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Sensorless Vector Control of Induction Motor Based On Extended Kalman Filter and Fuzzy Controller

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ABSTRACT: This paper depicts the vector control of an induction motor by the speed estimation utilizing an extended Kalman filter and fuzzy controller. In this paper, the rotor speed is viewed as a parameter, and the composite state is made out of the first state and the rotor speed. The extended Kalman filter is utilized to distinguish the speed of an induction motor and rotor flux in light of the deliberate amounts, for example, stator currents and DC join voltage. The assessed speed is utilized for vector control and general speed control. The current control is performed at synchronous rotating reference frame, and the assessed speed data is utilized for reference frame transformation of the current controller. PC reproduction of the speed control has been completed to affirm the speed's helpfulness estimation calculation. The error between the genuine speed and the evaluated speed is inside of a couple rpm even at the low and high speeds.

KEYWORDS**:** Induction motor, Vector Control, Extended Kalman filter, Fuzzy logic controller.

I. INTRODUCTION

In advanced control systems for induction motor drives, shaft mounted tachogenerator, resolver, or computerized shaft position encoder are utilized to get speed data. These bring down the system unwavering quality, particularly in mediocre situations. This displays an issue in the systems where motor speed transducers are not generally accessible. This has prompted a speed sensorless vector control. The customary ways to deal with speed sensorless vector control utilize the strategy for flux and slip estimation utilizing stator currents and voltages [1],[2]. The MRAS strategies are likewise used to gauge the speed of an induction motor [3]. As of late, the Kalman filter calculation is utilized for the parameter estimation of an induction motor [4]-[6], or for the speed estimation of a synchronous and an induction motor [7],[8]. In the speed estimation of an induction motor utilizing an extended Kalman filter calculation, a mechanical comparison is utilized as a part of Kalman filter which need the data about idleness of the motor and load, and just the currents are state variables, so the rakish speed of rotor flux is figured outside the extended Kalman filter. This paper shows an option speed sensorless vector control which utilizes an extended Kalman filter calculation to Appraise the motor speed and rotor flux, and along these lines builds up the vector control and additionally the general speed control. What's more, in this system just the stator currents and DC join voltage is the deliberate amounts. In any case, it is difficult to add to a precise system scientific model because of obscure burden varieties and system disturbances [2].Accordingly the Fuzzy Logic Control hypothesis (FLC) is generally utilized for the motor control purpose [5]. FLC is taking into account fuzzy set hypothesis, presented by Zadeh.[4].FLC does not require any accurate system numerical model and it can deal with nonlinearity of discretionary multifaceted nature and it is in view of the semantic guidelines. In this paper the Induction's speed motor which is running in Simulink/Matlab environment is assessed just by measuring the three phase stator data currents. What's more, with this assessed speed data, a fuzzy logic control system is created so that the motor's speed can be controlled accurately.

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II. MATHEMATICAL MODEL OF INDUCTION MOTOR

As generally iron losses, saturation of the electromagnetic circuit are ignored when adding to the scientific model of the induction motor. A dynamical model of induction motor in a stationary reference frame, by picking the stator currentsi_α ,$i_\beta$and the rotor flux$\psi_{r\alpha}$, $\psi_{r\beta}$ and the motor precise speed ω r as state variables is

$$\frac{dx}{dt} = Ax(t) + Bu(t), \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$
$$y(t) = cx(t), \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

Where$x$ is the state vector.

$$x = [i_{\alpha s}\, i_{\beta s}\, \psi_{\alpha r}\, \psi_{\beta r}\, \omega_r]^T, \ldots\ldots\ldots\ldots\ldots..(3)$$
$$y = [i_{\alpha s}\, i_{\beta s}\, i_{cs}]^T, \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(4)$$
$$u = [v_{\alpha s}\, v_{\beta s}], \ldots\ldots\ldots\ldots\ldots\ldots\ldots..(5)$$

$$A = \begin{bmatrix} -\lambda & 0 & \frac{\alpha}{\tau_r} & \omega_r \alpha & 0 \\ 0 & -\lambda & -\omega_r \alpha & \frac{\alpha}{\tau_r} & 0 \\ \frac{L_m}{\tau_r} & 0 & \frac{-1}{\tau_r} & -\omega_r & 0 \\ 0 & \frac{L_m}{\tau_r} & \omega_r & \frac{-1}{\tau_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Where

$$\lambda = \frac{R_s}{\sigma L_s} + \frac{R_r L_m^2}{\sigma L_s L_r^2}$$
$$time\ constant = \tau_r = \frac{L_r}{R_r}$$
$$\alpha = \frac{L_m}{\sigma L_s L_r}$$
$$\sigma = 1 - \frac{L_m^2}{L_s L_r}$$

R_s, R_r : Stator and Rotor resistances.
L_s, L_r : Stator and Rotor self inductances.
L_m : Mutual inductance. The two axis stator voltagesand currents in synchronously rotating frame are related tothe three phase representations by the following equation:

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$$\begin{bmatrix} f_{qs}^e \\ f_{ds}^e \end{bmatrix} = \begin{bmatrix} -\sin(\omega_e t) & cos(\omega_e t) \\ \cos(\omega_e t) & \sin(\omega_e t) \end{bmatrix} \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ 0 & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} f_{as} \\ f_{bs} \\ f_{cs} \end{bmatrix}$$

where$f$ may represent either the voltage or current. $\omega_e$isthe synchronous speed.

$$\omega_e = \omega_{sl} + \omega_r, \dots \dots \dots \dots \dots \dots \dots \dots . (6)$$

where$\omega_{sl}$is the slip speed and ω_r is the rotor speed. Thefield oriented control requires to keep the magnetizing current at a constant rated value by setting $i_{dr}^e = 0$ Hence thetorque producing current component can be adjusted inaccordance with the torque demand. The electromagnetictorque,

$$T_e = \frac{3PL_m}{4L_r} \lambda_{dr}^e i_{qs}^e, \dots \dots \dots \dots \dots \dots \dots \dots \dots (7)$$

whereλ_{dr} is the d axis rotor flux linkage.

III. EXTENDED KALMAN FILTER (EKF) ALGORITHM

In the dynamic model of induction motor, if the dimension of state vector is increased by adding an angular speed of rotor, then thestate model between nonlinear. So the extended Kalmanfilter has tobeused to estimate the parameter. In this case, the angular speedof the rotor is considered as a stateand a parameter. For the applicability of extended Kalman filter the system should be expressed in discrete state. Thediscrete state model and the output model are given by:

$$X(k+1) = f[X(k), k] + G(k)w(k), \dots \dots \dots \dots \dots \dots . . (8)$$

$$Y(k) = H(k)X(k) + v(k), \dots \dots \dots \dots \dots \dots (9)$$

Where

$G(k)$ =Weighting matrix.

$w(t)$ =Noise matrix of state model.

$v(t)$ =Nose matrix of output model.

In this model$f[X(k), k]$ is the nonlinearpart of state model. The extended Kalman filter re-linearize the nonlinear state model about each new estimate as it becomes available, and the new discrete state model and output model isdescribed by Eq. (10),(11).

$$X(k+1|k+1) = F(k)X(k+1|k) + G(k)w(k) + s(k), \dots \dots \dots \dots \dots \dots . . (10)$$

$$Y(k) = H(k)X(k|k) + v(k), \dots \dots \dots . (11)$$

Where

$$F(k) = \left. \frac{\delta f[x(k), k]}{\delta k} \right|_{x=x(k+1|k)}$$

$$s(k) = f[x(k+1|k)] - F(k)x(k+1|k)$$

From the above dynamic model therotor speed can be estimated by thefollowing extendedKalmanfilter algorithm.

Estimation of error covariance matrix:

$$P(k+1|k) = \Phi(k+1, k)P(k|k)\Phi^{\mathrm{T}}(k+1, k) + Q_d(k)$$

Computation of Kalman filter gain:

$$K(k+1) = \frac{P(k+1|k)H^T(k+1)}{[H(k+1)P(k+1)H^T(k+1) + R(k+1)]}$$

Update for error covariance matrix:

$$P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k)$$

State estimation:

$$x(k+1|k+1) = x(k+1|k) + K(k+1)(z(k+1) - h[x(k+1|k, k+1]$$

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IV. ESTIMATION OF ROTOR SPEED BY EXTENDED KALMAN FILTER ALGORITHM

Let the state variablesbe defined as followings.

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix} = \begin{bmatrix} i_{ds}(t) \\ i_{qs}(t) \\ \phi_{dr}(t) \\ \phi_{dq}(t) \\ \omega_r(t) \end{bmatrix}$$

Then the state model of the induction motor can be given as

$$x(t) = f[x(t), u(t), t] + Q(t)w(t)$$

Where

$$f[x(t), u(t), t] = [f_1(t), f_2(t), f_3(t), f_4(t), f_5(t)]^T$$

$$= \begin{bmatrix} -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma \tau_r}\right) x_1 + \frac{L_m}{\sigma L_r L_s \tau_r} x_3 + \frac{L_m}{\sigma L_s L_r} x_4 x_5 + \frac{1}{\sigma L_s} V_{ds} f \\ -\left(\frac{R_s}{\sigma L_s} + \frac{1-\sigma}{\sigma \tau_r}\right) x_2 + \frac{L_m}{\sigma L_r L_s} x_2 x_5 + \frac{L_m}{\sigma L_s L_r \tau_r} x_4 x_5 + \frac{1}{\sigma L_s} V_{ds} f \\ \frac{L_m}{\tau_r} x_1 - \frac{1}{\tau_r} x_3 - x_4 x_5 \\ \frac{L_m}{\tau_r} x_2 + x_3 x_5 - \frac{1}{\tau_r} x_4 \\ 0 \end{bmatrix}$$

$$\sigma = 1 - \frac{L_m}{L_s L_r}$$

$$G(t) = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \frac{1}{\sigma} \end{bmatrix}$$

$$w(t) = \begin{bmatrix} w_1(t) \\ w_2(t) \\ n(t) \end{bmatrix}$$

And the output matrix is given as follows

$$z(t_1) = h[x(t_i), t_i] + v(t_i)$$

Where

$$z(t_i) = \begin{bmatrix} i_{ds}(t) \\ i_{qs}(t) \end{bmatrix}$$

$$h[x(t_i), t_i] = \begin{bmatrix} i_{ds}(t_i) \\ i_{qs}(t_i) \end{bmatrix}$$

$x(t_0)$ is the initial condition with mean x_0 and covariance P_0, and$u(t)$ is deterministic input, $w(t)$ is a zero mean white Gaussian noise that is independent of $x(t_0)$ with covariance $Q(t)$. $v(t)$ is zero mean white Gaussian noise that is independent of $x(t_0)$ and $w(t)$ with covariance $R(t_i)$.The extended Kalman filter prediction equation is given by

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$$\hat{x}(k+1|k)=\hat{x}(k|k)+\int_{t_k}^{t_{k+1}} f[x(t|t_k),u(t),t]dt$$

In this case $u(t)$ is assumed tobe constantbetween t_k and t_{k+1}. The updated covariance is given by:

$$P(k+1|k)P(k|k)\Phi^{T}(k+1|k)+Q_d(k)$$

Where

$$\Phi(k+1|k)=e^{F(k)T_s}, T_s = sampling\ time$$

$$Q_d=\int \Phi(t_{k+1},\tau)G(\tau)Q(\tau)G^T(\tau)\Phi^T(t_{k+1},\tau)d\tau$$

$$F[k+1]=\left.\frac{\delta f[x(t),u(t),t]}{\delta x}\right|_{x=x(k+1|k)}$$

$$=\begin{bmatrix} -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) & 0 & \frac{L_m}{\sigma L_r L_s \tau_r} & \frac{L_m}{\sigma L_s L_r} x_5 & \frac{1}{\sigma L_s L_r} x_4 \\ 0 & -\left(\frac{R_s}{\sigma L_s}+\frac{1-\sigma}{\sigma\tau_r}\right) x_2 & \frac{-L_m}{\sigma L_r L_s} x_5 & \frac{L_m}{\sigma L_s L_r \tau_r} & \frac{1}{\sigma L_s L_r} x_2 \\ \frac{L_m}{\tau_r} & 0 & \frac{-1}{\tau_r} & -x_5 & -x_4 \\ 0\frac{L_m}{\tau_r}x_5 & \frac{-1}{\tau_r}x_4 & -x_3 & & \\ 0 & 0000 & & & \end{bmatrix}$$

The Kalman gain is given by

$$K(k+1)=\frac{P(k+1|k)H^T(k+1)}{[H(k+1)P(k+1)H^T(k+1)+R(k+1)]}$$

Where

$$H[k+1]=\left.\frac{\delta f[x(t),t]}{\delta x}\right|_{x=x(k+1|k)}$$

$$=\begin{bmatrix}1 & 0 & 0 & 0 & 0\\ 0 & 1 & 0 & 0 & 0\end{bmatrix}$$

V. FUZZY LOGIC CONTROLLER

Fuzzy logic is an approach to computer science that mimics the way a humanbrain thinks and solves problems [11]. The idea of fuzzy logic is to approximate decision making using natural language terms instead of quantitative terms. It is generally considered as modeling of information where it cannot be defined precisely, but some broad definitions can be formed. Because of its simplicity and effectiveness, Fuzzy-logic technology has gained many applications in scientific and industrial applications.

A typical architecture of FLC is shown below, which comprises of four principal comprises: a fuzzifier, a fuzzy rule base, inference engine, and a defuzzifier.

Fuzzifier: Used to transform crisp measured data (e.g. speed is 10 mph) into suitable linguistic values (i.e. fuzzy sets, for example, speed is too slow).

Fuzzy Rule Base: stores the empirical knowledge of the operation of the process of the domain experts.

Inference Engine: is the kernel of a FLC, and it has the capability of simulating human decision making by performing approximate reasoning to achieve a desired control strategy.

Defuzzifier: is utilized to yield a non fuzzy decision or control action from an inferred fuzzy control action by the inference engine.

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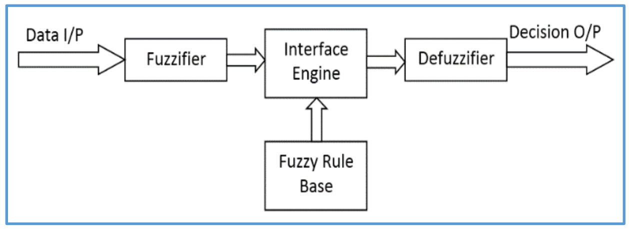

Figure 1: Block Diagram of Fuzzy Controller

VI. THE MODEL EXPLOITATION

The block diagram of the model is presented in figure 2. The EKF estimates the rotor speed ω_r using the three phase statorcurrents.The rotor speed is compared with the set speed toproduce the error in the speed. For the proposed FLC thespeed error and the rate of change of the speed error areconsidered as the input linguistic variables and the torqueproducing current component i_{qs}^e is considered as the output linguistic variable. The change of speed error

$$\Delta e(n) = \Delta\omega_r(n) - \Delta\omega_r(n-1)$$

And the speed error

$$\Delta\omega_r(n) = \Delta\omega_r^*(n) - \Delta\omega_r(n)$$

Using these equations, the synchronous speed ω_e is calculated assuming a value for slip.The rotor position θ_e is determined by integrating the synchronous speed.With theinformation of the rotor position the three phase statorcurrents are converted into synchronously rotating frame$\hat{\imath}_{qs}^e$and$\hat{\imath}_{ds}^e$.The quadrature axis current, i_{qs}^egenerated byFLC is compared with the estimated q axis current and

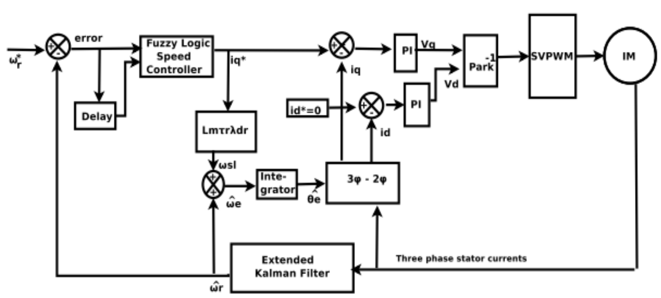

Figure 2: The block diagram representation of the proposed controller.

the error in q axis current is passed through a PI controller to get q axis voltage v_{qs}^e.The d axis current is set tozero which then compares with the estimated d axis current and passed through a PI controller to produce d axisvoltage. Then they undergo an inverse PARK transformation. A space vector PWM inverter is used to drive theInduction motor.

VII. SIMULATION AND RESULTS ANALYSIS

In the proposed vector control system, the voltage control is performed at synchronously rotating reference frame.Themotor speed ω_r is estimated using the EKF algorithm. The model is developed and simulated in Matlab/Simulink environment.

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Table 1: The specifications of the Inductionmotor used is:

Parameter	Value
Voltage	460V
Frequency	50Hz
Power	50HP
R_s	0.087Ω
R_r	0.228Ω
L_s	0.0008H
L_r	0.0008H
L_m	0.034H
J	1.662
B_m	0.1

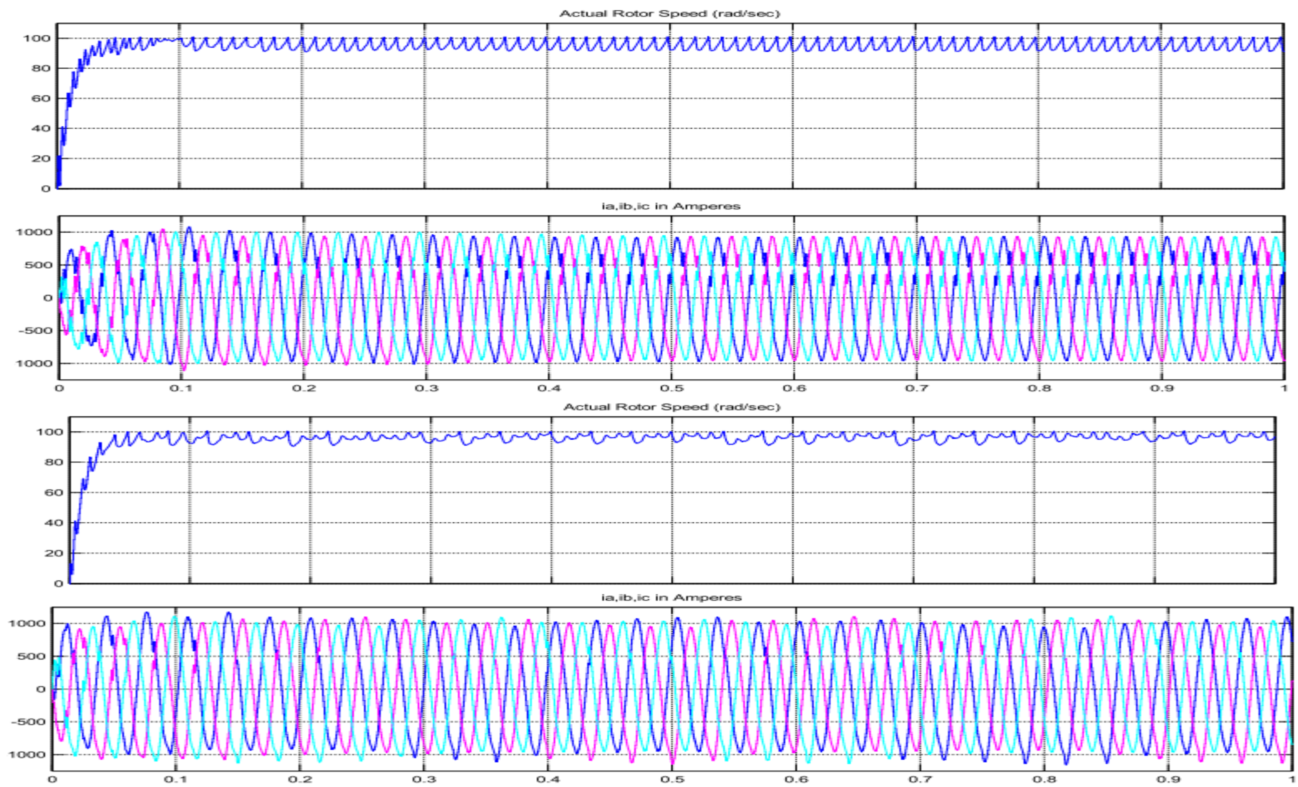

Figure 3: actual motor speed and phase currents in previous (top two graphs) and proposed technique (bottom two graphs).
Comparison between the previous method and the proposedmethod on the basis of figure 3. Reveals that the speed fluctuations and the current ripple in proposed method are much less, compared to the previous scheme.

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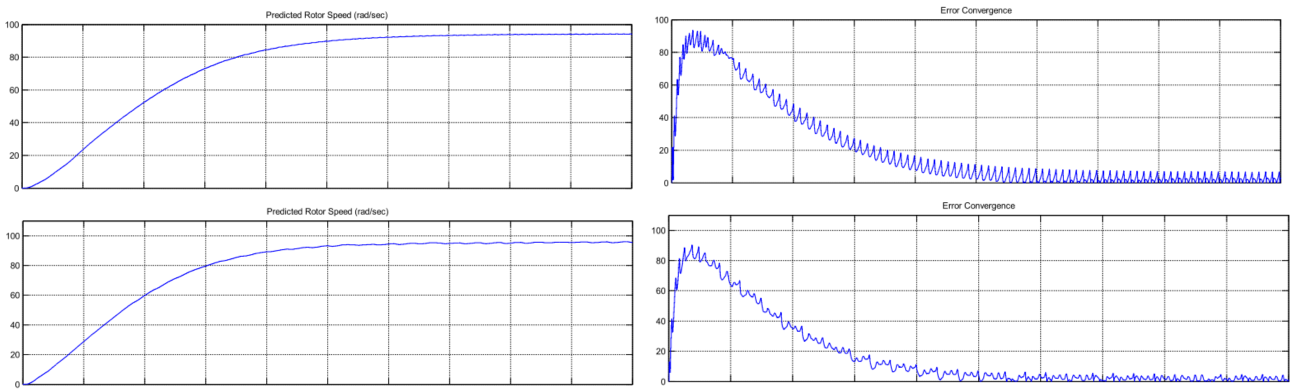

Figure 4: Motor speed estimation and estimation error convergence in previous (top graph) and proposed (bottom graph) technique.

The figure 4 graphs shows that the speed estimation in proposed technique is much better and quick responding. While the error converges much smoothly and quickly in the proposed technique.

VIII. CONCLUSION

An EKF estimator alongside FLC sensorless speed controller of an induction motor has been effectively simulated in Matlab/Simulink environment. The execution truly demonstrates that the controller can be utilized as a part of precise speed controller. The outcomes shows the efficacy of the Extended Kalman filter calculation for estimation purposes. The estimator is steady and fast for every single set speed. The FLC could follow and achieve all the set speeds rapidly. FLC has demonstrated its incredibleness in taking care of indeterminate parameters and unsettling influences. The controller execution has been tried for different step changes in speed in Simulink environment and discovered the same accuracy level in tracking them.

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