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MODELING OF PAM-BASED POSITION SERVOSYSTEM STATIC HYSTERESIS USING ANFIS

Alexander HOŠOVSKÝ

Faculty of Manufacturing Technologies,
Technical University of Košice, Prešov, SLOVAKIA

ABSTRACT :
This paper deals with static hysteresis modeling for the PAM-based (pneumatic artificial muscles) position servosystem by means of an adaptive neuro-fuzzy inference system. The hysteretic behavior is expressed in arm position-pressure difference dependence where the output variable (arm position) depends on the history of input variable (pressure difference). In this way, a first order (until input first reversal) curve and major loop of hysteresis are modelled, with separation technique being chosen for modeling. The function itself is approximated using adaptive neuro-fuzzy inference system which proved very effective in terms of approximation error even in case of sparse training sets. All the measurements and modelling processes are carried out in Matlab/Simulink with Fuzzy Logic Toolbox.
KEYWORDS:
ANFIS, hysteresis, major loop, fuzzy inference, approximation

1. INTRODUCTION

Hysteresis is a well-known phenomenon commonly found in magnetic, elastic or mechanic systems in engineering applications. When hysteretic behavior within some system is encountered, one cannot determine the system output based on the current input value only. Then the current output depends on the past extreme values of the input signal. Even though it is rather difficult to model, there are several methods for hysteresis modelling which found their widespread use in engineering practice. One of the most used is based on Preisach hysteresis model, which uses (in discrete case) a number of hysterons (representing non-ideal relay) with various on-off values and weighted outputs summed together to form the overall output. In order to calculate the current output, one has evaluate double integral and thus this method is computationally intensive. In case where the computation power would be an issue, off-line hysteresis modelling technique might be used.

There are many examples of hysteresis modelling using the Preisach model in combination with soft computing techniques. In [2], a neural network approach is used for approximating weight-input distance function. In this case, it is only possible to model symmetric hysteresis. In [9], a similar approach is used only that a neural network is used for approximating 2-D weight Preisach function. On the other hand, in [1] an inverse fuzzy Preisach model is used for modeling SMA hysteresis and then used for compensation in a real system. In [8], a different approach is chosen in which the hysteresis loop is modeled using fuzzy subtractive clustering technique with loop being separated into two parts (assuming continuity in the point of separation).

Pneumatic artificial muscles belong to the category of non-conventional actuator. Despite the fact that the very idea of actuators resembling biological muscles in some aspects of their performance is not a new one, the lack of advanced modelling techniques as well as computational issues in the period of their creation prevented their widespread use. Even today with such techniques available, the control as well as modelling of the systems based on PAM remains quite a challenge. Due to their construction (rubber tube being encased by a mesh made of fibers), they exhibit nonlinear and hysteretic behavior which together with specific features of mechanical systems are responsible for a static hysteresis of position-pressure difference dependence.

2. EXPERIMENTAL SETUP

The basic component of this setup was a pair of pneumatic artificial muscles (FESTO MAS-20). These muscles were installed as an antagonistic pair in order to actuate a revolute joint (Fig. 1). For controlling the amount of compressed air being fed in or out of the muscles, two twin-spool on-off valves were used (Matrix DMX821.104C224). These valves are designed for 24V DC and offer very good performance in terms of opening and closing times as well as possible frequencies of control signal. The arm position was measured by an optical encoder (IRC120) offering a resolution of 2500 pulses per revolution. Signal from the encoder was fed to I/O card (Humusoft MF624) equipped with 4 encoder inputs. The valve control signal was outputted through 4 digital outputs compatible with TTL logic. The PC was equipped with Intel Core2 Quad 8200 2.66 GHz running on 1333 MHz FSB and 4 GB RAM. The pressure difference was calculated using values of relative pressure in each of the muscles measured with two pressure sensors (PMD 60G-10V0QQ and Lutron PS-9302).

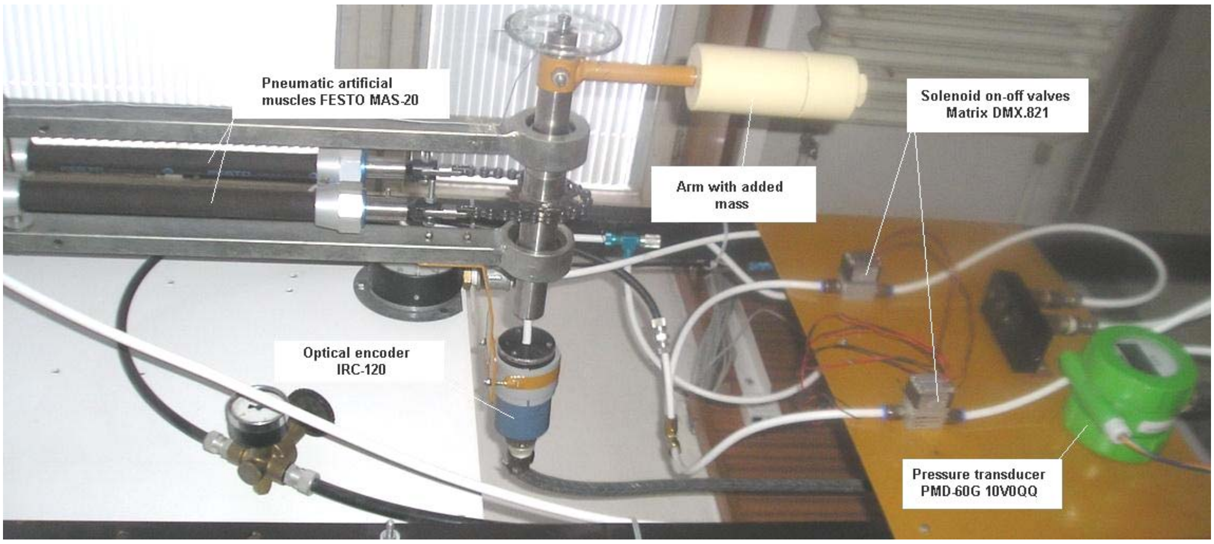

Figure 1. PAM-based position servosystem

3. ANFIS AND FUZZY SUBTRACTIVE CLUSTERING

ANFIS (Adaptive Neuro-Fuzzy Inference System) is an adaptive network formed by several layers, each containing a number of adaptive or fixed nodes. This system is highly effective in approximating unknown, even extremely complex nonlinear functions. According to [3], it generally achieves lower approximation errors when compared to other approximation techniques (say backpropagation multilayer perceptron, polynomial approximators, cascade-correlation neural networks...). The number of adjustable parameters is usually lower than in case of the aforementioned approximation techniques. By using a hybrid learning algorithm (combination of least-squares method and gradient descent), the learning times could be decreased by a significant amount.

In Fig.2, a basic schematic diagram of ANFIS is depicted. There are five layers, the first and the fourth contain adaptive nodes while the remaining nodes are fixed. In this example, two variables denoted x and y are assumed. Symbols A_i and B_i denote i-th fuzzy set defined on the respective universe of discourse. It is obvious that two fuzzy sets are defined on each of the universes of discourse in this case and there are also two rules:

1. If x is A_1 and y is B_1 then $f = p_1x + q_1y + r_1$
2. If x is A_2 and y is B_2 then $f = p_2x + q_2y + r_2$

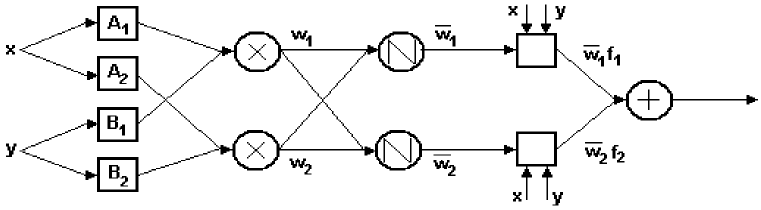

Figure 2. Schematic diagram of adaptive neuro-fuzzy inference system

The consequences of these rules imply Takagi-Sugeno type of a fuzzy system (first-order). In the first layer, the membership function for every input is determined (that is, μ_{Ai} and μ_{Bi}). If a generalized bell function is used as a membership function, it has the following form:

$$\mu_{Ai}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{1}$$

There are three adjustable (nonlinear) parameters a_i, b_i, c_i which affect the shape of a fuzzy set. There are actually *n* x *3* x *i* nonlinear parameters (for generalized bell function), where *n* denotes the number of input variables and *i* denotes the number of fuzzy sets on each of the universes of discourse.

In the second layer, the firing strength of every rule is defined using appropriate T-norm (usually taking the product of μ_{Ai} and μ_{Bi}). Thus, at the output of these nodes we have

$$w_i = \mu_{Ai}(x)\mu_{Bi}(y) \tag{2}$$

The third layer provides normalized firing strength at the output for each w_i, that is:

$$\overline{w}_i = \frac{w_i}{\sum_{i=1}^{k} w_i} \tag{3}$$

In the fourth layer, the normalized firing strength is multiplied by a consequent of each rule with parameters p_i, q_i, r_i in this form:

$$\overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{4}$$

The nodes in this layer are adaptive with parameters p_i, q_i, r_i being determined by means of least-squares method. The outputs from these nodes are then all summed in the last layer, so it can be written in the following form:

$$z = \sum_i \overline{w}_i f_i \tag{5}$$

It is clear from the paragraph above that there is a set of total parameters subdivided into the sets of nonlinear (premise – affecting the shape of membership functions) and linear (consequent) parameters. Their number is important as far as the risk of improper generalization is concerned (the low number of input-output data in a training set implies the low number of adjustable parameters in order to avoid a generalization problem)[4].

In order to characterize the dataset according to some criterion, several possibilities exist. ANFIS environment in Fuzzy Logic Toolbox offers grid partitioning and fuzzy subtractive clustering. As the results for fuzzy clustering algorithm were better, this method was chosen for data partitioning. This algorithm chooses cluster centers so that it characterizes a certain group of data better than the other one. In this case, the data points themselves are considered as possible cluster centers. If we consider a collection of *n*-points $\{x_1, ..., x_n\}$ in M-dimensional space, then in a first step so-called density measure is calculated according to the following formula [3]:

$$D_i = \sum_{j=1}^{n} \exp\left(-\frac{\|x_i - x_j\|^2}{(r_a/2)^2} \right) \tag{6}$$

r_a denotes some positive constant. It is obvious that the point that has many neighboring points in its vicinity will have higher density measure. After calculating the density measure for every point, the one with highest DM is chosen as a cluster center. Its density measure is then denoted D_{c1} and the density measures of all other points are revised using the following formula:

$$D_i = D_i - D_{c1} \exp\left(-\frac{\|x_i - x_{c1}\|^2}{(r_b/2)^2} \right) \tag{7}$$

r_b again denotes some positive constant (usually larger than r_a). Using this revision formula, the points in the vicinity of the first cluster will have their density measure significantly reduced, thus making them highly improbable candidates for another cluster center. In this way, a sufficient number of cluster centers that characterize the data set are chosen.

4. EXPERIMENTAL RESULTS

The static characteristic of this system can be graphically depicted with arm position β (in degrees) on ordinate and pressure difference p_d on abscissa (Fig. 3). The measurements were carried out in several runs for a major loop (between extreme position of the arm). The first-order curve (until first input reversal) was recorded only in the first run. For the purpose of hysteresis modeling, 104 data points were gathered during the measurements. Roughly one half of them was used as a training dataset while the other half was used for checking and testing.

In order to model the static hysteresis of this system, a separation technique was chosen. The hysteresis itself was divided into three separate curves represented by the first order curve (blue in Fig.3) and the major loop separated into an upper and lower part. 49 points in total were selected as a training set (Fig.4).

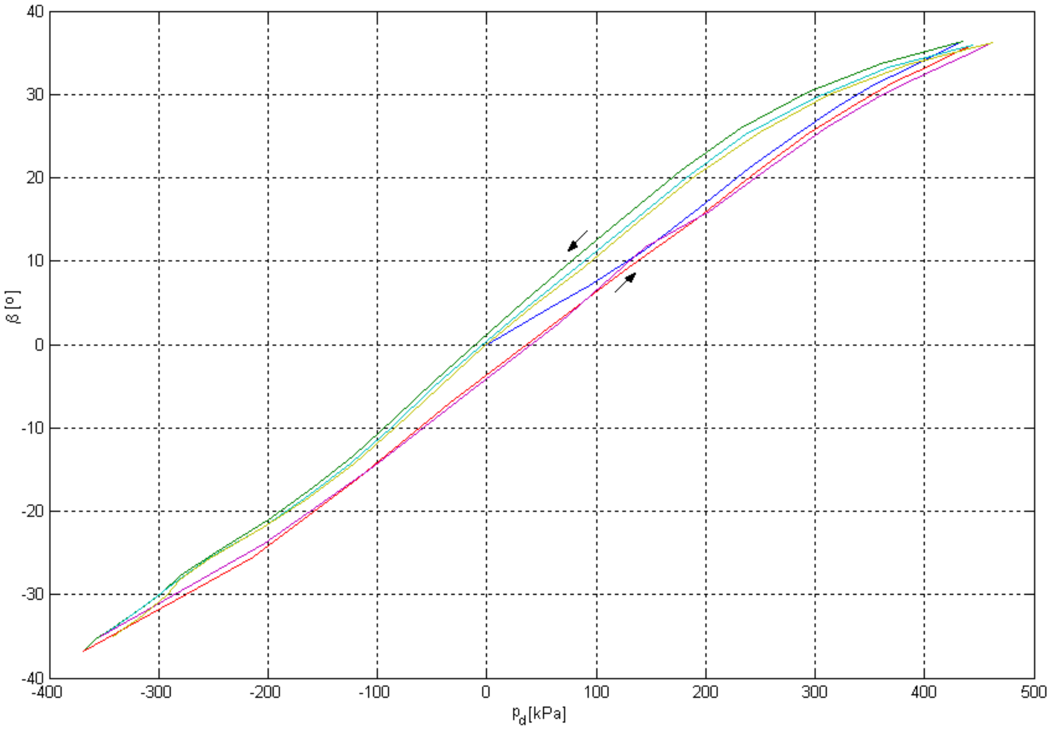

Figure 3. The static hysteresis of the PAM-based position servosystem

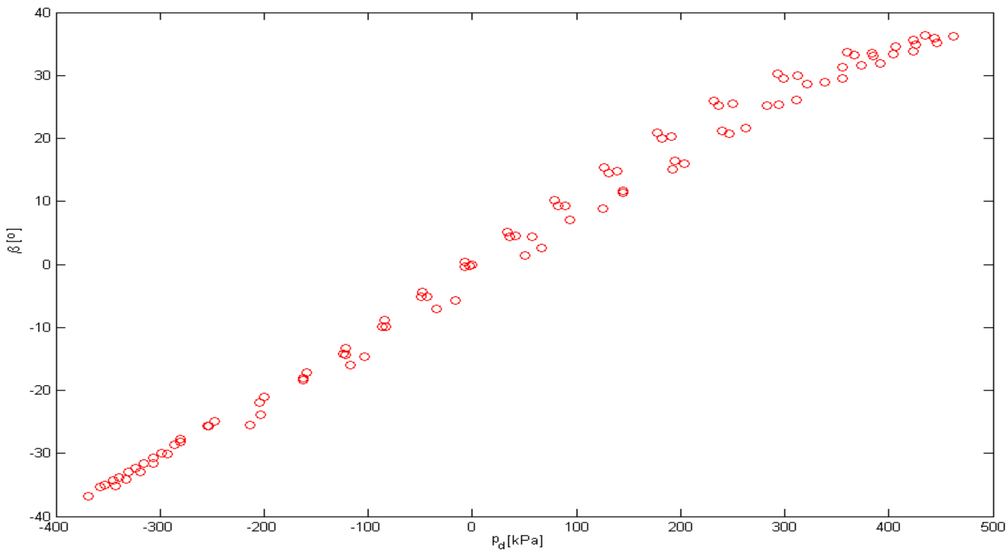

Figure 4. The data points of static hysteresis of the PAM-based position servosystem

At first, the first order curve was modeled. Its training set consisted of 13 points and the total number of parameters (6 linear and 6 nonlinear) was 12 so that the generalization problem could be avoided. Clustering parameters were set to the following values: range of influence 0.5, squash factor 1.25, accept ratio 0.5 and reject ratio 0.15. Fuzzy inference system was trained using hybrid method for 100 epochs. In this case, three gauss membership functions were distributed over the range of 0-435 kPa. The resulting approximation error was e = 0.079397. Both the training data set for this curve and the output of trained FIS are depicted in Fig.6. Since this is a 1-D data set, ANFIS would have the number of fuzzy sets equal to the number of rules (i.e.,three in this case) and the number of nonlinear parameters is thus 6 (1 x 2 x 3 for gauss function). The number of linear parameters in consequent parts of the rules was 6 (3 rules with 2 parameters each). The values of these parameters after training are shown below.

Table 1. The parameters of FIS1 after training

Rule	Premise		Consequents	
1	77.15	385	0.06353	8.58
2	76.34	93.73	0.07252	0.0741
3	76.32	240.5	0.0871	0.3191

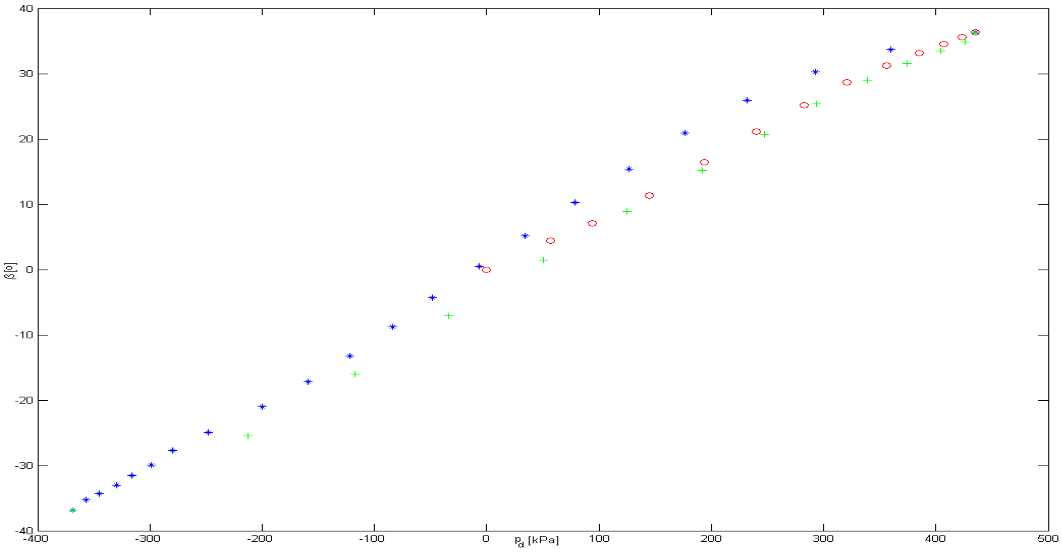

Figure 5. The training data set for three parts of the hysteresis

In order to use a separation technique for a hysteresis modeling, one has to provide the continuity of the points for every part of hysteresis. It is obvious from Fig.5, that the first-order curve last point is also the initial point of the upper part of hysteresis major loop. The upper hysteresis curve consisted of 22 training points allowing for 5-rule fuzzy inference system construction with 20 adjustable parameters in total (10 linear and 10 nonlinear). Clustering parameters were set to the following values: range of influence 0.25, squash factor 1.25, accept ratio 0.5 and reject ratio 0.15. The resulting FIS was trained in 100 epochs with final approximation error e = 0.11944. The FIS output for the upper curve plotted against the training and checking data set is in Fig.7.

Table 2. The parameters of FIS2 after training

Rule	Premise		Consequents	
1	70.93	-315.9	0.1013	0.6376
2	70.73	-121.6	0.1033	-1.007
3	71.67	34.06	0.09005	1.596
4	71.76	292.5	0.03588	20.74
5	72.58	177.5	0.06712	7.564

Figure 6. The training data set plotted against the FIS output for first-order curve

For the case of lower hysteresis curve modeling, 14 training points were used. Once again, due to rather low number of training points only three-rule fuzzy inference system could be used. The total number of parameters was 12 and clustering parameters were set to the following values: range of influence 0.5, squash factor 1.25, accept ratio 0.5 and reject ratio 0.15. The resulting FIS was trained in 100 epochs with final approximation error e = 0.324291. The FIS output for the upper curve plotted against the training data set is in Fig.8 with parameters of trained FIS shown below.

Table 3. The parameters of FIS3 after training

Rule	Premise		Consequents	
1	143.9	339.1	0.07384	3.596
2	144.5	-33.58	0.08173	-3.722
3	144	-368.8	0.0482	-19.22

The resulting errors of trained fuzzy inference systems for all three training data sets could be significantly lowered if the FIS with higher number of rules was used. Nevertheless, using FIS with higher number of rules would be possible only if there was a larger number of training data points. Thus, the number of rules for the fuzzy model was kept rather low in order to retain generalization property of the approximator. Due to the fact that separation technique was chosen for a modeling process, the resulting approximator actually consisted of three subsystems, each for modeling one part of the hysteresis curve. In Fig.9, an input-output relationship for this combined system is shown. This curve corresponds to the output recorded for the input changing within the maximum range of pressure difference in both directions.

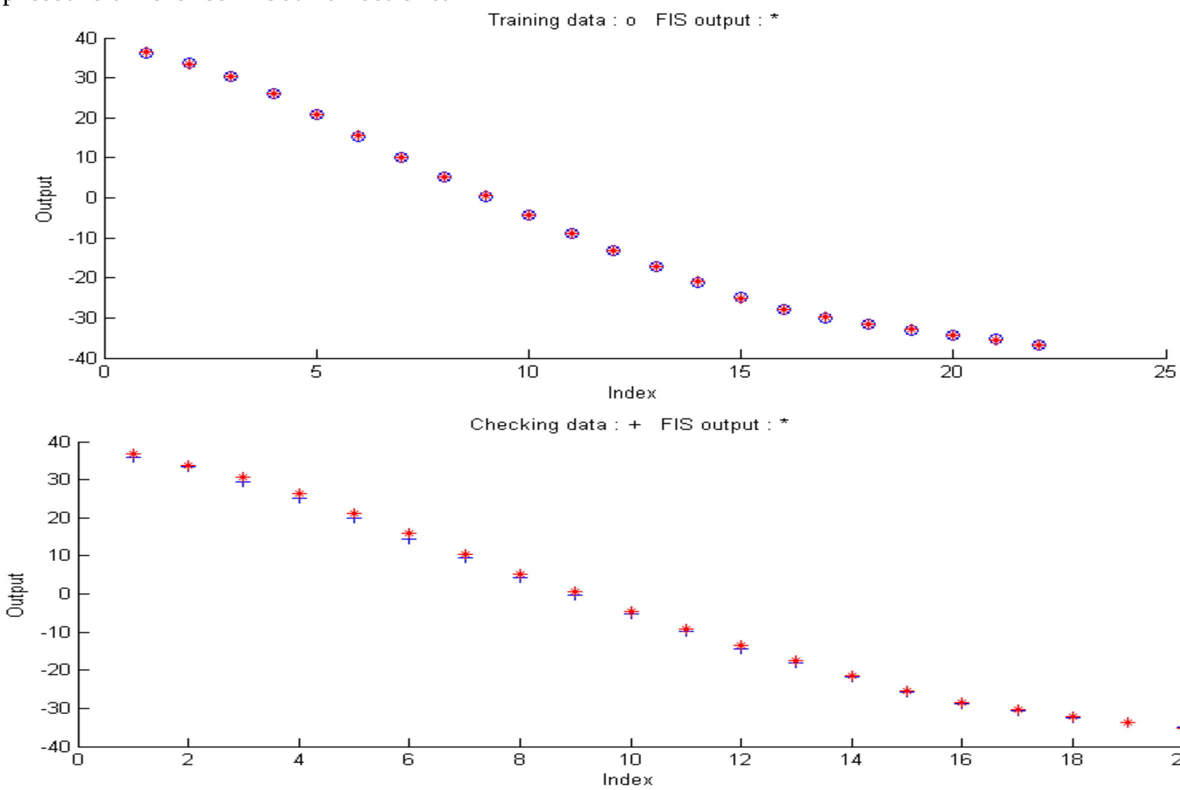

Figure 7. The training data set plotted against the FIS output for one half of major loop (top) and the same data set plotted against the checking data (above)

5. CONCLUSION

In this paper, a model of static hysteresis for the PAM-based position servosystem was created. Even though online identification of such hysteresis is considered preferable due to its capability to adapt to the changes within the system, it was decided to use the modeled hysteresis as a part of the offline servosystem model for the purpose of system analysis. Using a form of adaptive network for the hysteresis identification was considered as an alternative almost from the beginning due to its good flexibility, good approximation capabilities and possibility to work with rather sparse training data sets. It is clear from the results that some compromise between the approximation error and the generalization capability of the resulting approximation had to be found. Taking the scarcity of number of training data points into consideration, ANFIS proved to be useful tool even for such training sets. The number of rules for each of the fuzzy inference systems was chosen so that the generalization capability of the resulting approximator was not compromised (the total number of adjustable parameters was always lower than the number of training data points). Fuzzy clustering algorithm allowed for a lower approximation error when compared to a grid partitioning method. Given all the conditions, there was no significant benefit in increasing the number of epochs in training the FIS (ANFIS flexibility was reduced due to the lower number of training data points). In the course of hysteresis modeling, three FIS were actually constructed, each for every part of the curve. Thus, the first FIS would be activated only up to the first input reversal, being followed by the second FIS when the input is decreasing the third FIS when the output is increasing again.

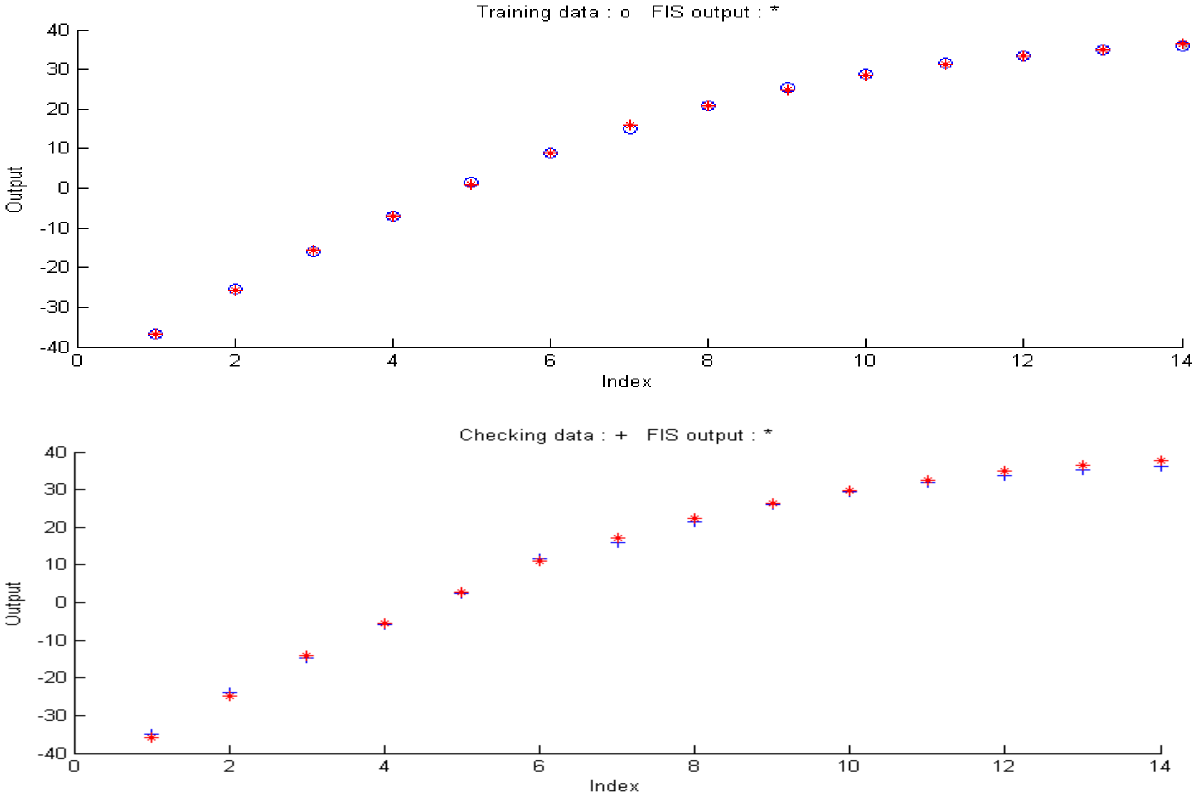

Figure 8. The training data set plotted against the FIS output for other half of major loop (top) and the same data set plotted against the checking data (above)

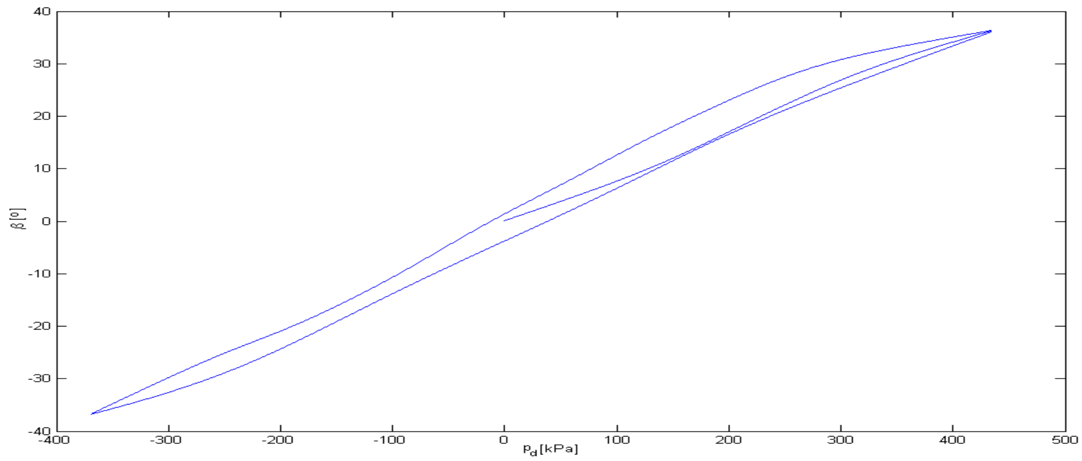

Figure 9. The resulting hysteresis model as the combined output of three separate FIS

For a further work, an inverse hysteresis model based on these results could be considered. Then the cascade blocks of hysteresis model and its inverse would allow for its compensation so as to provide almost linear input-output dependence.

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