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Intelligent robust PI adaptive control strategy for speed control of EV(s)

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Abstract

- The intensive non-linear system and plants of modern industry highly motivating researcher to extend and evolve non-linear control systems. In this study, in order to control a class of non-linear uncertain power systems in the presence of large and fast disturbances, a new simple indirect adaptive proportional-integral is proposed.

- For handling dynamic uncertainties, the proposed controller utilities the advantages of least squares support vectors regression (LS-SVR) to approximate unknown non-linear actions and noisy data.

Problem Statement

- Consider a class of single-input single-output nth order non-linear system in the following form

$$x^{(n)} = f\left(x, \dot{x},\ \ddot{x}, \dots, x^{(n-1)}\right) + g\left(x, \dot{x},\ \ddot{x}, \dots, x^{(n-1)}\right)u(t) + d(x, t)$$
$$y = x$$

- Assumptions:
    - $d(x, t) \leq D$
    - $X_d^T = \begin{bmatrix} x_d & \dot{x}_d & \dots & x_d^{(n-1)} \end{bmatrix}$
    - $\|x_d\| \leq \psi$

$$\boxed{E = x - x_d = \begin{bmatrix} e & \dot{e} & \dots & e^{(n-1)} \end{bmatrix}^T}$$

LS - SVR

- The goal is to Estimate Unknown Nonlinear Functions.

$$\{(x_k, y_k)|k = 1, 2, \dots, N\}, x_k \in R^n, y_k \in R$$

$$y(x) = w^T \varphi(x) + b$$

Defining Cos Function and Optimality Condition

$$\min J(w,e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^{N} e_k{}^2$$

$$y(k) = \; w^T \varphi(x_k) + b + e_k \;\; ,k = 1,2,\dots,N$$

- The Lagrangian is defined as follows:

$$L(w,b\,,e;\;\alpha) = J(w,e) - \sum_{k=1}^{N} \alpha_k \{w^T \varphi(x_k) + b + e_k - y_k\}$$

Defining Cos Function and Optimality Condition

- Karush – Kuhn – Tucker Optimality Condition:

$$\begin{cases} \dfrac{\partial L}{\partial w} = 0 \rightarrow w = \displaystyle\sum_{k=1}^{N} \alpha_k \varphi(x_k) \\ \dfrac{\partial L}{\partial b} = 0 \rightarrow \displaystyle\sum_{k=1}^{N} \alpha_k = 0 \\ \dfrac{\partial L}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma e_k \;\; , k = 1,2, \dots N \\ \dfrac{\partial L}{\partial \alpha_k} = 0 \rightarrow w^T \varphi(x_k) + b + e_k - y_k = 0 \end{cases}$$

Defining Cos Function and Optimality Condition

- After elimination of the variable w and e_k :

$$\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 & 1_N^T \\ 1_N & \Omega + \gamma^{-1} I_N \end{bmatrix} \begin{bmatrix} 0 \\ y \end{bmatrix}$$

$$\alpha = [\alpha_1, \ldots, a_N]$$

$$\mathbf{1}_N = [1; \ldots; 1]$$

$$y = [y_1; \ldots; y_N]$$

$$b = \frac{\mathbf{1}_N^{\mathrm{T}}(\Omega + \gamma^{-1} I_N)^{-1} y}{\mathbf{1}_N^{\mathrm{T}}(\Omega + \gamma^{-1} I_N)^{-1} \mathbf{1}_N^{\mathrm{T}}}$$

$$\alpha = (\Omega + \gamma^{-1} I_N)^{-1}(y - \mathbf{1}_N^{\mathrm{T}} b)$$

$$\rightarrow \quad y(x) = \sum_{k=1}^{N} \alpha_k \boxed{\boldsymbol{K}(x_k, x_l)} + b$$

$$\begin{aligned} \Omega_{kl} &= \varphi(x_k)^{\mathrm{T}} \varphi(x_l) \\ &= \boldsymbol{K}(x_k, x_l), \quad k, l = 1, \ldots, N \end{aligned}$$

Defining Cos Function and Optimality Condition

- Kernel Functions

Name	Kernel function expression
linear kernel	$k(x, x_i) = x^T x_i$
polynomial kernel	$k(x, x_i) = (t + x^T x_i)^d$
RBF kernel	$k(x, x_i) = \exp(-\|x - x_i\|^2/\sigma^2)$
MLP kernel	$k(x, x_i) = \tanh(\beta_0 x^T x_i + \beta_1)$

Defining The Controller

- The non-linear system can be rewritten in the following form

$$\dot{X} = AX + B\big(f(X,t) + g(X,t)u + d(X,t)\big)$$
$$y = CX$$

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & \dots & \dots & \dots & 0 \end{bmatrix}_{n\times n}$$

$$B^{\mathrm{T}} = [0 \cdots 0\ 1]_{1\times n}, \quad C = [1 \cdots 0\ 0]_{1\times n}$$

Defining The Controller

- Algebraic Part

$$x^{(n)} = f\left(x, \dot{x},\ \ddot{x}, \dots, x^{(n-1)}\right) + g\left(x, \dot{x},\ \ddot{x}, \dots, x^{(n-1)}\right)u(t) + d(x, t)$$

$$y = x$$

$$u = \frac{1}{g(X, t)}[-f(X, t) - d(X, t) + x_d^{(n)} - K^{\mathrm{T}}E]$$

$\pm AX_d$

$$\dot{X} - \dot{X}_d = (A - BK^T)E \rightarrow \dot{E} = \boxed{(A - BK^T)}E$$

Hurwitz

Defining The Controller

- Analytic Part

$$u = \frac{1}{\hat{g}(X|W_g)}[-\hat{f}\left(X|W_f\right) - S(E^{\mathrm{T}}\boldsymbol{P}B|W_s) + x_d^{(n)} - \boldsymbol{K}^{\mathrm{T}}E]$$

$$\hat{f}\left(X|W_f\right) = W_f\beta(X)$$

$$\hat{g}\left(X|W_g\right) = W_g\beta(X)$$

$$\beta = [1\ K\left(x, x_1\right)\ \cdots K\left(x, x_i\right) \cdots\ K\left(x, x_N\right)]$$

Defining The Controller

- Analytic Part - Assumptions

$$W_f^* = \arg\min_{W_f \in R^M} \left[\sup_{X \in R^n} \left| \hat{f}\left(X|W_f\right) - f(X,t) \right| \right]$$

$$W_g^* = \arg\min_{W_g \in R^M} \left[\sup_{X \in R^n} \left| \hat{g}\left(X|W_g\right) - g(X,t) \right| \right]$$

- The minimum Approximation Error:

$$\omega = f(X,t) - \hat{f}\left(X|W_f^*\right) + \left(g(X,t) - \hat{g}\left(X|W_g^*\right)\right)u$$

  - Since f and g are bounded:

$$|\omega| < \Phi$$

Defining The Controller

- Proposed PI Controller:

$$\left(E^{\mathrm{T}}\boldsymbol{P}B|W_s\right) = \begin{cases} \boldsymbol{W}_s^{\mathrm{T}}\psi(E^{\mathrm{T}}\boldsymbol{P}B) = K_p E^{\mathrm{T}}\boldsymbol{P}B + \\ K_I \int\left(E^{\mathrm{T}}\boldsymbol{P}B\right)\,\mathrm{d}t, & \left|E^{\mathrm{T}}\boldsymbol{P}B\right| \le \Omega \\ \hat{D}_\omega\, sgn\left(E^{\mathrm{T}}\boldsymbol{P}B\right), & \left|E^{\mathrm{T}}\boldsymbol{P}B\right| > \Omega \end{cases}$$

$k_1 = 2$ and $k_2 = 1$,

$$(A - B\boldsymbol{K}^{\mathrm{T}})^{\mathrm{T}}\boldsymbol{P} + \boldsymbol{P}(A - B\boldsymbol{K})^{\mathrm{T}} = -\boldsymbol{Q}$$

$$\boxed{Q = \mathrm{diag}(10,10) \qquad P = \begin{bmatrix} 15 & 5 \\ 5 & 5 \end{bmatrix}}$$

$$\psi\left(E^{\mathrm{T}}\boldsymbol{P}B\right) = \left[E^{\mathrm{T}}\boldsymbol{P}B, \quad \int\left(E^{\mathrm{T}}\boldsymbol{P}B\right)\mathrm{d}t\right]^{\mathrm{T}}$$

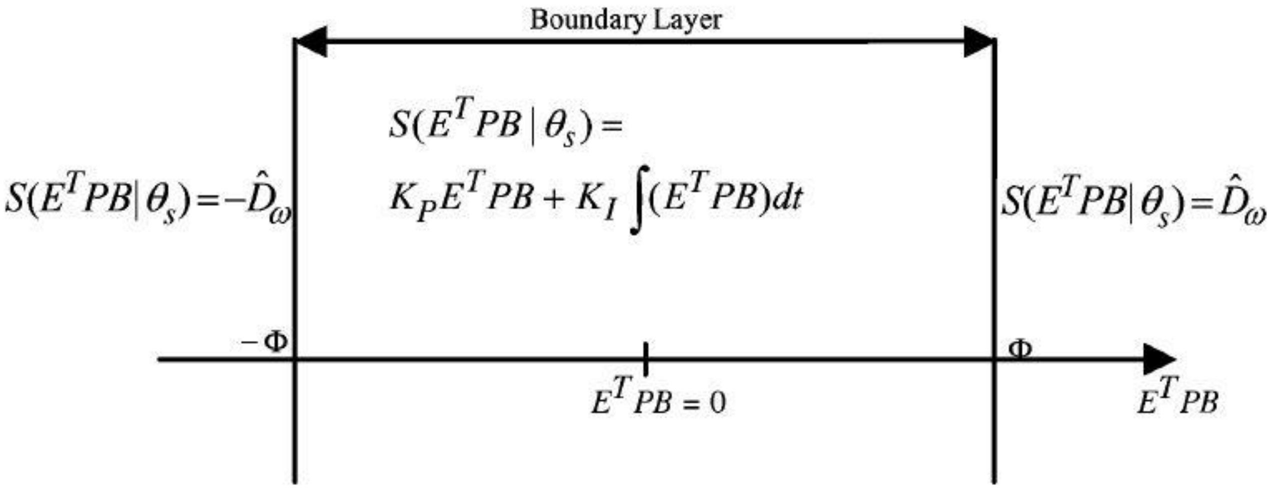
$$\boldsymbol{W}_s^{\mathrm{T}} = [K_p, K_I]$$

$$\hat{D}_\omega = \hat{D} + \hat{\Phi}$$

Defining The Controller

- Proposed PI Controller:

$$\left(E^{\mathrm{T}}\boldsymbol{P}B|W_s\right) = \begin{cases} \boldsymbol{W}_s^{\mathrm{T}}\psi(E^{\mathrm{T}}\boldsymbol{P}B) = K_p E^{\mathrm{T}}\boldsymbol{P}B + \\ K_I \int\left(E^{\mathrm{T}}\boldsymbol{P}B\right)\,\mathrm{d}t, & \left|E^{\mathrm{T}}\boldsymbol{P}B\right| \le \Omega \\ \hat{D}_\omega\, sgn\left(E^{\mathrm{T}}\boldsymbol{P}B\right), & \left|E^{\mathrm{T}}\boldsymbol{P}B\right| > \Omega \end{cases}$$



Lyapunov Function

- The candidate:

$$V = \frac{1}{2}E^{\mathrm{T}}\boldsymbol{P}E + \frac{1}{2\Gamma_1}\tilde{W}_f^{\mathrm{T}}\tilde{W}_f + \frac{1}{2\Gamma_2}\tilde{W}_g^{\mathrm{T}}\tilde{W}_g + \frac{1}{2\Gamma_3}\tilde{W}_s^{\mathrm{T}}\tilde{W}_s + \frac{1}{2\Gamma_4}\tilde{D}_\omega^2$$

$$\tilde{W}_s = W_s^* - W_s$$

$$\tilde{D}_\omega = D_\omega - \hat{D}_\omega$$

Lyapunov Function

- Differentiating with respect to time, we have:

$$
\begin{aligned}
\dot{V} = & -\frac{1}{2}E^{\mathrm{T}}\boldsymbol{Q}E + E^{\mathrm{T}}\boldsymbol{P}B\omega + \tilde{W}_f^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X) + \frac{1}{\Gamma_1}\dot{\tilde{W}}_f\right) \\
& + \tilde{W}_g^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X)u + \frac{1}{\Gamma_2}\dot{\tilde{W}}_g\right) \\
& + \tilde{W}_s^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\psi(E^{\mathrm{T}}PB) + \frac{1}{\Gamma_3}\dot{\tilde{W}}_s\right) + \frac{1}{\Gamma_4}\tilde{D}_\omega\dot{\tilde{D}}_\omega \\
& + E^{\mathrm{T}}\boldsymbol{P}Bd(X,t) - E^{\mathrm{T}}\boldsymbol{P}BS(E^{\mathrm{T}}\boldsymbol{P}B|W_s^*).
\end{aligned}
$$

Lyapunov Function

- Differentiating with respect to time, we have:

$$
\begin{aligned}
\dot{V} \le & -\frac{1}{2}E^{\mathrm{T}}\boldsymbol{Q}E + \tilde{W}_f^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X) + \frac{1}{\Gamma_1}\dot{\tilde{W}}_f\right) \\
& + \tilde{W}_g^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X)u + \frac{1}{\Gamma_2}\dot{\tilde{W}}_g\right) \\
& + \tilde{W}_s^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\psi\left(E^{\mathrm{T}}\boldsymbol{P}B\right) + \frac{1}{\Gamma_3}\dot{\tilde{W}}_s\right) + \frac{1}{\Gamma_4}\tilde{D}_\omega\dot{\tilde{D}}_\omega + |E^{\mathrm{T}}\boldsymbol{P}B||\omega| \\
& + |E^{\mathrm{T}}\boldsymbol{P}B||d(X,t)| - \left|E^{\mathrm{T}}\boldsymbol{P}B\right|\left|S\left(E^{\mathrm{T}}\boldsymbol{P}B|W_s^*\right)\right|
\end{aligned}
$$

$$
\begin{aligned}
\dot{V} \le & -\frac{1}{2}E^{\mathrm{T}}\boldsymbol{Q}E + \tilde{W}_f^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X) - \frac{1}{\Gamma_1}\dot{W}_f\right) \\
& + \tilde{W}_g^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\beta(X)u - \frac{1}{\Gamma_2}\dot{W}_g\right) \\
& + \tilde{W}_s^{\mathrm{T}}\left(E^{\mathrm{T}}\boldsymbol{P}B\psi\left(E^{\mathrm{T}}\boldsymbol{P}B\right) - \frac{1}{\Gamma_3}\dot{W}_s\right) \\
& - \frac{1}{\Gamma_4}\tilde{D}_\omega\dot{\tilde{D}}_\omega + \left|E^{\mathrm{T}}\boldsymbol{P}B\right|D_\omega - \left|E^{\mathrm{T}}\boldsymbol{P}B\right|\hat{D}_\omega .
\end{aligned}
$$

Lyapunov Function

- As a result, Adaptation Laws are obtained as follows

$$\dot{W}_f = \Gamma_1 E^T PB\beta(X)$$

$$\dot{W}_g = \Gamma_2 E^T PB\beta(X)u$$

$$\dot{W}_s = \Gamma_3 E^T PB\psi(E^T PB)$$

$$\dot{\hat{D}}_\omega = \Gamma_4 |E^T PB|$$

Lyapunov Function

- With respect to the Adaptation Laws:

$$\dot{V} \le -\frac{1}{2} E^{\mathrm{T}} \boldsymbol{Q} E \le 0$$

$$E(t), \tilde{W}_f(t), \tilde{W}_g(t), \tilde{W}_s(t), \tilde{D}_\omega(t) \quad \in \quad L^\infty$$

Closed Loop Stability

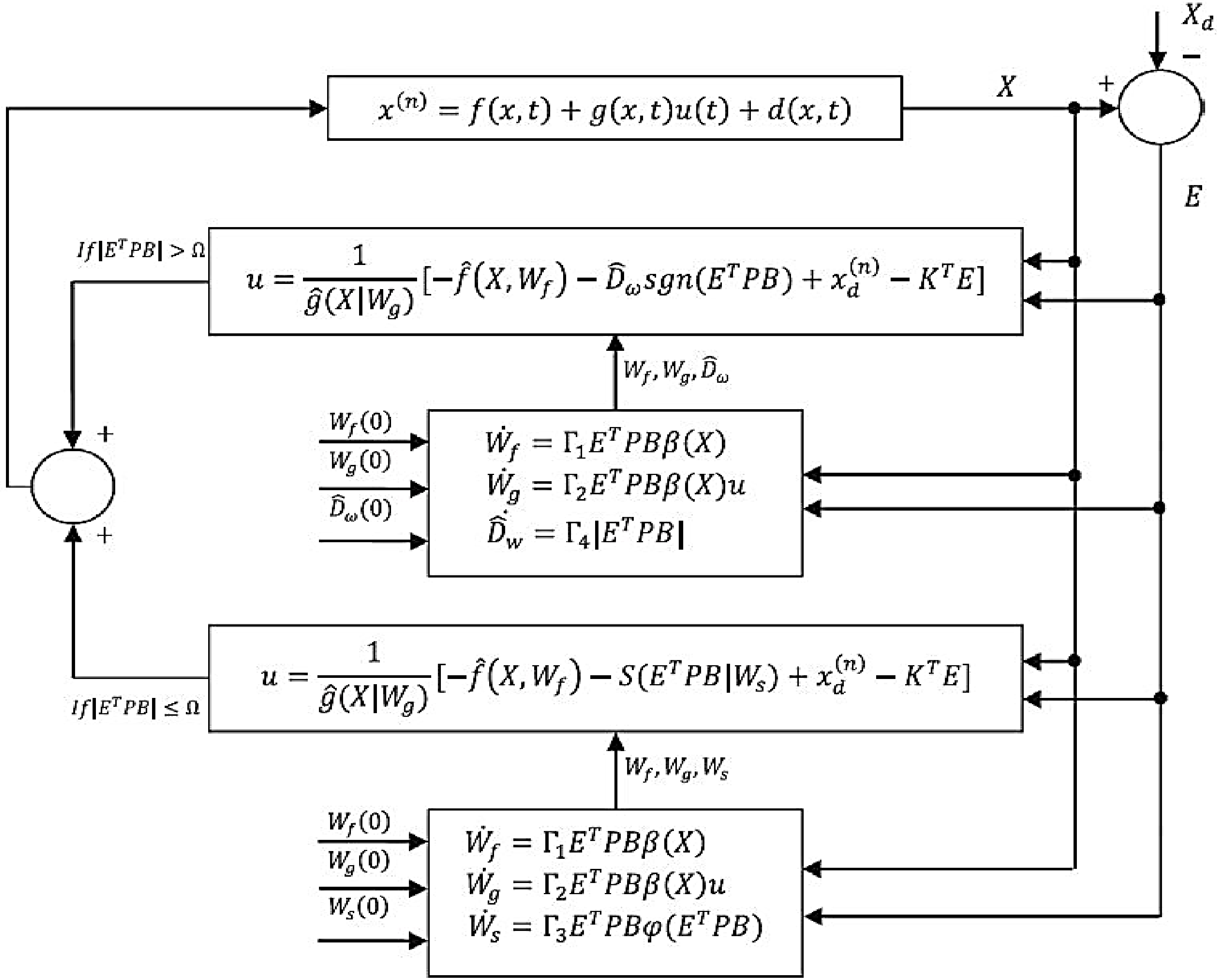
- Barbalat's Lemma:

$$W(t) = \frac{1}{2}E^T QE \leq -V$$

$$V\left(E(t), \widetilde{W}_f(t), \widetilde{W}_g(t), \widetilde{W}_s(t), \widetilde{D}_\omega(t)\right) \leq V\left(E(0), \widetilde{W}_f(0), \widetilde{W}_g(0), \widetilde{W}_s(0), \widetilde{D}_\omega(0)\right)$$

$$\int_0^t \mathcal{W}(\tau)\,\mathrm{d}\tau \leq V\left(E(0),\ \tilde{W}_f(0), \tilde{W}_g(0), \tilde{W}_s(0), \tilde{D}_\omega(0)\right) - V\left(E(t),\ \tilde{W}_f(t), \tilde{W}_g(t), \tilde{W}_s(t), \tilde{D}_\omega(t)\right)$$

$$\lim_{t\to\infty} \int_0^t \mathcal{W}(\tau)\,\mathrm{d}\tau < \infty \longrightarrow \lim_{t\to\infty} \dot{V}(t) and\ E(t) = 0$$



X_d
$-$
$+$
X
E
$x^{(n)} = f(x,t) + g(x,t)u(t) + d(x,t)$
$If|E^TPB| > \Omega$
$u = \frac{1}{\hat{g}(X|W_g)}[-\hat{f}(X,W_f) - \hat{D}_\omega sgn(E^TPB) + x_d^{(n)} - K^TE]$
$W_f, W_g, \hat{D}_\omega$
$W_f(0)$
$W_g(0)$
$\hat{D}_\omega(0)$
$\dot{W}_f = \Gamma_1 E^TPB\beta(X)$
$\dot{W}_g = \Gamma_2 E^TPB\beta(X)u$
$\dot{\hat{D}}_w = \Gamma_4|E^TPB|$
$+$
$+$
$If|E^TPB| \leq \Omega$
$u = \frac{1}{\hat{g}(X|W_g)}[-\hat{f}(X,W_f) - S(E^TPB|W_s) + x_d^{(n)} - K^TE]$
W_f, W_g, W_s
$W_f(0)$
$W_g(0)$
$W_s(0)$
$\dot{W}_f = \Gamma_1 E^TPB\beta(X)$
$\dot{W}_g = \Gamma_2 E^TPB\beta(X)u$
$\dot{W}_s = \Gamma_3 E^TPB\varphi(E^TPB)$

Simulation

- Motor Model:

Motor		Vehicle	
$L_a + L_f$ (mH)	6.008	m (kg)	800
$R_a + R_f$ (Ω)	0.12	A (m^2)	1.8
B (N.M.s)	0.0002	ρ(kg/m^3)	1.25
J (kg m^2)	0.05	C_d	0.3
L_{af} (mH)	1.766	ϕ (°)	0
V (V)	$0 \sim 48$	μ_{rr}	0.015
i (A)	78A (250 max)	r (m)	0.25
ω_{nom} (r/min)	2800 ($v = 25$ km/h)	G	11

$$(L_a + L_{\mathrm{field}})\frac{\mathrm{d}i}{\mathrm{d}t} = V - (R_a + R_f)i - L_{af}\,i \cdot \omega$$

$$\left(J + m\frac{r^2}{G^2}\right)\frac{\mathrm{d}\omega}{\mathrm{d}t} = L_{af}\,i^2 - B\omega - \frac{r}{G}(\mu_{rr} mg + \frac{1}{2}\rho A C_d v^2 + mg \sin\phi)$$

Simulation

- Motor Model:

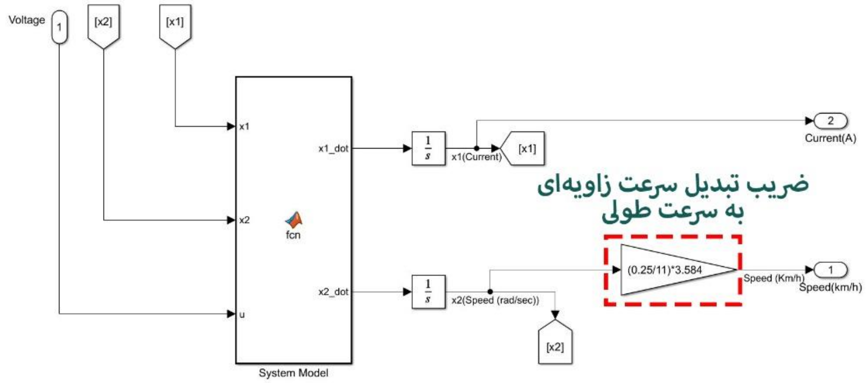
$$X = \begin{bmatrix} i \\ \omega \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

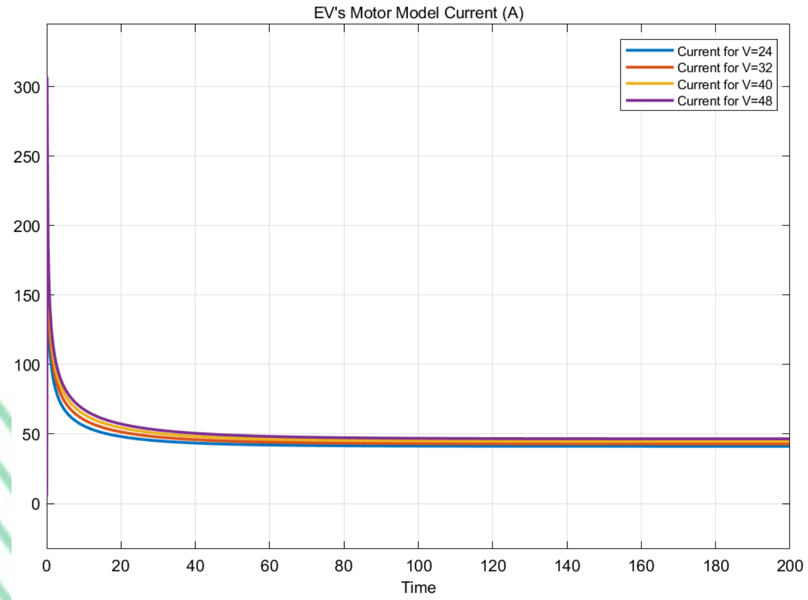
$$f(x) = \begin{bmatrix} \left(\dfrac{1}{L_a + L_{\text{field}}}\right) \times \left\{-\left(R_a + R_f\right) \cdot x_1 - \; L_{af} \cdot x_1 \cdot x_2\right\} \\ \left(\dfrac{1}{J + m\left(r/G\right)^2}\right) \times \left\{ \begin{matrix} L_{af} \cdot x_1^2 - Bx_2 - \left(\dfrac{r}{G}\right) \times \\ \left(\mu_{rr} mg + \dfrac{1}{2}\rho A C_d \left(\dfrac{r}{G}\right)^2 x_2^2 + mg sin\varphi\right) \end{matrix} \right\} \end{bmatrix}$$

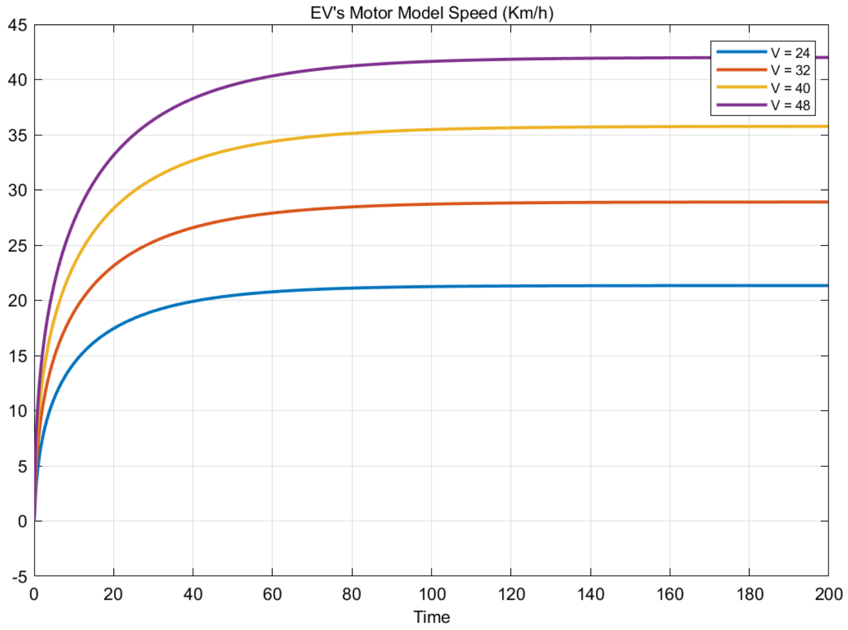
$$g(x) = \begin{bmatrix} \left(\dfrac{1}{L_a + L_{\text{field}}}\right) \\ 0 \end{bmatrix}$$

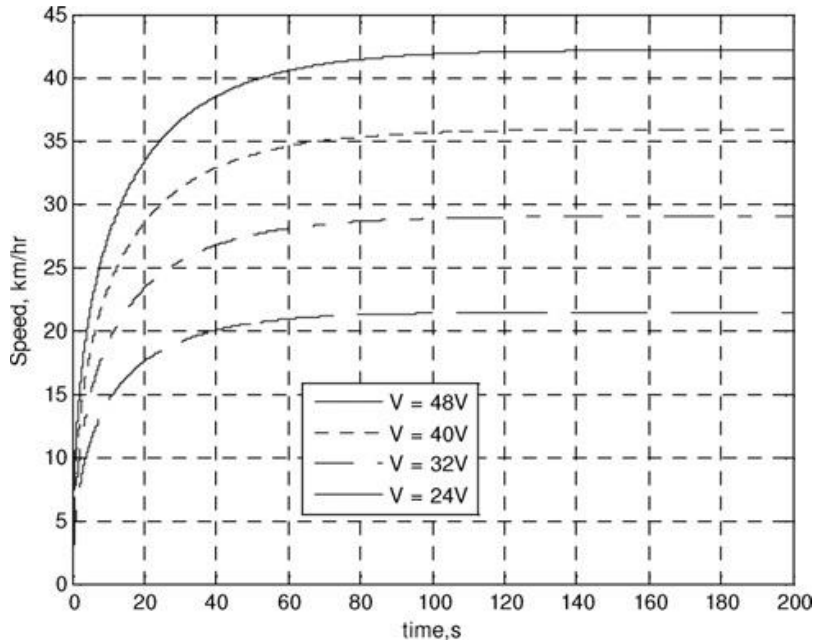
Simulation

- Open Loop Response:



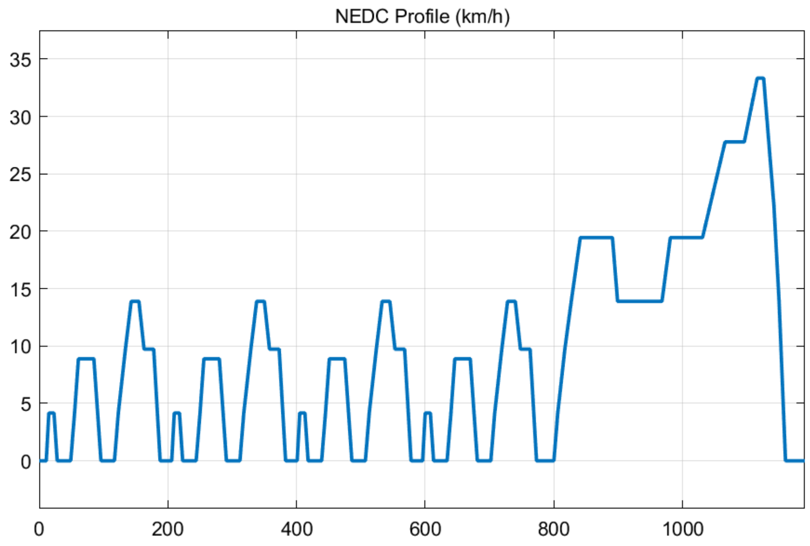


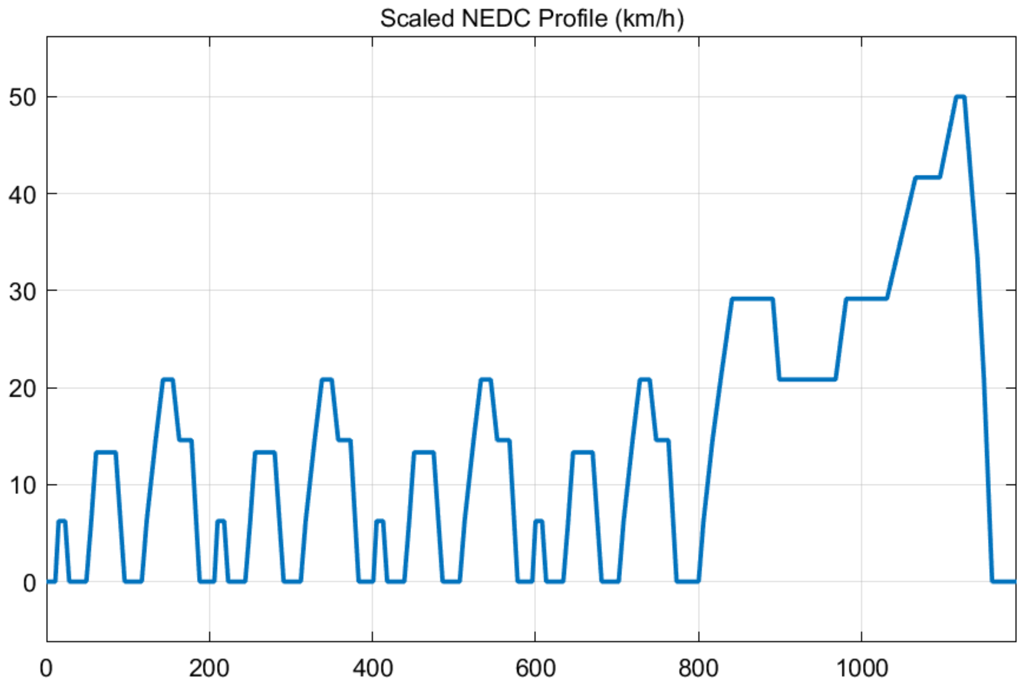




Simulation

- Desired Speed Values (NEDC):

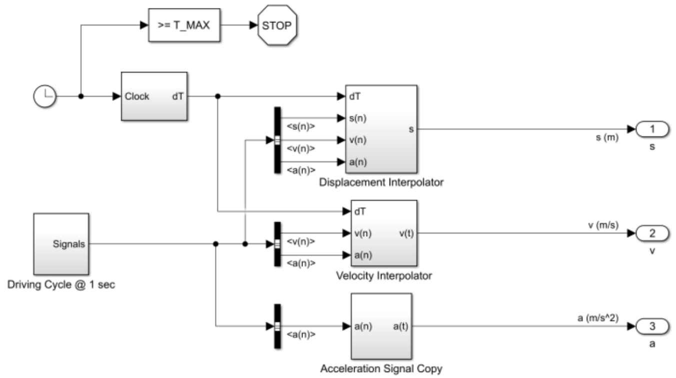


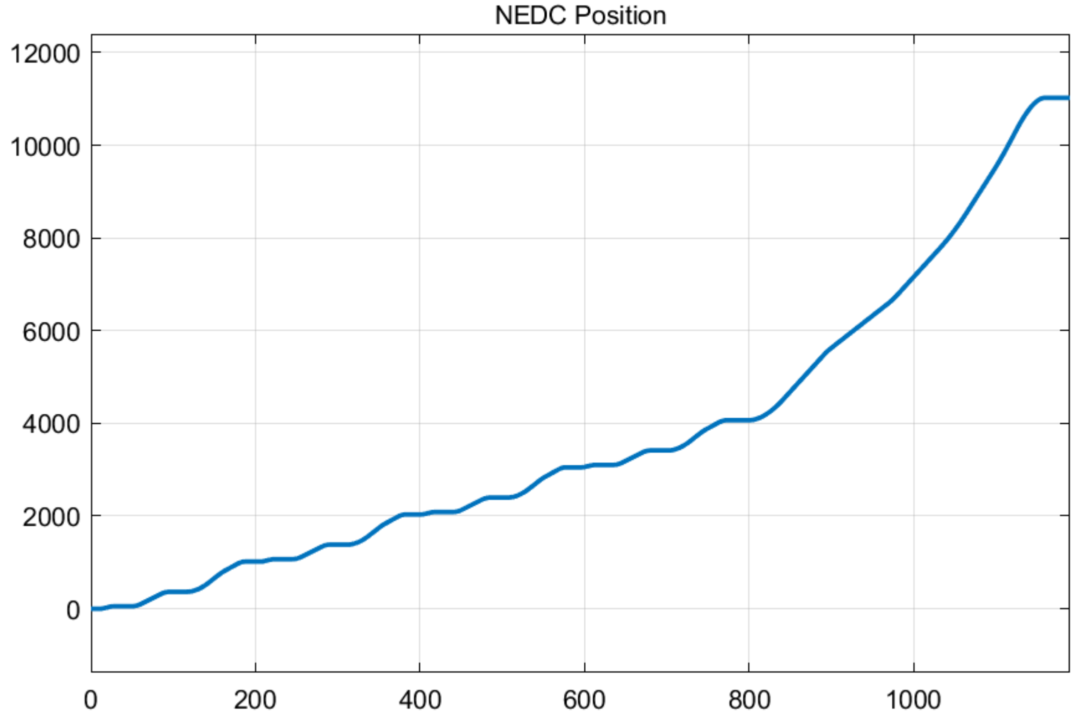


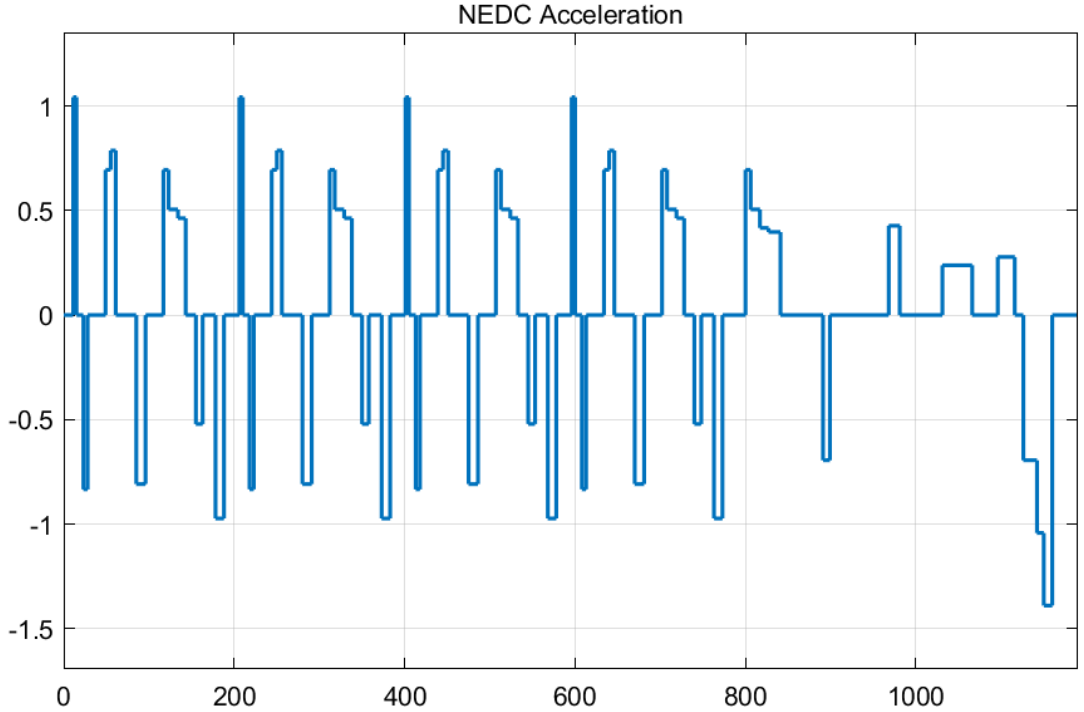
$$\omega = G\frac{v}{r}\ \text{rad.s}^{-1}$$

Simulation

- NEDC Profiles:



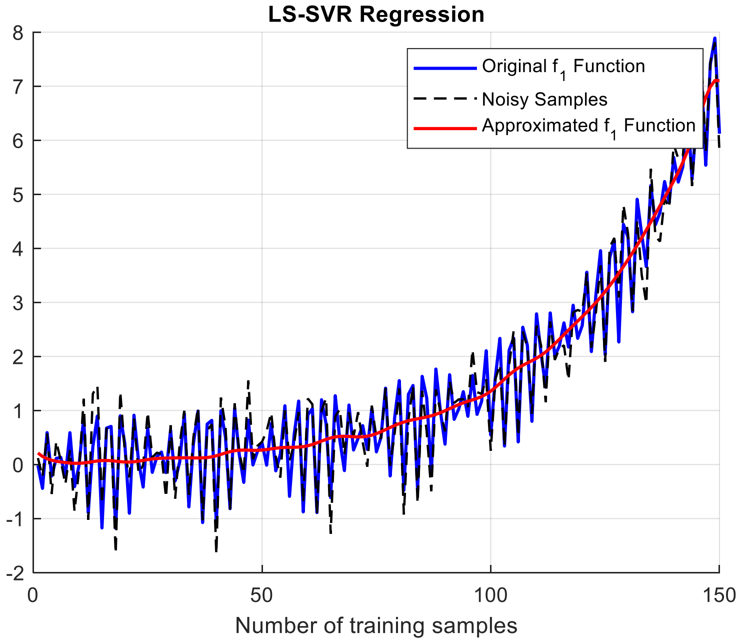


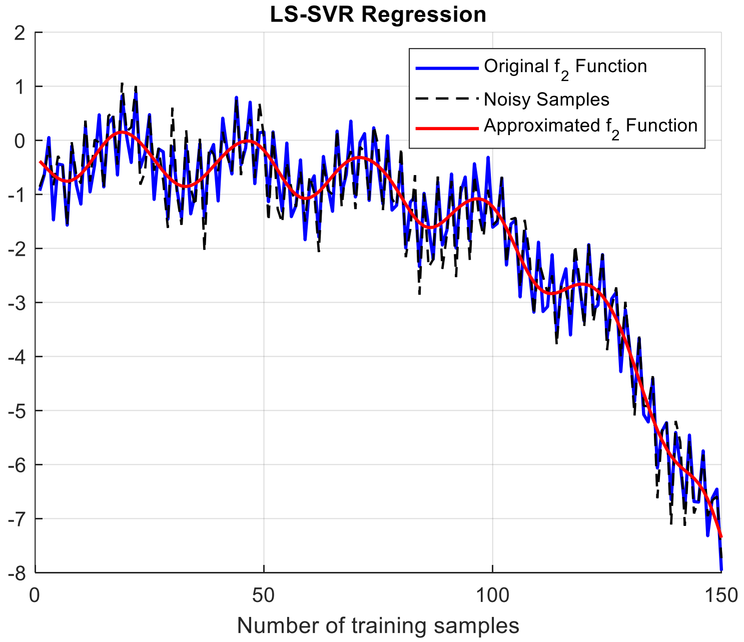


Simulation

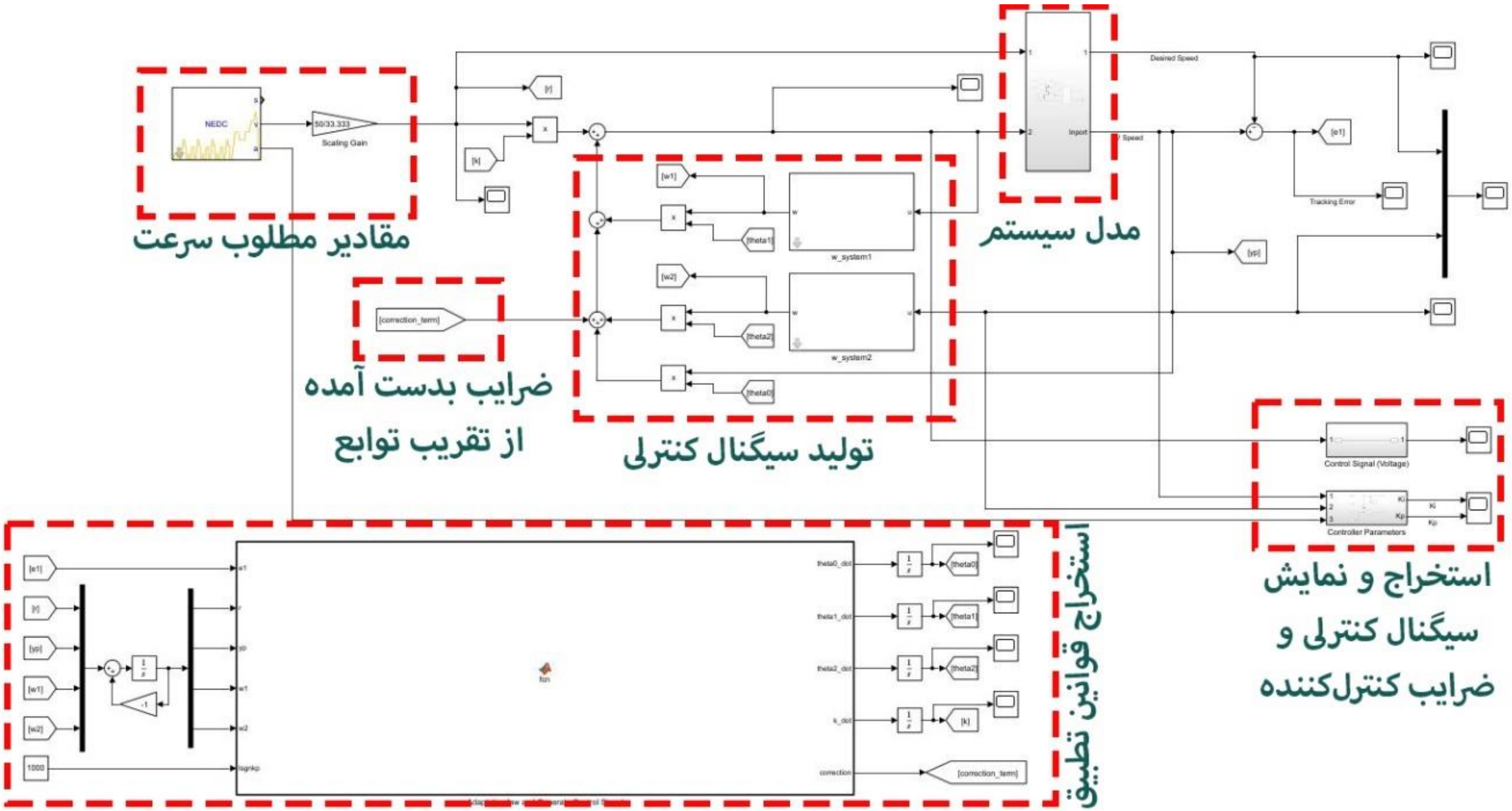
- Approximate f_1 and f_2 using LS-SVR:

```
C = 100; %Parameter defined to avoid overfitting
g = 0.01;%Radial Basis Function learning parameter, is equal to 1/2sigma^2
```



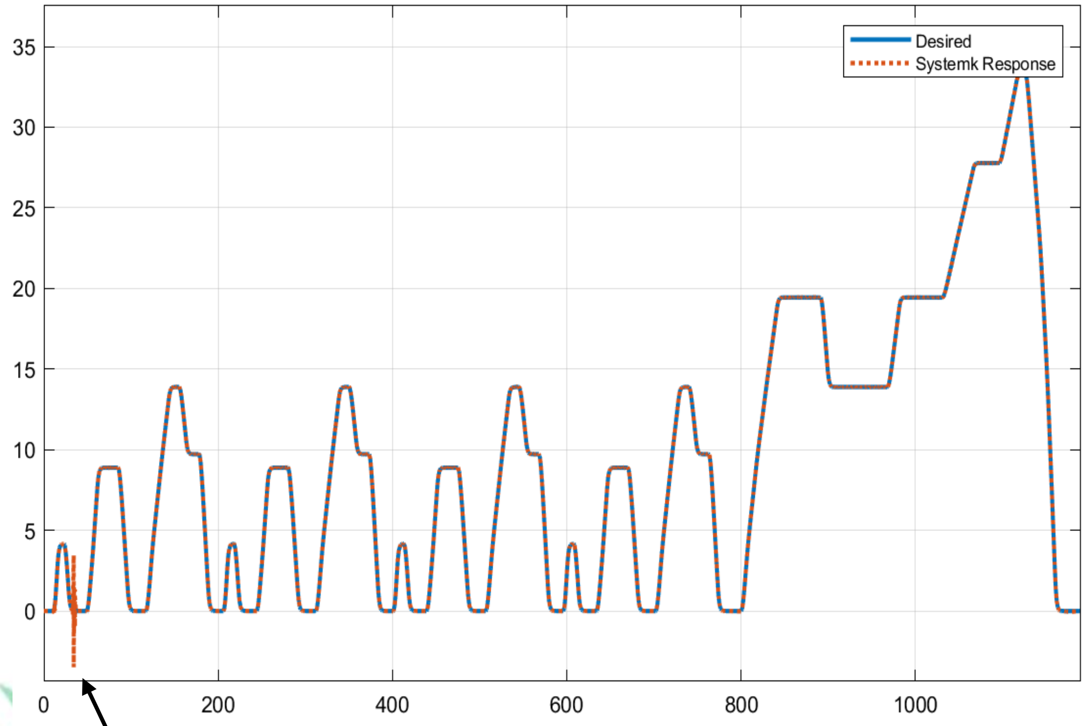


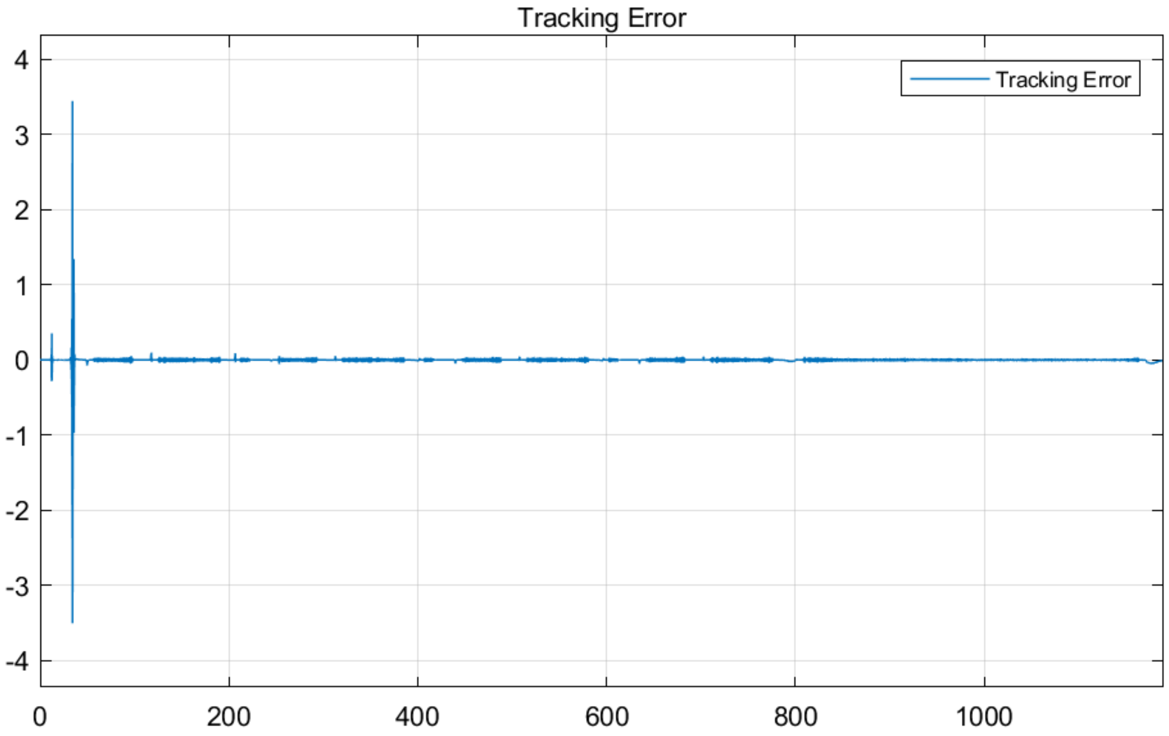
Proposed Control Algorithm



Proposed Control Algorithm

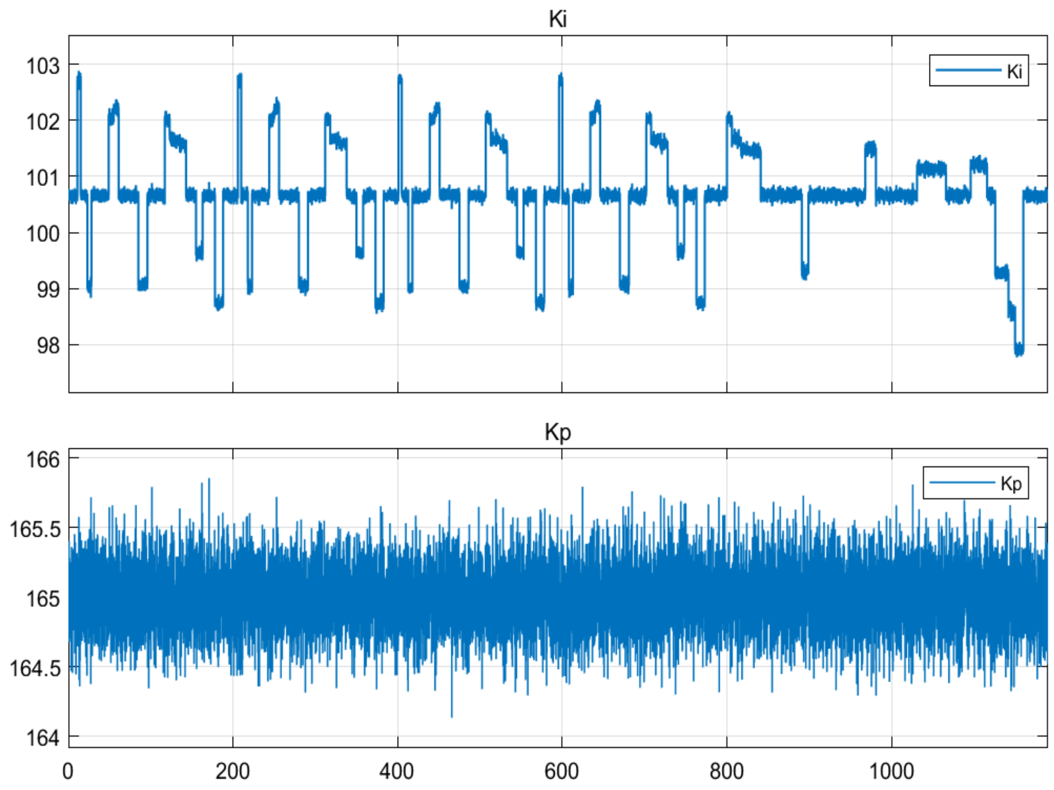
- By applying the NEDC Profiles as Desired input, The Response is:

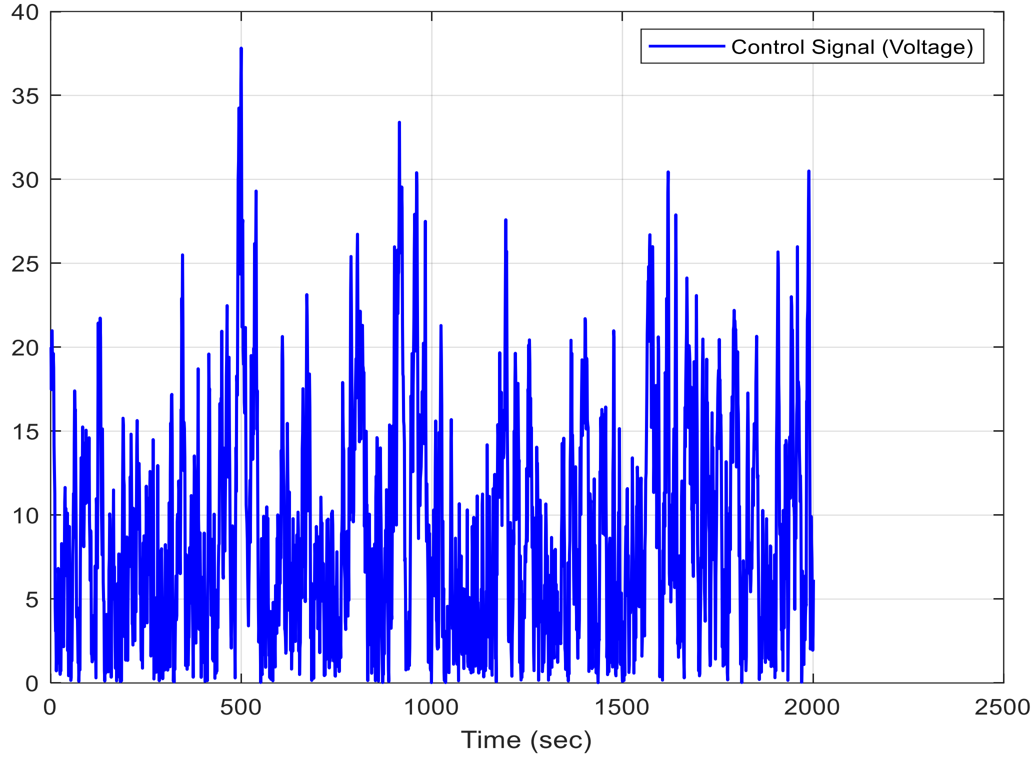




5 cos(2Πt) @ t=35

Proposed Control Algorithm

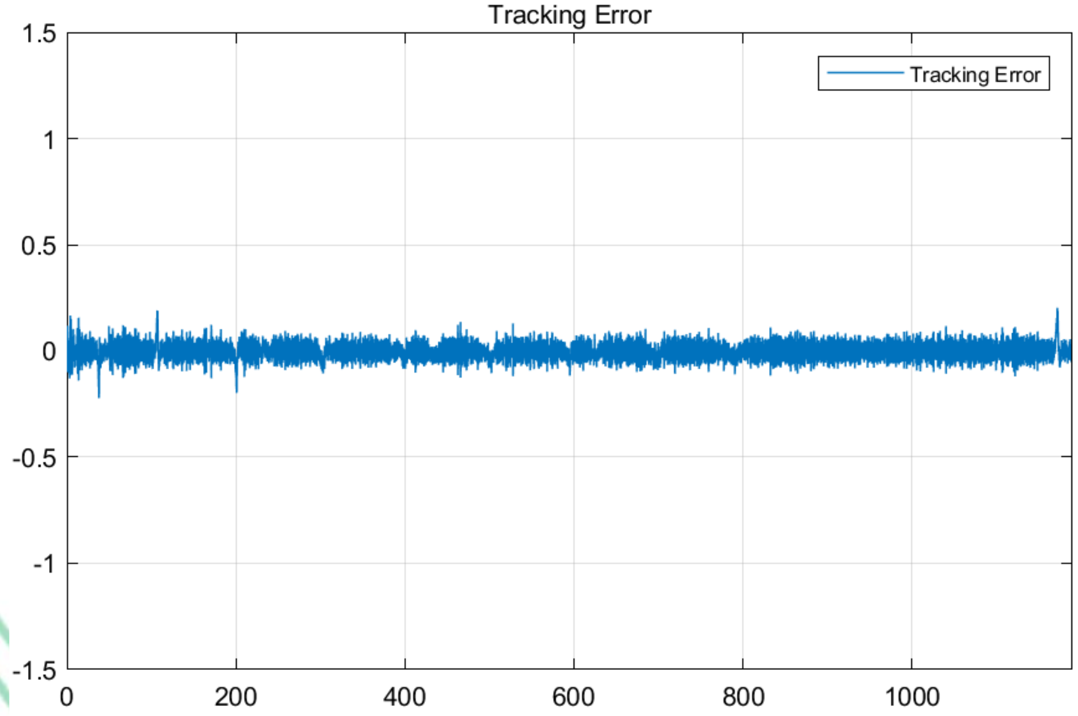


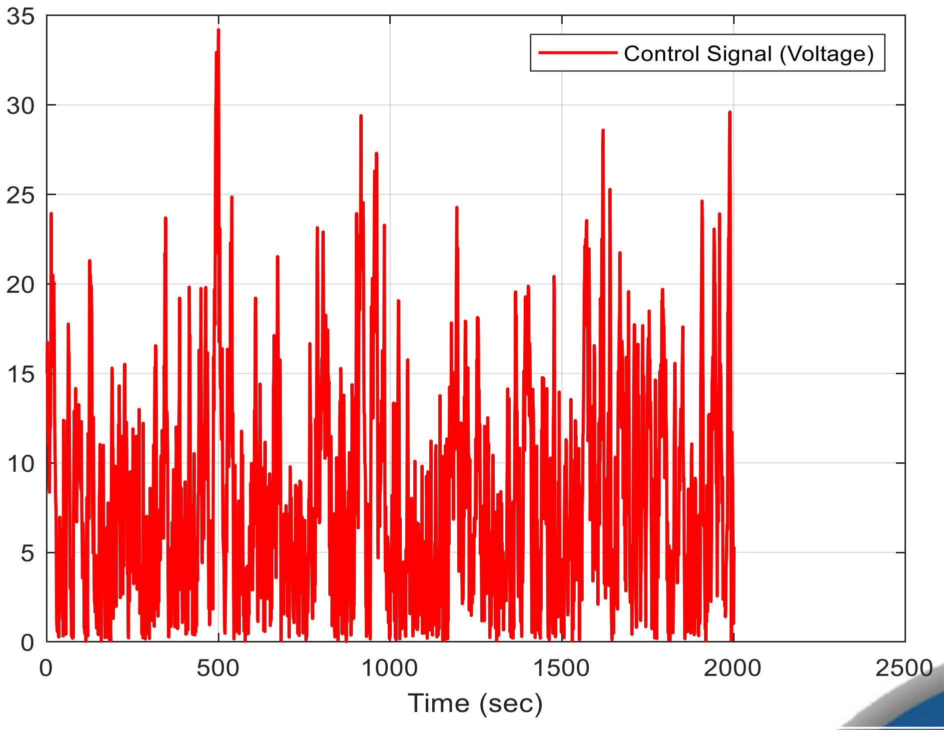


Proposed Control Algorithm

- Learning Rate's Effect
  - $\Gamma_i = 100$

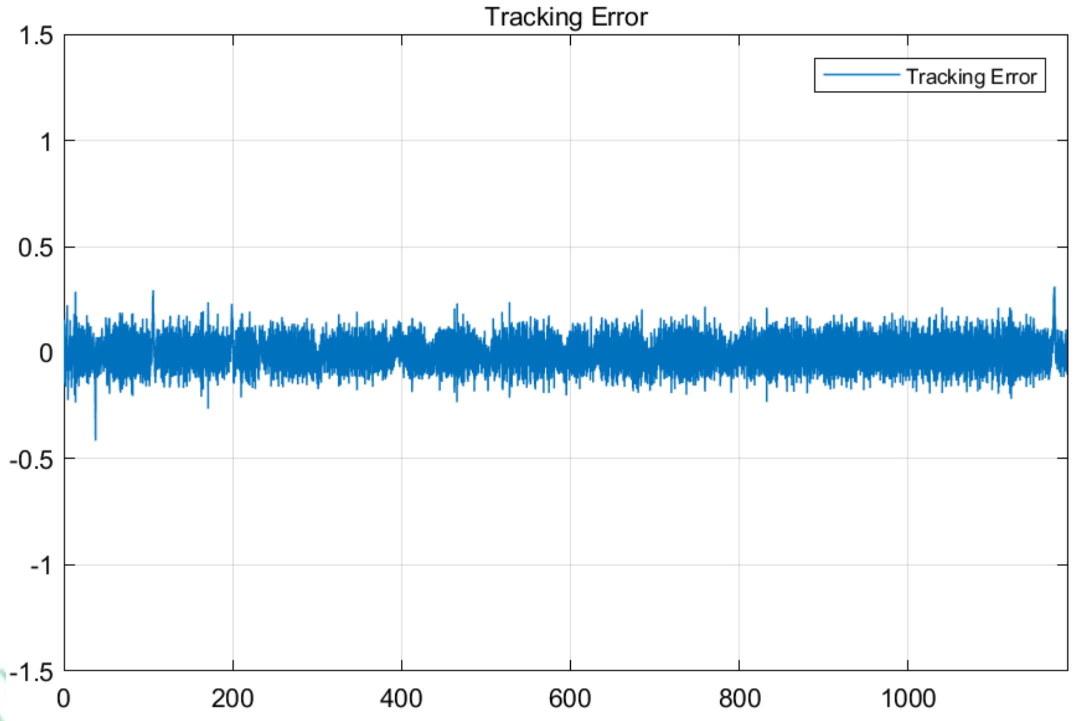
$\Gamma_i = [100 \quad 150 \quad 200]$

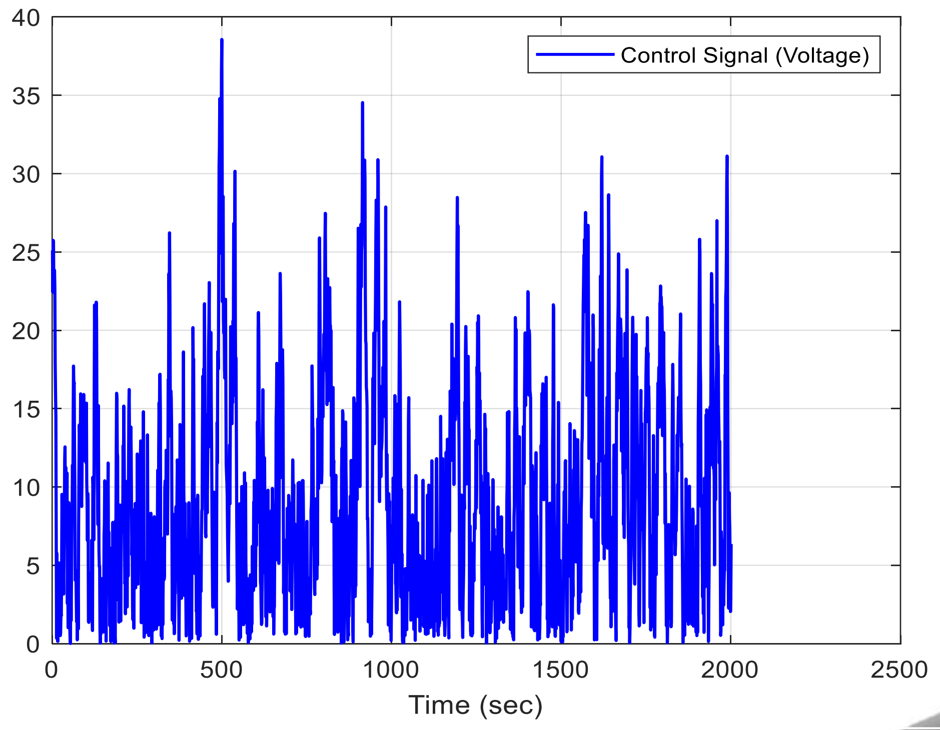




Proposed Control Algorithm

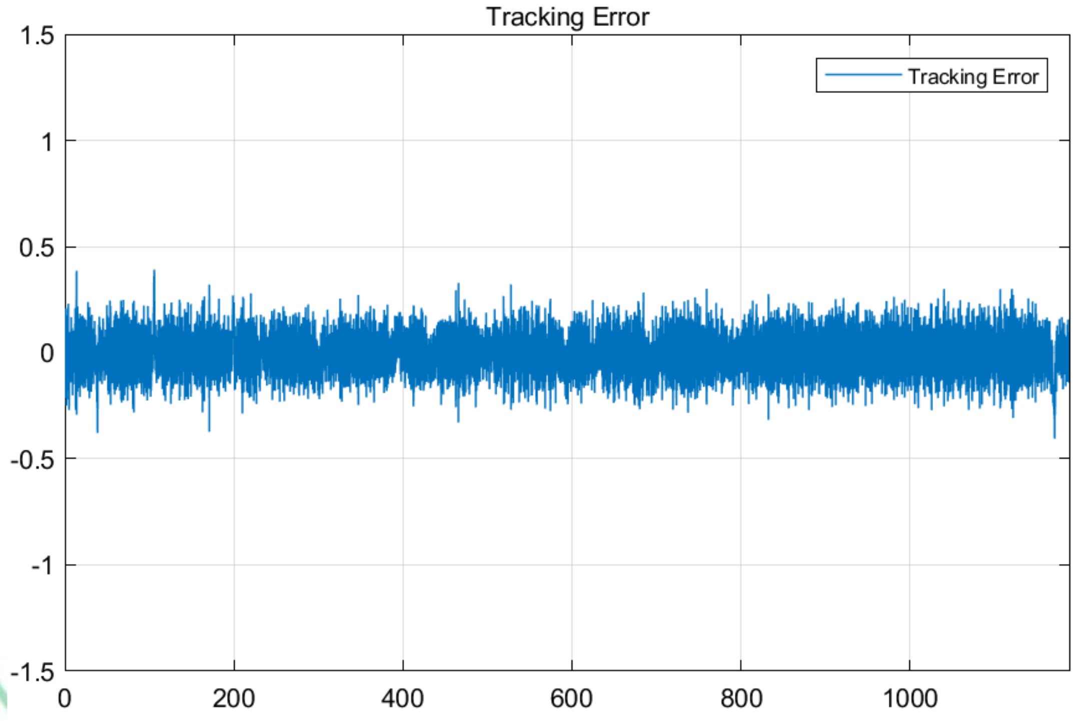
- $\Gamma_i = 150$

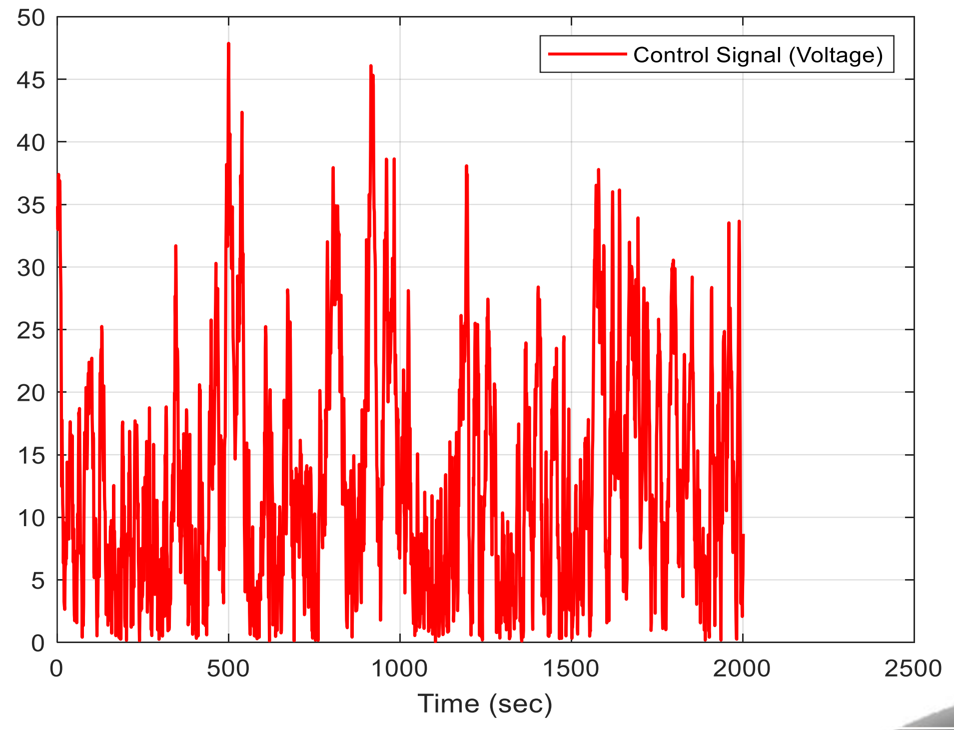




Proposed Control Algorithm

- $\Gamma_i = 200$





Thanks For Your Attention

References

[1] M. H. Khooban, O. Naghash-Almasi, T. Niknam, and M. Sha-Sadeghi, “Intelligent robust PI adaptive control strategy for speed control of EV(s),” IET Sci. Meas. Technol., vol. 10, no. 5, pp. 433–441, 2016.

[2] Q. Huang, Z. Huang, and H. Zhou, “Nonlinear optimal and robust speed control for a light-weighted all-electric vehicle,” IET Control Theory Appl., vol. 3, no. 4, pp. 437–444, 2009.

[3] W. Wei, “On disturbance rejection for a class of nonlinear systems,” Complexity, vol. 2018, pp. 1–14, 2018.

[4] E. Wei, T. Li, J. Li, Y. Hu, and Q. Li, “Neural network-based adaptive dynamic surface control for inverted pendulum system,” in Advances in Intelligent Systems and Computing, Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 695–704.

[5] B. Hammer and K. Gersmann, “A note on the universal approximation capability of support vector machines,” Neural Process. Lett., vol. 17, no. 1, pp. 43–53, 2003.

References

[6] J. L. J. Lowry, Electric Vehicle Technology Explained. London, England: ISTE Ltd and John Wiley & Sons, 2003.

[7] S. S. Keerthi and C.-J. Lin, “Asymptotic behaviors of support vector machines with Gaussian kernel,” Neural Comput., vol. 15, no. 7, pp. 1667–1689, 2003.

[8] S. An, W. Liu, and S. Venkatesh, “Fast cross-validation algorithms for least squares support vector machine and kernel ridge regression,” Pattern Recognit., vol. 40, no. 8, pp. 2154–2162, 2007.

[9] S. Wang and B. Meng, “Parameter selection algorithm for support vector machine,” Procedia Environ. Sci., vol. 11, pp. 538–544, 2011.

[10] S. Lin, X. Liu, Y. Rong, and Z. Xu, “Almost optimal estimates for approximation and learning by radial basis function networks,” Mach. Learn., vol. 95, no. 2, pp. 147–164, 2014.

References

[11] C.-N. Ko and C.-M. Lee, "Short-term load forecasting using SVR (support vector regression)-based radial basis function neural network with dual extended Kalman filter," Energy (Oxf.), vol. 49, pp. 413–422, 2013.

[12] C.-C. Chuang, "Fuzzy weighted support vector regression with a fuzzy partition," IEEE Trans. Syst. Man Cybern. B Cybern., vol. 37, no. 3, pp. 630–640, 2007.

[13] B. De Moor, J. P. Vandewalle, J. A. Suykens, T. Van Gestel, and J. De Brabanter, Least Squares Support Vector Machines. World Scientific Publishing Company, 2002.

[14] H. Yang, F. Luo, and Y. Xu, "Robust control based on LS-SVM for uncertain nonlinear system," in 2008 IEEE Conference on Cybernetics and Intelligent Systems, 2008.

[15] C. Xie, C. Shao, and D. Zhao, "Indirect adaptive control for a class of unknown nonlinear systems based on LS-SVM," in The 2010 IEEE International Conference on Information and Automation, 2010.

References

[16] Y. Gao, Y. Liu, H. Wang, and P. Li, “Adaptive control of a class of nonlinear discrete-time systems with online kernel learning,” IFAC proc. vol., vol. 41, no. 2, pp. 7937–7942, 2008.

[17] H. Zargarzadeh, T. Dierks, and S. Jagannathan, “Adaptive neural network-based optimal control of nonlinear continuous-time systems in strict-feedback form: ADAPTIVE NN-BASED OPTIMAL CONTROL,” Int. J. Adapt. Control Signal Process., vol. 28, no. 3–5, pp. 305–324, 2014.

[18] H.-J. Rong and G.-S. Zhao, “Stable indirect adaptive fuzzy-neuro control for a class of nonlinear systems,” in International Conference on Fuzzy Systems, 2010.

[19] G. Feng, “A survey on analysis and design of model-based fuzzy control systems,” IEEE Trans. Fuzzy Syst., vol. 14, no. 5, pp. 676–697, 2006.

[20] M. Shahsadeghi, M. H. Khooban, and T. Niknam, “A robust and simple optimal type II fuzzy sliding mode control strategy for a class of nonlinear chaotic systems,” J. Intell. Fuzzy Syst., vol. 27, no. 4, pp. 1849–1859, 2014.

[21] M. R. Soltanpour, P. Otadolajam, and M. H. Khooban, “Robust control strategy for electrically driven robot manipulators: adaptive fuzzy sliding mode,” IET Sci. Meas. Technol., vol. 9, no. 3, pp. 322–334, 2015.

References

[22] T. Niknam and M. H. Khooban, “Fuzzy sliding mode control scheme for a class of non-linear uncertain chaotic systems,” IET Sci. Meas. Technol., vol. 7, no. 5, pp. 249–255, 2013.

[23] L.-X. Wang, “Stable adaptive fuzzy controllers with application to inverted pendulum tracking,” IEEE Trans. Syst. Man Cybern. B Cybern., vol. 26, no. 5, pp. 677–691, 1996.

[24] G. F. Montúfar, “Universal approximation depth and errors of narrow belief networks with discrete units,” 2013.

[25] M. Ghaemi, S. K. Hosseini-Sani, and M. H. Khooban, “Direct adaptive general type-2 fuzzy control for a class of uncertain non-linear systems,” IET Sci. Meas. Technol., vol. 8, no. 6, pp. 518–527, 2014.

[26] C.-H. Wang, T.-C. Lin, T.-T. Lee, and H.-L. Liu, “Adaptive hybrid intelligent control for uncertain nonlinear dynamical systems,” IEEE Trans. Syst. Man Cybern. B Cybern., vol. 32, no. 5, pp. 583–597, 2002.