EML 6531-Adaptive Control Project 5

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1)Simulation Section for the Standard-Gradient Based Adaptive Update law

1) Control Gains used:

- K_1 multiplying r in the control law
- α multiplying e in the definition of the error signal r
- Matrix Γ in the adaptive update law

The values of which were tuned as follows:

$$K_1 = 10,\ \beta = 20,\ \alpha = 1 \text{ and } \Gamma = \begin{bmatrix} 300 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 20 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 80 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 20 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 15 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 15 \end{bmatrix}$$

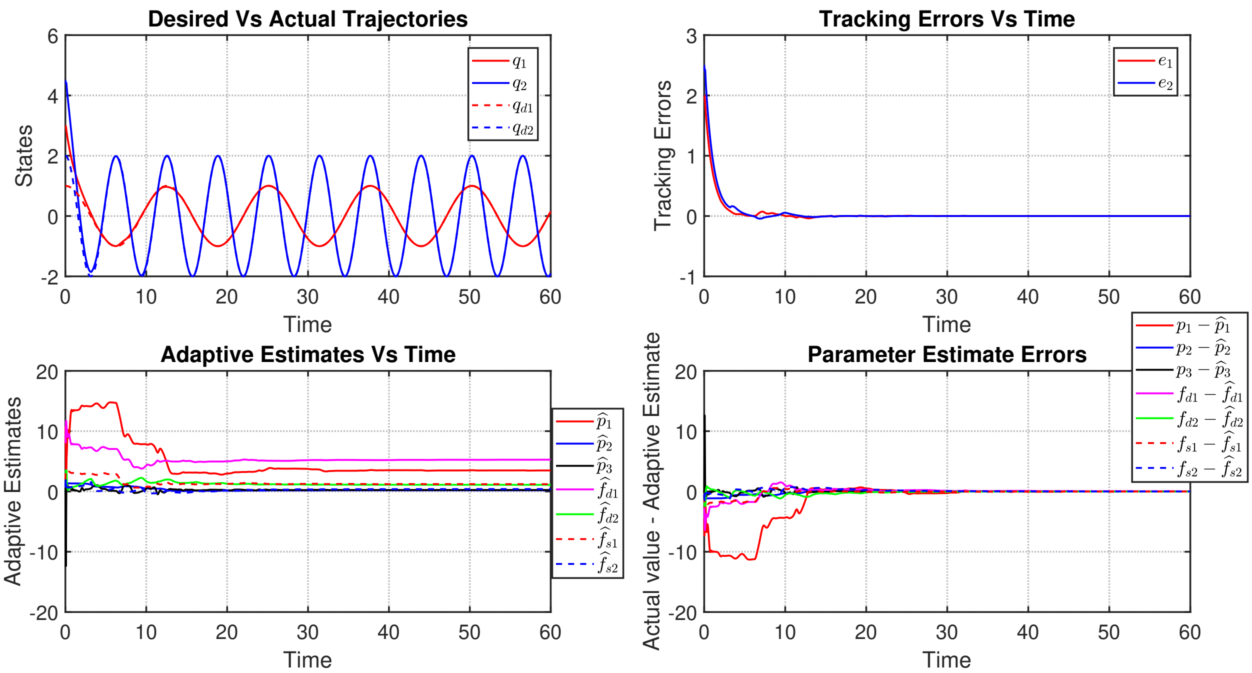

Figure 1: Standard Adaptive Control

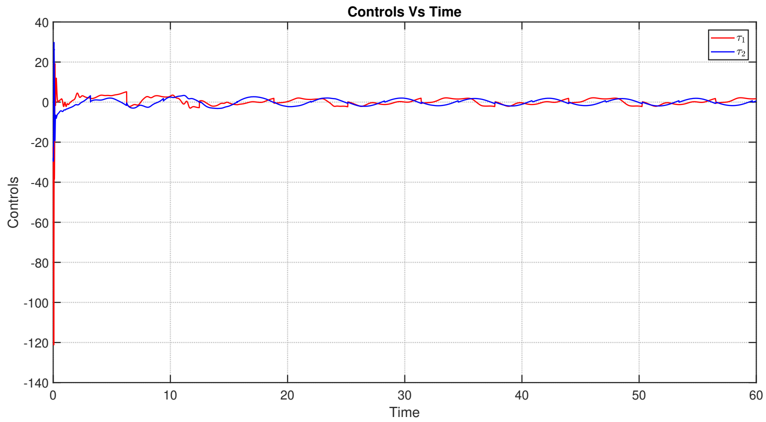

Figure 2: Control Inputs for Standard Adaptive Control

Maximum values of the torques are 121.1820 Nm and 29.7807 Nm respectively.

2)Simulation Section for Repetitive Learning Controller

1) Control Gains used:

- K multiplying r in the control law
- K_n multiplying ρ^2 in the control law
- K_l multiplying r in the update law for $\widehat{w}$
- β, the maximum absolute value that the saturation function can take
- α multiplying e in the definition of the error signal r
- Matrix Γ in the adaptive update law for $\widehat{f_{s_1}}$ and $\widehat{f_{s_2}}$

The values of which were tuned as follows:
$K = \begin{bmatrix} 30 & 0 \\ 0 & 6 \end{bmatrix}$, $K_n = \begin{bmatrix} 2 & 0 \\ 0 & 0.05 \end{bmatrix}$, $K_l = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$, $\beta = 6$, $\alpha = 1$ and $\Gamma = \begin{bmatrix} 300 & 0 \\ 0 & 300 \end{bmatrix}$.

NOTE: K, K_n and K_l have been chosen to be diagonal matrices instead of scalar constants to ensure that the control torques are deliverable by the motors while getting a good performance. (The maximum torque for motor 1 is 250 Nm, while the maximum torque for motor 2 is 30 Nm)

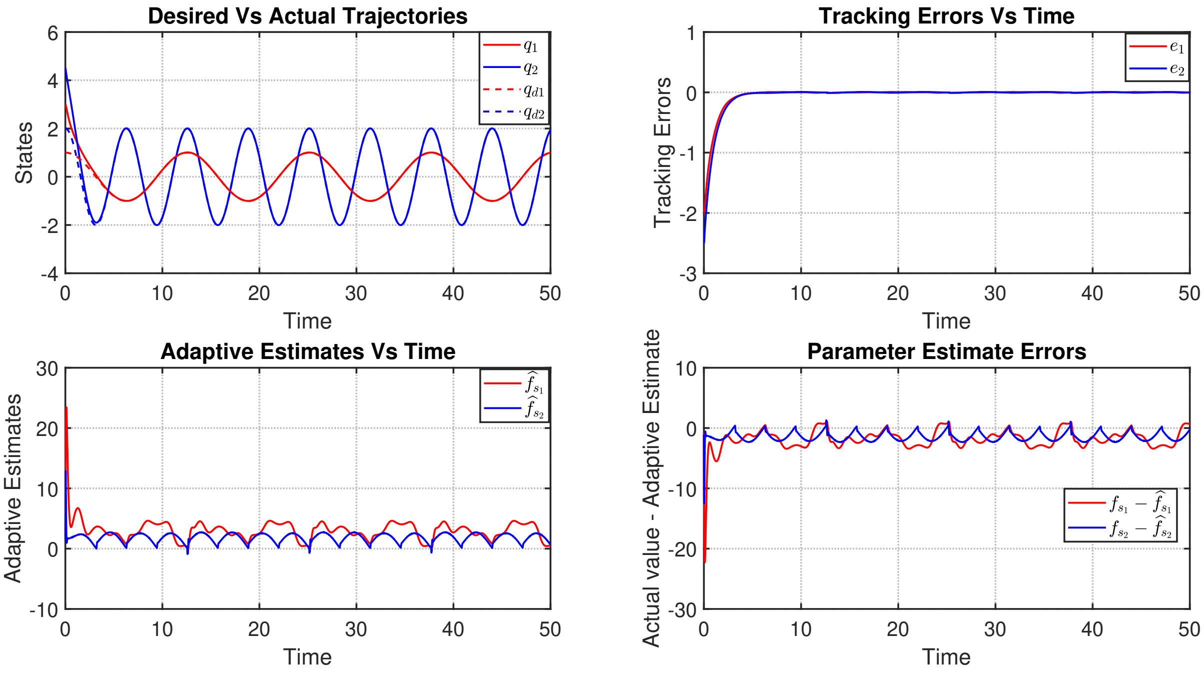

Figure 3: Repetitive Learning Control

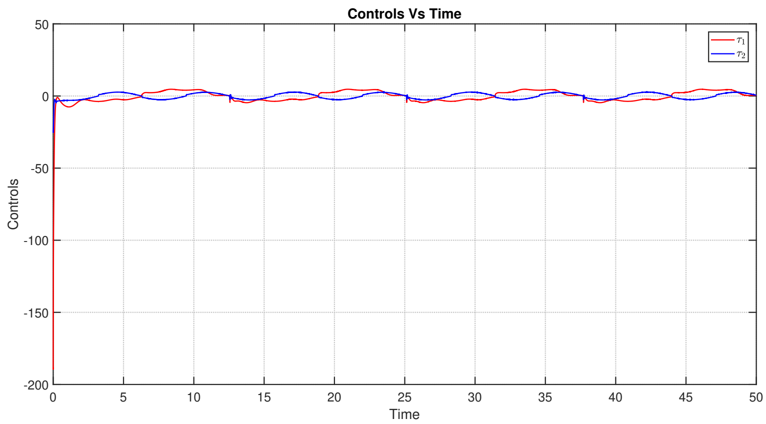

Figure 4: Control Inputs for Repetitive Learning Control

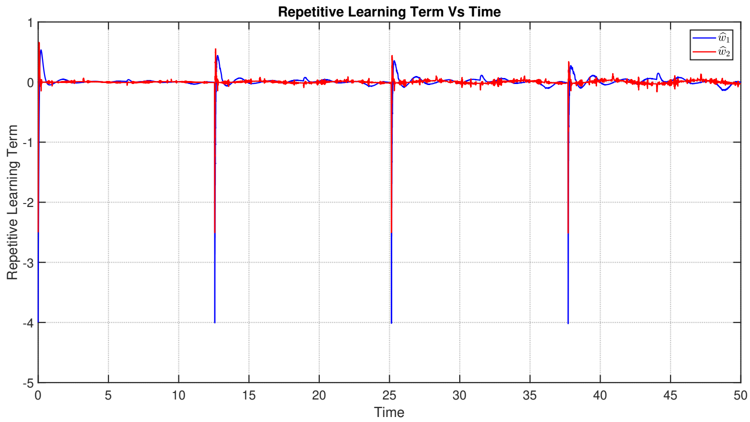

Figure 5: Repetitive Learning Term Vs Time

Maximum values of the torques are 189.4751 Nm and 25.3064 Nm respectively.

3)Discussion Section

- Increasing the gain K_1 in the *Standard-Adaptive Controller* or the gains K, K_n and K_l in the *Repetitive Learning Controller* increases the speed of convergence of the tracking error to zero. However, this comes at the cost of a bigger control effort.The gains are therefore fixed based on the maximum control torques that the motors are capable of delivering.

- Before comparing the performances of the two controllers, it needs to be made clear that it's not a level playing ground. The standard-adaptive controller makes use of the structure of the dynamic model. The only unknown thing is some constant parameters in the model. On the other hand, the repetitive-learning controller is a non-model-based controller. It has to get the job done without any (or with very little) knowledge of the dynamic model. In this problem, it only knows the structure of the static-disturbance-dynamics and nothing else.

- ***Tracking-Error Convergence:*** The tracking error comes close to zero much faster with the repetitive-learning controller as compared to the standard adaptive controller within the given maximum torque specifications. However, eventually, the standard-adaptive controller achieves a tracking error which is much closer to zero as compared to the repetitive-learning controller's. This has to do with the difference in the amount of model-knowledge available to the controllers.

- ***Convergence of the adaptive estimates:*** The adaptive estimates for the standard-adaptive controller include $\widehat{p}_1$, $\widehat{p}_2$, $\widehat{p}_3$, $\widehat{f}_{d1}$, $\widehat{f}_{d2}$, $\widehat{f}_{s_1}$ and $\widehat{f}_{s_2}$. The adaptive estimates for the repetitive-learning controller (with a small standard-adaptive part) include $\widehat{f}_{s_1}$ and $\widehat{f}_{s_2}$.

  - *Standard Adaptive Controller:* Lyapunov analysis does not prove the convergence of the adaptive estimates to the actual parameter values. However, simulation shows the adaptive estimates converging to the actual values. A bigger learning-gain-matrix, Γ, causes faster convergence at the cost of a higher control effort.
  - *Repetitive Learning Controller:* Lyapunov analysis does not prove the convergence of the adaptive estimates. Neither is the simulation seen to achieve any convergence of the estimates. Again, this can be ascribed to the fact that the controller has no knowledge of a major portion of the dynamic model (not even the structure). The estimate errors keep oscillating about zero and can be kept to a minimum by tuning Γ in combination with the other control gains.