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Design and Simulation of a Novel Clustering based Fuzzy Controller for DC Motor Speed Control

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Abstract

This research article proposes the speed control of a DC Motor (series as well as shunt motor). The novelty of this article lies in the application of kernel based hybrid c-means clustering (KPFCM) in the design of fuzzy controller for the speed control of DC Motor. The proposed approach provides a mechanism to obtain the reduced rule set covering the whole input/output space as well as the parameters of membership functions for each input variable. The performance of the proposed clustering based fuzzy logic controller is compared with that of its corresponding conventional fuzzy logic controller in terms of several performance measures such as rise time, peak overshoot, settling time, integral absolute error (IAE) and integral of time multiplied absolute error (ITAE) and in each case, the proposed scheme shows improved performance over its conventional counterpart. Also it shows that the proposed controller scheme gives much faster results as it reduces the computational time.

Keywords: DC Motor, Fuzzy control, Kernel, Clustering, Validity index

1. Introduction

Inspite of the development of power electronics resources, the direct current machines are becoming more and more useful in so far as they have found wide applications i.e. automobiles industry (electric vehicle), the electric traction in the multi-machine systems etc. The speed of DC motor can be adjusted to a great extent so as to provide easy control and high performance. There are several conventional and numeric controllers intended for controlling the DC motor speed: PID controllers, fuzzy logic controllers; or the combination between them, fuzzy neural networks etc. The nonlinearity of the series/shunt-connected motors complicates their use in applications that require automatic speed control. Major problems in applying a conventional control (Liu et. al 1999) algorithm in a speed controller are the effects of non-linearity in a DC motor. One of intelligent technique, fuzzy logic by Zadeh is applied for controller design in many applications. The advantage of fuzzy control methods is the fact that they are not sensitive to the accuracy of the dynamical model. In motion control systems, fuzzy logic can be considered as an alternative approach to conventional feedback control. It has been demonstrated in the literature that dynamic performance of electric drives as well as robustness with regard to parameter variations can be improved by adopting the non-linear speed control techniques. Fuzzy control is a non-linear control and it allows the design of optimized non-linear controller to improve the dynamic performance of conventional

regulators. Several works are reported in literature (Iracleous and Alexandris 1995; B. Singh et. al 2000; Montiel et. al 2007) where conventional controller is combined with the fuzzy controller to improve the response of the DC motor under non-linearity, load disturbances, parameter variations etc.

From the application of fuzzy control arise two problems: how to select the fuzzy control rules and how to set the membership functions. Two approaches are normally used to accomplish this task. One consists of acquiring knowledge directly from skilled operators and translates it into fuzzy rules. This process, however, can be difficult to implement and time consuming. As an alternative, fuzzy rules can be obtained through machine learning techniques, where the knowledge of the process is automatically extracted or induced from sample cases or examples. Many machine learning methods developed for building crisp logic systems can be extended to learn fuzzy rules. A very popular machine learning method is artificial neural network (ANN), which has been developed to mimic biological neural system in performing learning control and pattern recognition. The application of hybrid fuzzy logic and NN has been presented in a number of papers (Rubaai et.al 2000, Horng 2002).They are mainly focused either on the translation of fuzzy reasoning or on the introduction of fuzzy concepts into NN. As the system is constructed, a fuzzy logic controller controls the speed of DC motor and learning from a NN, which is used to implement the input-output relationships of FLC without reproducing the fuzzy reasoning.

Clustering techniques have been recognized as a powerful alternative approach to develop fuzzy systems. The purpose of clustering is to identify natural grouping of data from a large set to produce a concise representation of a system's behavior. Each cluster essentially identifies a region in the data space that contains a sufficient mass of data to support the existence of a fuzzy input/output relationship. Because a rule is generated only when there is a cluster of data, the resultant rules are scattered in the input space rather than placed according to grid-like partitions in the input space. This fundamental feature of clustering–based rule extraction methods helps avoid combinational explosion of rules with increasing dimension of the input space. Also, because clustering step provides good initial rule parameter values, the subsequent rule parameter optimization process usually converges quickly and to a good solution. The fuzzy c-means clustering algorithm (Bezdek 1981) is one well known example of such clustering algorithm. Recently, kernel methods for clustering attract more and more attentions. The kernel-based methods are algorithms that, by replacing the inner product with an appropriate positive definite function, implicitly perform a nonlinear mapping of the input data to a high dimensional feature space. Several studies on kernel-based clustering (Zhang and Chen 2002; Camastra and Verri 2005) indicate that kernel clustering algorithms are more accurate and more robust than the conventional clustering algorithms. Clustering algorithms typically require the user to pre specify the number of cluster centers and their initial locations. Different researchers have used different validity indices to decide the number of clusters. Our clustering method called kernel based hybrid c-means clustering (KPFCM) (Tushir and Srivastava 2010) with a kernelized Xie-beni validity index (Yuhua and Hall 2006) forms the basis of the present work. The clusters are determined where each cluster center belongs to one rule in fuzzy logic. If there are more rules in Fuzzy rule base, there is a drawback of more rule firing and high computational time. To avoid that, it is proposed to eliminate rule redundancy through fuzzy clustering for parameter identification.

2. Dynamic Modeling of DC Motor

Historically, DC machines are classified according to the connection of the field circuit with respect to the armature circuit. In shunt machines, the field circuit is connected in parallel with the armature circuit while DC series machines have the field circuit in series with armature where both field and armature currents are identical.

2.1 DC Series Motor

As its name indicates, the field circuit is connected in series with the armature and therefore the armature and field currents are the same. The equivalent circuit of a DC series motor is shown in Figure 1a.

The equation of the armature circuit is:

$$(L_a + L_F)(di_a / dt) = V - (R_a + R_F)i_a = K_b\phi\omega \quad (1)$$

The motion equation is:

$$J(d\omega / dt) = K_t\phi i_a - T_L \quad (2)$$

2.2 DC Shunt Motor

In shunt machine, the field circuit is connected in parallel with the armature circuit. It has the following equivalent circuit (Figure 1b).

The mathematical model of the electromechanical system is as follows:

$$d\theta / dt = \omega \quad (3)$$

$$J(d\omega / dt) = T_m - B\omega - T_L \quad (4)$$

$$L_F(di_F / dt) + (R_{adj} + R_F)i_F = V \quad (5)$$

Where

$T_m = K_m\phi i_a$, T_m = Electromagnetic torque, $\phi = K_F i_F$, ϕ = Flux in armature

$i_a = (V - E_A)/R_a$, i_a = Armature current, $E_b = K_b\phi\omega$, E_b = Back Emf

T_L = Load torque, V = Terminal voltage, L_F = Field Inductance, J = Rotor moment of inertia

L_a = Armature inductance, B = Viscous friction co-efficient, θ = Angular position, ω = speed

3. Clustering Analysis

Cluster analysis divides data into groups such as similar data objects belong to the same cluster and dissimilar data objects to different clusters. The resulting data partition improves data understanding and reveals its internal structure. Kernel methods (Christianini and Taylor 2000; Girolami 2002) have been successfully applied in solving various problems in machine learning community. A kernel function is a generalization of the distance metric that measures the distance between two data points as the data points are mapped into a high dimensional space in which they are more clearly separable. By employing a mapping function $\Phi(x)$, which defines a non–linear transformation: $x \to \Phi(x)$, the non-linearly separable data structure existing in the original data space can possibly be mapped into a linearly separable case in the higher dimensional feature space. The determination of the optimum number of the clusters is the most important problem in the cluster analysis. In the present work, a reformulated kernelized Xie-Beni validity index is used to determine the optimum number of clusters.

3.1 Kernel-Based Hybrid c-means Clustering Method and Corresponding Partition Validity

Our model called Kernel-based hybrid c-means clustering (KPFCM) adopts a kernel-induced metric different from the Euclidean norm in original possibilistic fuzzy c-means clustering by Pal et. al (2005). KPFCM minimizes the following objective function:

$$J_{KPFCM}(U,V,T) = \sum_{k=1}^{N}\sum_{i=1}^{c}(au_{ik}^{m} + {}_{\eta}bt_{ik}^{\eta})\left\|\Phi(x_k) - \Phi(v_i)\right\|^2 + \sum_{i=1}^{c}\gamma_i\sum_{k=1}^{N}(1 - t_{ik}) \quad (6)$$

where, $\left\|\Phi(x_k) - \Phi(v_i)\right\|^2$ is the square of distance between $\Phi(x_k)$ and $\Phi(v_i)$.

$X = \{x_1, x_2 ....., x_N\}$ is a set of vectors in an n-dimensional feature space, $V = (v_1, v_2 ....., v_c)$ is a c-tuple of prototypes, N is the total number of feature vectors, c is the number of clusters, u_{ik} is the grade

of membership of feature point x_k in cluster v_i and $m \in [1, \alpha)$ is a weighting exponent called fuzzifier, a possibilistic (t_{ik}) membership that measures the absolute degree of typicality of a point in any particular cluster Here a>0, b>0, m>1 and η>1. The constants a and b defines the relative importance of fuzzy membership and typicality values in the objective function.

The distance in the feature space is calculated through the kernel in the input space as follows:

$$\begin{aligned}\|\Phi(x_k) - \Phi(v_i)\|^2 &= (\Phi(x_k) - \Phi(v_i)).(\Phi(x_k) - \Phi(v_i)) \\ &= \Phi(x_k).\Phi(x_k) - 2\Phi(x_k)\Phi(v_i) + \Phi(v_i)\Phi(v_i) \\ &= K(x_k, x_k) - 2K(x_k, v_i) + K(v_i, v_i)\end{aligned}$$

If we adopt the Gaussian function as a kernel function i.e. $K(x, y) = \exp(-\|x - y\|^2 / 2\sigma^2)$, where σ defined as kernel width, is a positive number, then $K(x, x) = 1$. Thus (6) can be rewritten as

$$J_{KPFCM}(U,V,T) = 2\sum_{k=1}^{N}\sum_{i=1}^{c}(au_{ik}^m + bt_{ik}^\eta)(1 - K(x_k, v_i)) + \sum_{i=1}^{c}\gamma_i \sum_{k=1}^{N}(1 - t_{ik})^\eta \quad (7)$$

Given a set of points X, we minimize $J_{KPFCM}(U,V,T)$ in order to determine U, V, T.

$$u_{ik} = (1/(1 - K(x_k, v_i)))^{1/m-1} / \sum_{j=1}^{c}(1/(1 - K(x_k, v_j)))^{1/m-1} \quad (8)$$

$$t_{ik} = 1/1 + ((2b(1 - K(x_k, v_i)) / \gamma_i)^{1/(\eta-1)} \quad (9)$$

$$v_i = \sum_{k=1}^{N}(au_{ik}^m + bt_{ik}^\eta)K(x_k, v_i)x_k / \sum_{k=1}^{N}(au_{ik}^m + bt_{ik}^\eta)K(x_k, v_i) \quad (10)$$

It is suggested to select γ_i as

$$\gamma_i = H(2\sum_{k=1}^{N}u_{ik}^m(1 - K(x_k, v_i))) / (\sum_{k=1}^{N}u_{ik}^m) \quad (11)$$

Typically, H is chosen as 1.

Xie and Beni (1991) proposed a fuzzy clustering validity function which measures compactness and separation of fuzzy clustering. The kernelized Xie –beni validity metric can be reformulated as follows:

$$\begin{aligned}KXB(V, X) &= \sum_{k=1}^{n}\sum_{i=1}^{c} u_{ik}^m \|\Phi(x_k) - \Phi(v_i)\|^2 / (n \min_{i,j} \|\Phi(v_i) - \Phi(v_j)\|^2 \\ &= \sum_{k=1}^{N}\sum_{i=1}^{c} u_{ik}^m [2 - 2 * K(x_k, v_i)] / (n \min_{i,j} [2 - 2 * K(v_i, v_j)]) \\ )\end{aligned} \quad (12)$$

Using (8), (12) can be rewritten as:

$$= \sum_{k=1}^{N}\sum_{i=1}^{c}([1 - K(x_k, v_i)]^{1/(m-1)} / \sum_{j=1}^{c}[1 - K(x_k, v_i)]^{1/(m-1)})^m * [2 - 2 * k(x_k, v_i)] / (n \min_{i,j}[2 - 2 * K(v_i, v_j)])$$

$$= 2 * \sum_{k=1}^{N} (\sum_{j=1}^{c} [1 - K(x_k, v_j)]^{\frac{1}{m-1}})^{1-m} / (n * \min_{i,j} 2 * [1 - K(v_i, v_j)]) \quad (13)$$

The number of clusters is determined so that the smaller KXB means a more compact and separate clustering. The goal should therefore be to minimize the value of KXB.

4. Controller Structure

Unlike conventional control, which is based on mathematical model of a plant, a fuzzy logic controller (FLC) usually embeds the intuition and experience of a human operator and sometimes those of designers and researchers. While controlling a plant, a skilled human operator manipulates the process input (i.e. controller output) based on e and Δe with a view of minimizing the error within shortest possible time. The controlled variable of fuzzy controller is u(t). In this paper, all membership functions for the conventional fuzzy controller inputs (e and Δe) and the controller output are defined on the common normalized domain [-1, 1]. We use symmetric triangles (except the two MFs at the extreme ends) with equal base and 50% overlap with neighboring MFs. Here, the seven membership functions are shown in Figure 3. The next step is to design the rule base. If the number of MFs for inputs is 7, the corresponding rules are 7^2 =49 (Table 1). The objective here is to justify whether the system after the proposed clustering (with less number of rules) can provide the same level of performance as that of original one (system with 49 rules). For the identification of the proposed clustering based controller, we used system identification technique through exploratory data analysis where the controller outputs for different e and Δe are available. Here we can generate the data by sampling input variables (e and Δe) uniformly and computing the value of u for each sampled point. To extract the minimum rules, KPFCM clustering is performed in the input space of each class of data. The clusters found in the data of a given group identify regions in the input space that map into the associated class. Hence, each cluster center may be translated into a fuzzy rule for identifying the class. Each rule has the following form:

Rule i: If x_1 is A_{i1} and …. and x_n is A_{in} THEN $y_i = c_{i0} + c_{i1} + ... + c_{in} x_n$ (14)

Where $i = 1,2,.....,l, l$ the number of IF-THEN rules, c_{ik}'$s (k = 0,1,...., n)$ are the consequent parameters. y_i is an output from the i^{th} IF –THEN rule, and A_{ij} is the membership function (Gaussian type) in the i^{th} rule associated with the j^{th} input feature.

The membership function A_{ij} is given by

$$A_{ij}(x_j) = \exp(-0.5 * ((x_j - a_{ij}) / \sigma_{ij})^2) \quad (15)$$

with a_{ij} being the center and σ_{ij} , the variance of the Gaussian curve.

There are several approaches to optimize the parameters. One approach is to apply a gradient descent method to optimize the parameters $a_{ij}, \sigma_{ij}, c_{ij}$ in (14) and (15) to reduce the root-mean-square output error with respect to the training data. Another approach also involves using the Takagi-Sugeno rule format, but it combines optimizing the premise membership functions by back propagation with optimizing the consequent equations by linear least squares estimation. This is the ANFIS methodology developed by Jang (1993). We have used this approach in the paper.

5. Simulation and Analysis

In this section, we show the simulation results for speed control of DC motor using the proposed clustering based controller and the conventional controller. The Conventional Fuzzy controller uses 49 rules and 7 membership functions to compute output. Now our main aim is to extract a smaller set of rules using kernel-based hybrid c-means clustering. Here, KPFCM clustering with kernelized Xie-beni index is used to determine the number of rules. Thus four clusters (rules) are extracted. After the number of rules is determined, a fuzzy controller based on TS model using Gaussian membership function is designed with KPFCM clustering providing with an initial guess for the parameters of the antecedent membership functions i.e. the center and the width of the Gaussian membership function. The output response using these rules may not be closed to the desired response. ANFIS is used for training to modify the above parameters. Figure 3 shows the initial and final membership functions of the input variables (e and Δe).

Then, the performance of the proposed controller (identified System) is compared with the conventional one.

5.1.1 DC Series Motor

Simulation experiments under different operation status are carried out based on the fore established model. The simulink model for the DC series motor is shown in Figure 4. The parameters used for DC series motor can be taken reference for simulation, as shown in appendix A. The two curves in Figure 5a are the simulation curves of the rated running state for DC series motor respectively under the control of conventional fuzzy controller and the proposed controller. For a clear comparison between the conventional fuzzy controller and the proposed clustering based fuzzy controller, several performance measures such as peak overshoot (%Mp), settling time, rise time, integral absolute error (IAE) and integral-of-time-multiplied-absolute error (ITAE) are computed as shown in table 2. Using proposed controller, the rise time and settling time improves whereas for other measures, both the controllers give approximately the same performance. However, under load disturbance, the performance of the proposed scheme shows improved results. Figure 5b shows the response of the system with a 40 % load disturbance applied at t=5 secs. Table 3 shows the values of peak overshoot, settling time, IAE and ITAE computed under this condition. After 5 seconds, the rated speed of the DC series motor is suddenly increased and then decreased by 20% as shown in Figure 6 and Figure 7. As can be seen, under the condition of given speed changing, the proposed clustering based controller compared with conventional fuzzy controller, is able to quickly reaches a steady state and has better tracking performance.

5.2.2 DC Shunt Motor

In this section, DC shunt motor is used in simulation. Figure 8 shows the simulink model of DC shunt motor. The machine parameters are given in appendix A. Figure 9a shows the simulation results of the two controllers when the external load disturbance is zero. The performance of the two controllers is listed in table 4. At the time t=15 secs, the external load torque is decreased by a step of 40 % (Figure 9b).The system again reaches the steady state after transient period. Table 5 shows the values of peak overshoot, settling time, IAE and ITAE computed under this condition. The illustrated figures verify that a significant improvement has been achieved using the proposed clustering based controller. Initially the motor is operated at the steady state. At the time t=20 secs, an increased step of 20 % of initial set point ω_r occurs and then a decreased step of 20 % of initial set point as shown in Figure 10 and Figure 11, the rotor speed tracks the new set point after a transient period. Obviously, the external load torque is assumed constant. Comparisons with the conventional fuzzy controller indicate the improvement achieved. After reducing the number of rules using clustering, the computation becomes fast. The computation time is measured and the results are shown in table 6. Thus it can be seen that the proposed controller performs better than the conventional fuzzy controller.

6. Conclusion

The proposed approach is used to extract the minimum number of rules from the given input-output data. The proposed approach is able to reduce the number of rules from 49 to 4 rules giving improved level of performance. The proposed scheme was applied to the speed control of DC series as well as DC shunt motor. Performance of the proposed clustering based FLC was also compared with corresponding conventional FLC's with respect to several indices such as peak overshoot (%Mp), settling time, rise time, Integral of absolute error (IAE) and integral-of-time-multiplied absolute error (ITAE) and from the simulation, it shows that the proposed controller can track the reference speed satisfactorily even under load torque disturbances. Another advantage of the proposed method is the reduced computational time as the number of rules decreases from 49 rules to 4 rules. It can thus be concluded that proposed control scheme can be successfully applied to the problem of designing a robust control for the DC motor system.

Appendix A

DC Series Motor parameters:

L_F =44mH, R_F=0.2 ohms, V =125V, L_a =18mH, R_a =0.24 ohms, J = 0.5kgm^2, K_b=0.55, Kt=3

DC Shunt Motor parameters:

La=18 mH, Ra=0.24 ohm, Kt=Km=1000, J=0.5 kgm^2, K_b =0.7, Lf=10H, R_f=120 ohms, K_f=K_{b1}=0.05

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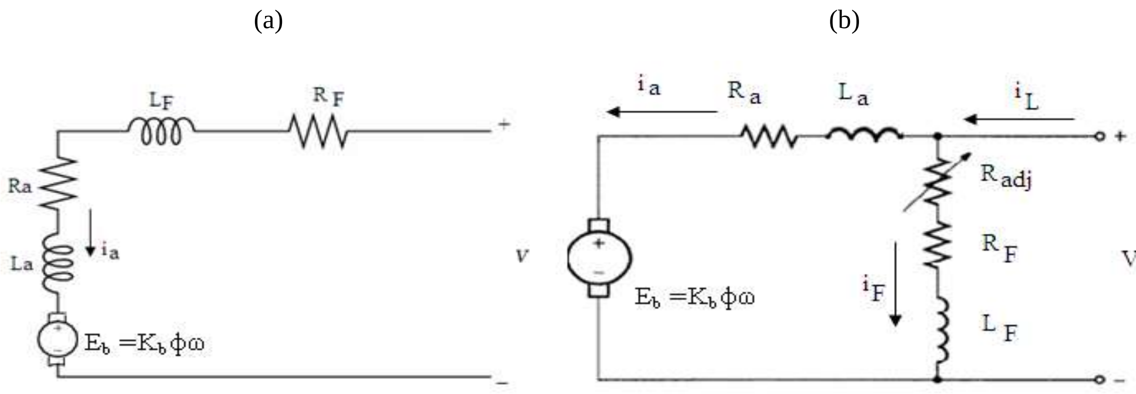


Figure 1 Equivalent Circuit of (a) DC Series Motor (b) DC Shunt Motor

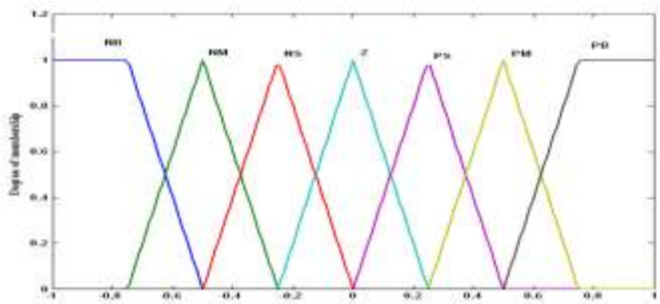


Figure 2 MFs for e , Δe and Δu

NB: Negative Big, NM: Negative Medium, NS: Negative Small, Z: Zero; PS: Positive Small, PM: Positive Medium, PB: Positive Big

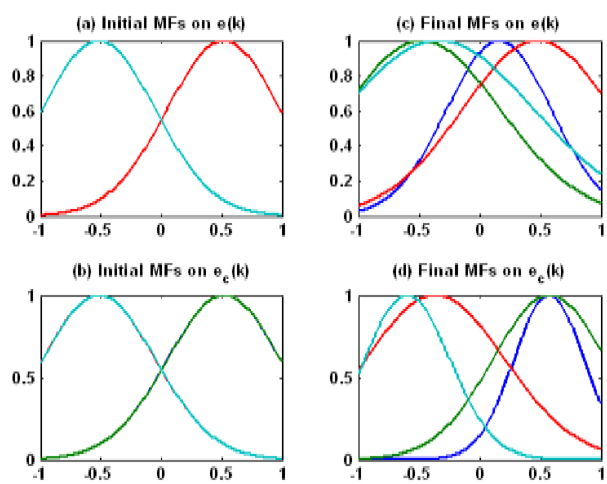


Figure 3 Initial and Final membership functions of e and Δe

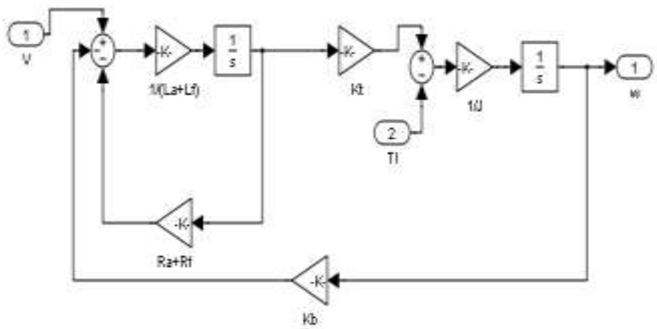
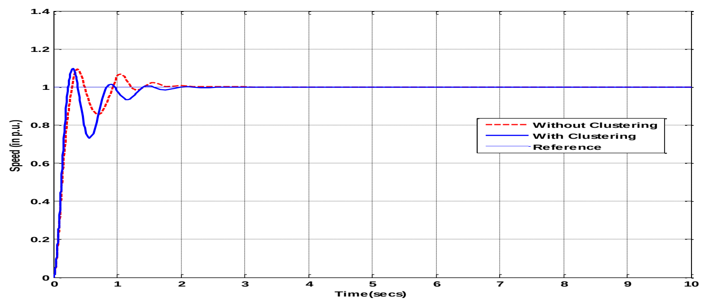


Figure 4 Simulink Model of DC series motor

(a)



(b)

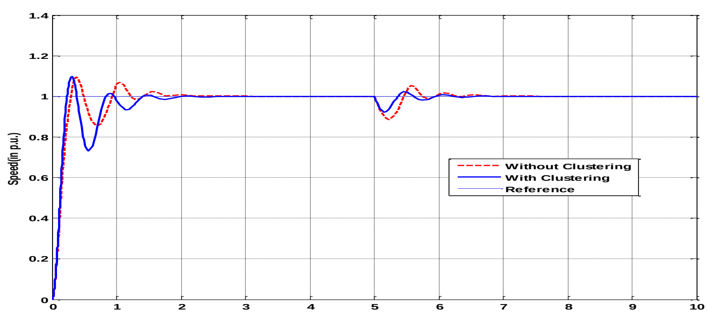


Figure 5 Speed response of DC series motor (a) without load disturbance (b) with load disturbance

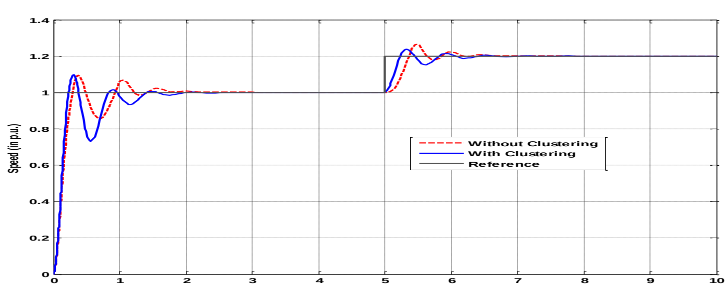


Figure 6 Speed response of DC series motor with sudden increase in speed

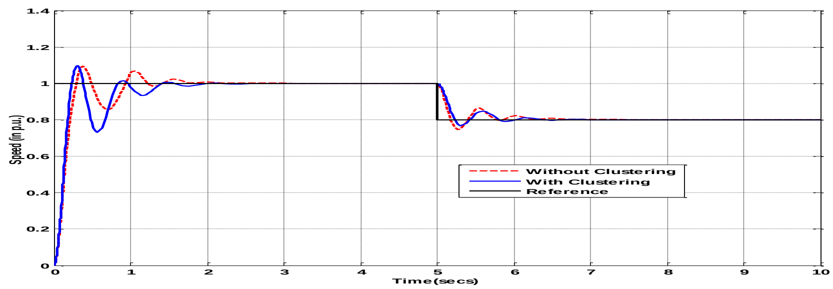


Figure 7 Speed response of DC series motor with sudden decrease in speed

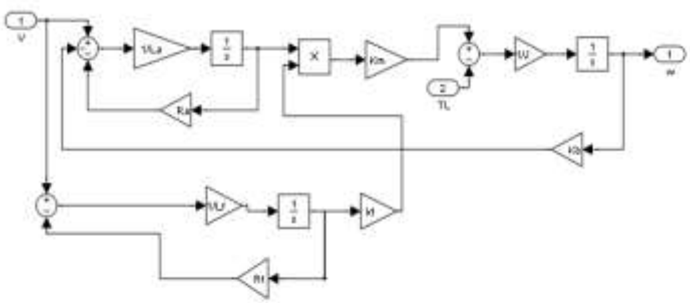
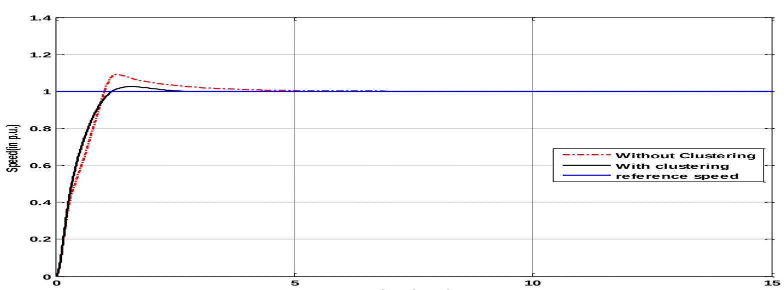


Figure 8 Simulink model of DC Shunt Motor

(a)



(b)

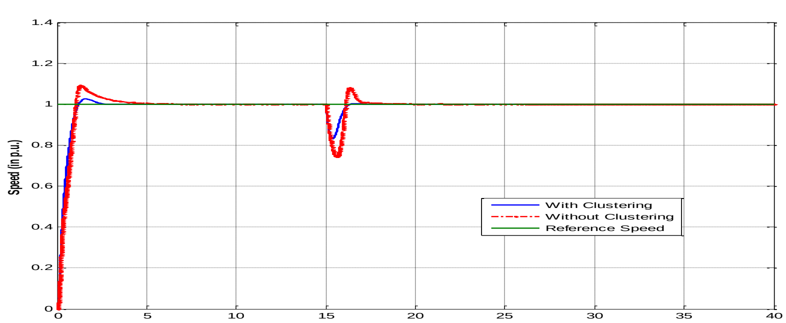


Figure 9 Speed response of DC Shunt motor (a) without load disturbance (b) with load disturbance

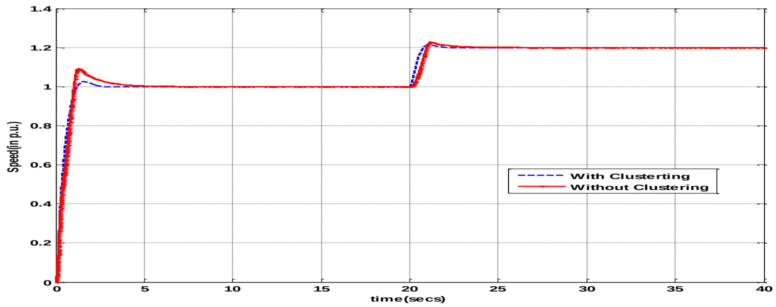


Figure 10 Speed response of DC Shunt motor with sudden increase in speed

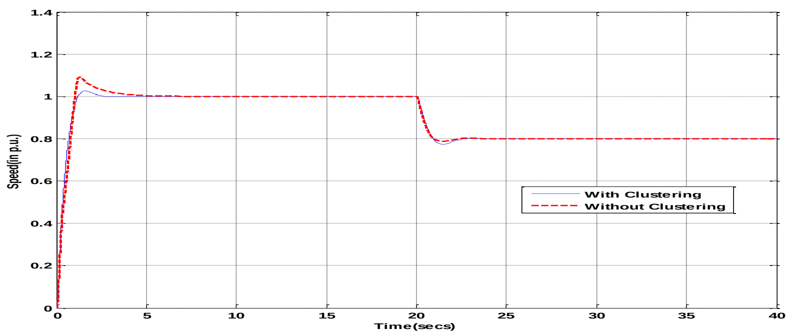


Figure 11 Speed response of DC Shunt motor with sudden decrease in speed

Table 1

Rule Base

Δe_i / e_i	**NB**	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NB	NB	NB	NM	NS	NS	ZE
NM	NB	NM	NM	NM	NS	ZE	PS
NS	NB	NM	NS	NS	ZE	PS	PM
ZE	NB	NM	NS	ZE	PS	PM	PB
PS	NM	NS	ZE	PS	PS	PM	PB
PM	NS	ZE	PS	PM	PM	PM	PB
PB	ZE	PS	PS	PM	PB	PB	PB

Table 2

Numerical results of experiment on DC series motor without load disturbance

	tr (secs)	%Mp	ts (secs)	IAE	ITAE
Conventional FLC	0.25	9	1.58	0.22	0.082
Proposed	**0.15**	**10**	**1.3**	**0.23**	**0.086**

Controller					

Table 3

Numerical results of experiment on DC series motor with load disturbance

	%Mp	ts (secs)	IAE	ITAE
Conventional FLC	11.4	5.72	0.271	0.363
Proposed Controller	**7**	**5.5**	**0.26**	**0.242**

Table 4

Numerical results of experiment on DC shunt motor without load disturbance

	tr (secs)	%Mp	ts (secs)	IAE	ITAE
Conventional FLC	0.79	9	3.03	0.588	0.432
Proposed Controller	**0.74**	**3**	**1.86**	**0.445**	**0.17**

Table 5

Numerical results of experiment on DC shunt motor with load disturbance

	%Mp	ts	IAE	ITAE
Conventional FLC	26	16.78	0.823	4.14
Proposed Controller	**16**	**16.1**	**0.53**	**1.83**

Table 6

Computational Time of experiment on DC motor with conventional fuzzy controller and the proposed clustering based controller

	DC Series Motor		DC Shunt Motor	
	Conventional FLC	Proposed Controller	Conventional FLC	Proposed Controller
Without Load disturbance	4.38 secs	**0.625 secs**	6.12 secs	**0.296 secs**
With Load disturbance	3.96 secs	**0.545 secs**	9.17 secs	**0.34 secs**
With sudden Increase in Reference Speed	6.08 secs	**0.286 secs**	8.48 secs	**1.35 secs**
With sudden Decrease in Reference Speed	4.21 secs	**0.302 secs**	7.29 secs	**0.268 secs**