Abstract—This paper presents a study on the implementation of a Supervised Adaptive Neuro-Fuzzy Inference System (S-ANFIS) controller for a permanent magnet synchronous motor applied to the power train system of a Hybrid Electric Vehicle (HEV). An ANFIS model implementation aims to optimize the parameters of a fuzzy system through a learning algorithm and a set of inputs and outputs, which are responsible for the learning process. The comparative study presented in this research work, focuses on an evaluation between a conventional and a S-ANFIS controller based on their performance, complexity, response-time, accuracy and efficiency for the power train system of a HEV. Also, it is demonstrated the importance and benefits of using artificial intelligence in control techniques for power train systems control. The comparative results are analyzed, discusses and based on them further research work has been defined.

Index Terms—Supervised Adaptive Neuro-Fuzzy Inference System, Hybrid Electric Vehicle, AC motors, permanent magnet synchronous motor, vector control, artificial neural network, power train system.

I. INTRODUCTION

The implementation of Artificial Intelligence (AI) control techniques for automotive applications has reached important design levels in order to avoid negative environmental and economic impacts. Nowadays, the problems that affect the environment have a serious impact over humanity, e.g.: acid rain, greenhouse effect, respiratory failures, chronic diseases, and even cancer. The current technology in the auto-industry has a lot of fault on this environmental problem. Since some years ago, one of the most important solutions proposed by industry and academia has been the implementation of new green energy sources in order to decrease the levels of pollution. It is known that one of the biggest pollution sources in the world comes from the gas vehicles emissions. For this reason, many different solutions have been proposed with the intention to manufacture vehicles with fewer gas emission and desirable rates of fuel consumption.

In this order, different academic, auto-industry and other research groups involved in vehicles’ development performance area have been working in the improvement of different Engine Control Units (ECU) to achieve higher power engine performance and fewer gas exhaust emission, better control techniques, innovation in power train systems and design of new hybrid vehicle concepts. In this way, several research works have been developed about AI systems for automotive applications.

In the automotive control area, numerous research works have been proposed to optimize the performance of fuel injection systems with the application of intelligent control systems. In 2005, M. Mohebbi & M. Charhgard [1] developed a control strategy based on an adaptive neuro-fuzzy inference system method that was applied to parallel hybrid electric vehicles. The objective was to adjust the throttle in the combustion engine to achieve the maximum output torque of the vehicle while minimizing fuel consumption used by the internal combustion engine. The inputs of the system were the desired torque and the battery pack SOC (state of charge). The results showed a significant performance improvement of the vehicle with the ANFIS model proposed in comparison with Mohebbi’s previous work [2] where it was implemented a fuzzy control system to achieve the same objective proposed with the ANFIS model [1].

For an adaptable intelligent control to the different loads of an engine’s requirements, it is useful to implement an Adaptive Neuro-Fuzzy Inference System (ANFIS) that combines the benefits of an AI network with the benefits of the fuzzy inference system in a single model. This structure allows having two intelligent approaches achieving good reasoning in quality and quantity. In other words, this structure has fuzzy reasoning and AI network calculation [3].

The ANFIS controller implemented in this work is based on an existed vector control, which is used in a HEV model (see Fig. 6). The vector control is implemented to control the electromagnetic torque and rotor flux in a Permanent Magnets Synchronous Motor (PMSM). It is known that vector control is widely implemented for AC asynchronous and/or synchronous machines used as industrial drives or to any other power application. The idea with vector control is to control AC machines as DC machines by means of a decoupled control of the rotor flux magnitude and the torque-producing current [4]. Thus, the ANFIS model is used to learn the vector control responses and later on makes the replacement of the conventional controller by the S-ANFIS controller, then the system responses with the conventional and S-ANFIS controllers are compared and evaluated.

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The development of this study is presented in seven sections. In section II, the analysis of an ANFIS model is introduced in order to understand clearly how the algorithm works. In section III, the definition of supervised control is provided in order to understand how it is trained by the ANFIS controller and why this becomes a supervised controller. In section IV, the definition of vector control is given in order to understand how the vector control works and the importance of its implementation in AC machines. In section V, the S-ANFIS controller implementation and results are presented. In section VI, is discussed the results obtained from the S-ANFIS controller implementation in order to define which controller has the best performance in terms of performance, complexity, response-time, accuracy and efficiency. Finally, in the last section, conclusions from the simulations carried-on and final results obtained are exhibited.

II. ANFIS MODEL

An ANFIS model combines the artificial neural network’s benefits with the fuzzy inference system’s profits in a single model. This kind of model has become very popular due to its characteristics such as: fast- and accurate- learning, and the capacity of data management [5]. The main objective of ANFIS is to optimize fuzzy system’s parameters (in the way to obtain an accurate answer to a problem) through a learning algorithm implementation and a set of inputs and outputs which are responsible of the learning process. Those sets are used to build a fuzzy inference system, from here the membership function parameters are adjusted by a hybrid training algorithm, which combines gradient descent and the least-square method. The least-squares method is actually the major driving force that leads to fast training, while the gradient descent serves to slowly change the underlying membership function that generates the basic functions for the least-squares method [6]. This type of adjustment allows the fuzzy model to learn the data set that we are providing.

The adaptive neuro-learning works in a similar form as a neural network. The adaptive neuro-learning model provides a procedure of fuzzy modeled to learn information from a set of data [7]. In this particular case, we have a previous set of inputs and outputs data and if we do not know how the behavior of the system is, we cannot configure a determined number of membership functions. The Fig. 1 shows the general structure of the ANFIS.

![Fig. 1. ANFIS General Structure](image)

The associated parameters to the membership functions change during the learning process. These variations are calculated due to a vector, which is called: “gradient”. This vector is useful to know how approximate are the results of the ANFIS outputs in relation to the reference outputs. Once the gradient is obtained, many routines of optimization are applied to adjust the parameter and minimize the error [8]. It is important to take into account that two different rules cannot share the same membership function, although the number of rules is the same that the number of membership functions of the output.

To illustrate Sugeno type rules having outputs that linear combination of their inputs are:

\[ \text{if } x \text{ is } A_1 \text{ AND } y \text{ is } B_1, \text{ then } f_1 = p_1 x + q_1 y + r_1 \]
\[ \text{if } x \text{ is } A_2 \text{ AND } y \text{ is } B_2, \text{ then } f_2 = p_2 x + q_2 y + r_2 \]

Fundamentally, ANFIS is a graphical network representation of Sugeno-type fuzzy systems, endowed with neural learning capabilities. The next sub-section explains in detail how the hybrid learning algorithm works, which is the learning method implemented in this work.

A. Hybrid Learning Algorithm

Fig. 1 depicts an ANFIS structure and how adaptive neuro-learning and fuzzy models are combined. Moreover, an important part of ANFIS is related to the learning algorithms. For this work, a hybrid learning algorithm was implemented; this one is a combination of least square and backpropagation method [9]. Considering the least square part and an output \( y \) by the parameterized equation:

\[ y = \theta_1 f_1(u) + \theta_2 f_2(u) + \ldots + \theta_n f_n(u) \quad (1) \]

Where:
\[ u = [u_1, \ldots, u_n]^T \] is the model inputs vector.
\( f_1, \ldots, f_n \) are known functions.
\( \theta_1, \ldots, \theta_n \) are unknown parameters.

Substituting each data pair in equation (1) a set of linear equations is obtained.

\[ A\theta = y \quad (2) \]

Where:
\[ A = \begin{bmatrix} f_1(u_1) & \ldots & f_n(u_1) \\ \vdots & \ddots & \vdots \\ f_1(u_m) & \ldots & f_n(u_m) \end{bmatrix} \]
\[ \theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix} \]
\[ y = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \]
An error vector is introduced to account for the modeling error:

\[ A\theta + e = y \quad (3) \]

Searched for \( \theta = \hat{\theta} \) which minimizes sum of squared error...

\[ E(\theta) = \sum_{i=1}^{m} (y_i - a^T_i \theta)^2 = e^T e \quad (4) \]

The equation (4) is called the objective function. The squared error in (4) is minimized when \( \theta = \hat{\theta} \), called: “Least Squares Estimator (LSE)” that satisfies the normal equation...

\[ A^T A \hat{\theta} = A^T y \quad (5) \]

If \( A^T A \) is non-singular then...

\[ \hat{\theta} = (A^T A)^{-1} A^T y \quad (6) \]

Moreover, for the back-propagation learning the main part concerns to how to recursively obtain a gradient vector in which each element is defined as the derivative of an error measure with respect to a parameter. Considering the output function of node \( i \) in layer \( l \)

\[ x_{l,i} = f_{l,i}(x_{l-1,1}, \ldots, x_{l-1,N(l-1)}, \alpha, \beta, \gamma, \ldots) \quad (6) \]

Where \( \beta, \gamma, \alpha, \ldots \) are the parameters of this node. Hence, the sum of the squared error defined for a set of \( P \) entries, is defined as:

\[ E_p = \sum_{k=1}^{N(l)} (d_k - x_{l,k})^2 \quad (7) \]

Where \( d_k \) is the desired output vector and \( x_{l,k} \) both for the \( k^{th} \) of the \( p^{th} \) desired output vector. The basic concept in calculating the gradient vector is to pass from of derivative information starting from the output layer and going backward layer by layer until the input layer is reached. The error signal is defined as...

\[ \epsilon_{l,i} = \frac{\partial E_p}{\partial x_{l,i}} \rightarrow \epsilon_{l,i} = -2(d_i - x_{l,i}) \quad (8) \]

If \( \alpha \) is a parameter of the \( i^{th} \) node at layer \( l \), Thus, it is obtained the derivative of the overall error measure \( E \) with respect to \( \alpha \) is...

\[ \frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E}{\partial \alpha} \quad (9) \]

Thus for the generic parameter \( \alpha \) is...

\[ \Delta \alpha = -\eta \frac{\partial E}{\partial \alpha} \quad (10) \]

Where \( \eta \) is the learning rate. So, for parameter \( \alpha \) is defined...

\[ \alpha_{\text{new}} = \alpha_{\text{old}} - \eta \frac{\partial E}{\partial \alpha} \quad (11) \]

For hybrid learning algorithm, each epoch consists of a forward pass and a backward pass. In the forward pass equations (2) and (6) are implemented. Hence, the error measure for each training data pair is to be calculated. Then (8) is applied to find the derivative of those error measures. Thus, the error signal is obtained. In the backward pass, these error signals propagate from the output end towards the input end. The gradient vector is found for each training data entry. At the end of the backward pass for all training data pairs, the input parameters are updated by steepest descent method as given by equation (11).

Based on an ANFIS model and understanding its operation mode, it is now presented the development of the S-ANFIS control.

### III. Supervised Control

A conventional control design (e.g. on-off control, PID type controllers, etc.) implies three steps: 1) Plant characterization, 2) Controller design, and 3) Controller implementation. In these steps, it is possible to summarize the conventional control design process. Now, depending on the application, assumptions made and the desired performance of the control, it is chosen a tuning method to be applied in order to set the controller operation point within desired values. The method to design conventional controllers is widely applied to several applications in industry drives and processes control among other applications. Also, good control strategies designs have effective results for certain disturbances in the process or system. Despite that, for several processes and/or systems unexpected disturbances appear often, reason why control techniques capable to deal with those disturbances are quite useful in order to improve controller response. Thus, AI techniques are implemented in order to deal with those unexpected problems.

![Fig. 2. ANFIS Training](image)
controller but with the capability to deal with a higher number of disturbances; it also improves performance in terms of time response and accuracy. This defines the proposed controller in this work as a Supervised Adaptive Neuro-Fuzzy Inference (S-ANFIS) controller.

Fig. 3. S-ANFIS Scheme

Fig. 3 is the representation of the S-ANFIS implementation for the PMSM control loop.

IV. VECTOR CONTROL

Vector control of AC machines is an efficient approach to control speed of AC motors used for industrial drives. In Germany, Hass and Blaschke developed the principles of field oriented control [11], which was the beginning of what is known now as vector control. This control technique consists in to achieve an independent control of the rotor flux and the torque of an AC machines. This is possible by means of a decoupling of torque and rotor flux, which is possible with the vector control. In other words, vector control is a technique implemented to control AC machines like DC machines.

The expression for the electromagnetic torque of a DC machines is given for:

\[ T = K' t \psi n \]  

Where:
- \( I_a \): stator current
- \( I_f \): rotor current
- \( K' \): proportional constant

The important variables of (12) are \( I_a \) and \( I_f \), because these are the control variables for a DC machine and may be considered as orthogonal or decoupled vectors. In normal conditions \( I_f \) maintains a constant value equal to the nominal value, which makes the torque proportional to the stator current \( I_a \). This allows to decouple \( I_f \) (magnetic flux) and the stator current (torque). This method implemented in DC machines can be applied to AC machines as well, if the AC motor model is referred to a rotatory orthogonal axis at synchronous speed. Fig. 4 shows the basic idea of vector control.

Fig. 4. Vector Control Scheme

The Fig. 4 represents the general scheme of a vector control implementation. The components \( i_{qs} \) and \( i_{ds} \) are analogous to the stator current \( (I_a) \) and rotor current of a DC motor correspondly. Now the torque for an AC machine is given by:

\[ T = K |\psi n| I_{qs} I_{ds} = T = K' i_{qs} i_{ds} \]  

It is possible to note that expression (13) is similar to the expression (12). Therefore, the torque of an AC machine is expressed as the analogous of the DC machine torque [16].

Now, the variables of the expression (13) are decoupled. The processes implicated from the inputs variables \( (i_{qs} \) and \( i_{ds} )\) to the controller outputs are schematically explained in Fig. 5.

Fig. 5. Transformation Processes in Vector Control.
The transformation between stationary (s) to synchronous (e) frame references is achieved thanks to the unitary vector rotation $(\cos(w_1t) + j\sin(w_1t))$ applied. The first transformation made is called Inverse Park Transformation and the second (last step before the AC motor) is called: Inverse Clarke Transformation [12]. Another important part to mention is the requirement of a pulse width modulation (PWM) method, since the AC motor torque and the magnetic flux are closely related with stator current. Thus, the PWM method is applied to have a reliable controller signals transmission, reason by which is desires to have a low harmonics number [13].

This work mixes the techniques already defined and now it is presented a S-ANFIS controller for a PMSM of the HEV’s train power system. Next, it is presented the S-ANFIS implementation, the comparison with the conventional control vector and further analysis.

V. S-ANFIS CONTROLLER IMPLEMENTATION

In this section the controllers’ results are presented for further comparison and analysis. First the plant’s characteristics are presented.

A. Plant definition

The model used to implement the S-ANFIS controller is a PMSM into the HEV’s power train. The PMSM’s characteristics are listed in table1.

Table 1. PMSM’s Characteristics

<table>
<thead>
<tr>
<th>Permanent Magnet Synchronous Motor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power</td>
</tr>
<tr>
<td>Voltage</td>
</tr>
<tr>
<td>Poles</td>
</tr>
</tbody>
</table>

Also in the HEV model is implemented a DC/DC converter, batteries package of nickel-iron with a capacity of 21 kW, a combustion engine of 57 kW/ 6000 rpm, a planetary gear transmission to couple the energy sources (e.g. power delivered by engine and motor). The model was taken from Simulink-Matlab [14]. The model is shown in Fig. 6.

This work is limited to present the S-ANFIS controller implementation for the PMSM of a HEV’s power train. The other systems implicated as the vehicle dynamics, internal combustion engine and planetary gear subsystem are not explained in this paper.

Next, the control vector results for the HEV’s power train system are presented.

B. Conventional Vector Control

The vector control implemented takes the rotor speed $(w, \text{rad/s})$, rotor angle theta $(\theta, \text{rad})$, the torque $(N.m)$ controlled and the feedback current obtained after the inverter processing. Hence, with these variables calculated the stator and rotor currents are used in order to obtain the three-phases current for the PMSM, it is also calculated the PWM to modulate the controller’s output signals. The vector control result is presented in Fig. 7.

![Fig. 7. Vector Control Result](image1)

The Fig. 7 presents the currents and PWM results, when a conventional vector control is implemented to control a PMSM.

C. S-ANFIS Controller

The S-ANFIS controller is trained with vector control inputs and outputs. This data set allows us to train ANFIS for further implementation as a supervised controller. For the training process sets of intervals that gather the most relevant or important value ranges (e.g. most representative data sets) were used. Five membership functions were used for each input (the inputs were the same mentioned for the vector control) and it was implemented a hybrid training process. The result obtained is presented in Fig. 8.

![Fig. 8. S-ANFIS Controller Result](image2)

The results presented for the S-ANFIS controller shown how the pulses are modulated for the signal output changes.
VI. RESULTS DISCUSSION

Two control techniques were defined in order to understand the controller proposed in this paper. Now, the results obtained from the implementation and development processes are analyzed:

1. The current results for both controllers are within the desired values. Thus, the S-ANFIS training process was the most appropriate, since the desired results were obtained and the controller has an efficient performance.

2. The PWM response for the S-ANFIS controller has some variations when the current changes from decrease to increase. Those variations are result of the training process and correspond to variations in the system.

3. A S-ANFIS controller has an easier implementation when the actions and inputs are identified. Also the controller proposed is less complex than the vector controller.

A supervised control implementation is a great technique for systems in which disturbances can change the controller performance. Also, supervised control let designers and/or engineers to control processes, machines and mechanisms for different operation points.

VII. CONCLUSIONS

The implementation of S-ANFIS controller in a HEV model has given good results in terms of accuracy, simplicity and the capability to deal with unexpected disturbances. However, several variables need to be set in order to reach the desired control performance. Also from the results obtained, it is possible to note:

1. The PWM response for the S-ANFIS controller has some variations for current changes, which can be reflected in rotor speed variations. These variations can be minimized with a training process that has more membership functions, but this implies more computer resources used.

2. The training process takes a considerable time but when the training results are implemented the system maintains its stability and works faster.

3. The hybrid training process facilitates the convergence to the tolerance error and made the design process faster.

From the experience acquired in the development process done in this work, some inferences are listed:

1. For implementing a supervised control is mandatory to gather a set of inputs and targets from an existing controller and plant.

2. To develop an ANFIS controller the desired plant outputs and its corresponding inputs must be clear.

3. In the design process of controllers based on ANFIS or ANN, the most difficult part is to define how many neurons (or membership functions) are needed for the system and the correct set of values for the training process. The definition of these parameters is often an iterative process.

In this work the implementation of a S-ANFIS controller based on vector control was presented, and the performance obtained from the controller proposed was efficient.

A lot of AI controls can be implemented in order to improve mechanisms, machines and process. This research group will continue seeking improvements of HEV system in order to reach better level of control efficiency.

REFERENCES


