compared to the SMC strategy where we can see oscillation due to this drop voltage. A step change in $V_{ref}$ is as well the origin of transient responses as shown in Figure.12.a, the ANFIS strategy is faster than that of obtained by SMC, the drop voltage is as well deeper than the ANFIS strategy. The transient responses of the Figure.12.b due to drop voltage in $V_{ref}$, the ANFIS strategy is still faster and stable than that of obtained by SMC.

6. Conclusion

In this paper, ANFIS controller design is based on SMC approach data proposed to control a buck DC/DC converter. The rules base and Control techniques of sliding mode, finite-time asymptotic convergence, and to reduce fuzzy rules was obtained. The different results demonstrate that the performance of the system is strongly affected by the selection of datasets for training the ANFIS system. It has been proven that by using different training data sets, the performance of the ANFIS can be improved. If the datasets used for testing is extremely different from the one of the training dataset, then the system fails to catch the essential features of the dataset. Therefore, the performance of the system is affected by the design of the datasets. Compared to the SMC strategy proposed in [5], The ANFIS strategy proposed in this paper offers the best performances of the both ATSMC and
PID-SMVC methods described in [5], whereas the ANFIS strategy proposed is characterized by the best dynamic performance of each the strategy cited.

References