Parameter estimation via EKF

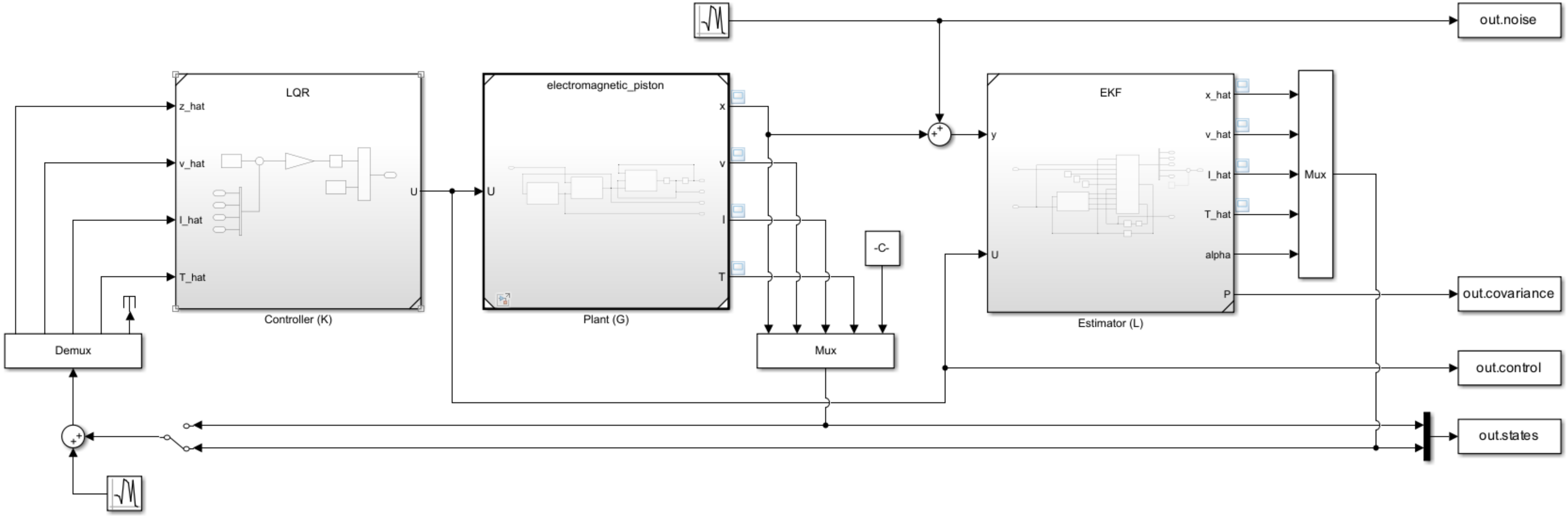
Implementation of an Extended Kalman Filter (EKF) to estimate the unknown value of a parameter of the system.

$$\ddot{x} + c\dot{x} + k_1 x + k_3 x^3 = \alpha i$$
$$(L_0 + \beta_1 T + \beta_2 T^2)\dot{i} + Ri = u$$
$$\dot{T} = \frac{1}{C_T}\left[Ri^2 - h(T - T_{env})\right]$$

$$\mathbf{x} = \begin{bmatrix} x \\ v \\ i \\ T \\ \alpha \end{bmatrix} \qquad u = [V]$$

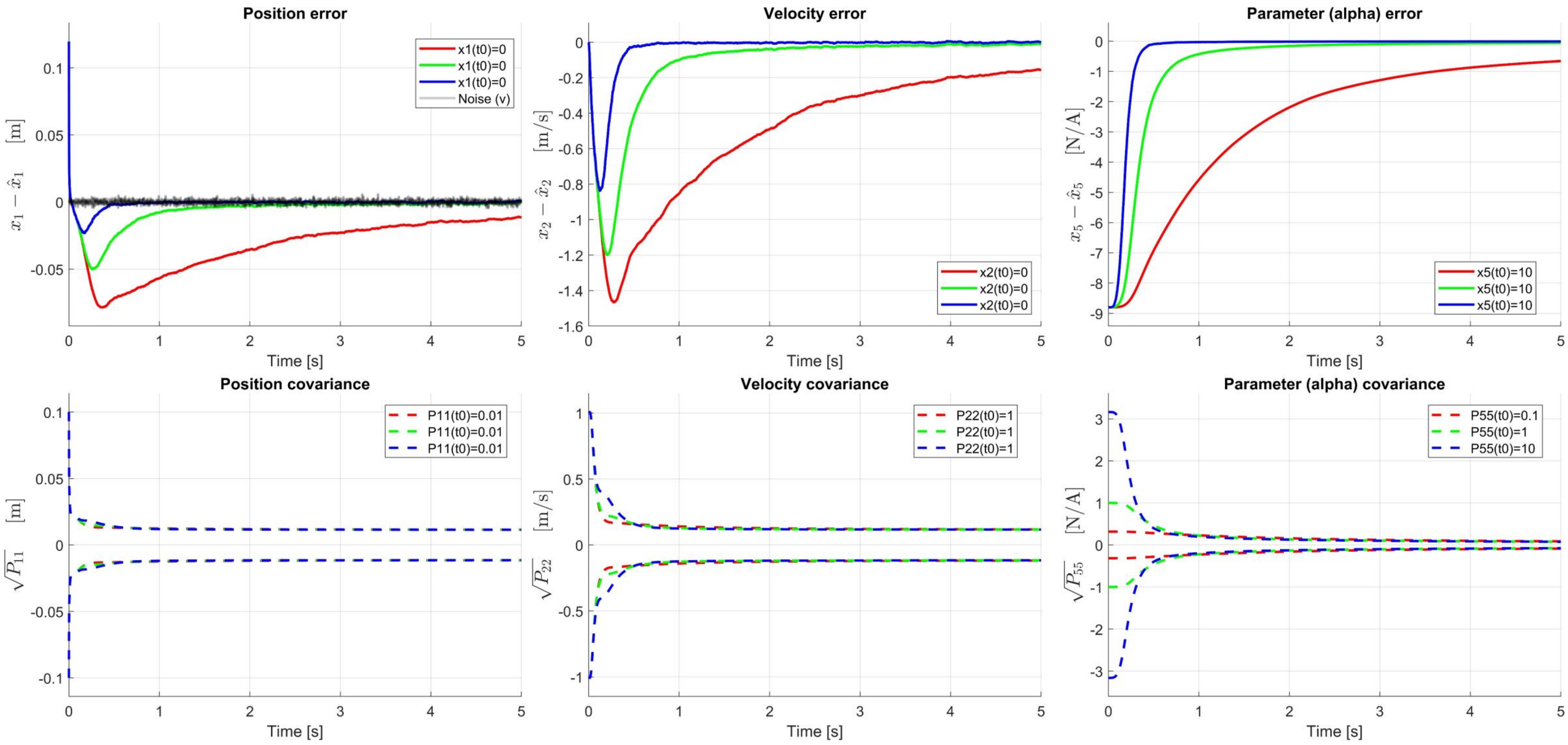
$$A(\mathbf{x}, u) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ \frac{-k_1 - 3k_3 x_1^2}{m} & \frac{-c}{m} & \frac{x_5}{m} & 0 & \frac{x_3}{m} \\ 0 & 0 & \frac{-R}{L(x_4)} & \frac{Rx_3 - u}{L(x_4)^2}\frac{dL(x_4)}{dT} & 0 \\ 0 & 0 & \frac{2Rx_3}{C_T} & \frac{-h}{C_T} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \qquad B(\mathbf{x}, u) = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{L(x_4)} \\ 0 \\ 0 \end{bmatrix}$$

For the design of the EKF, we considered the augmented system with the additional state α (parameter be identified). The update of the estimates is based only on x_1. Different values for both $P_{0,EKF}$, Q_{EKF} and R_{EKF} were considered to observe their effects on the filter operation.



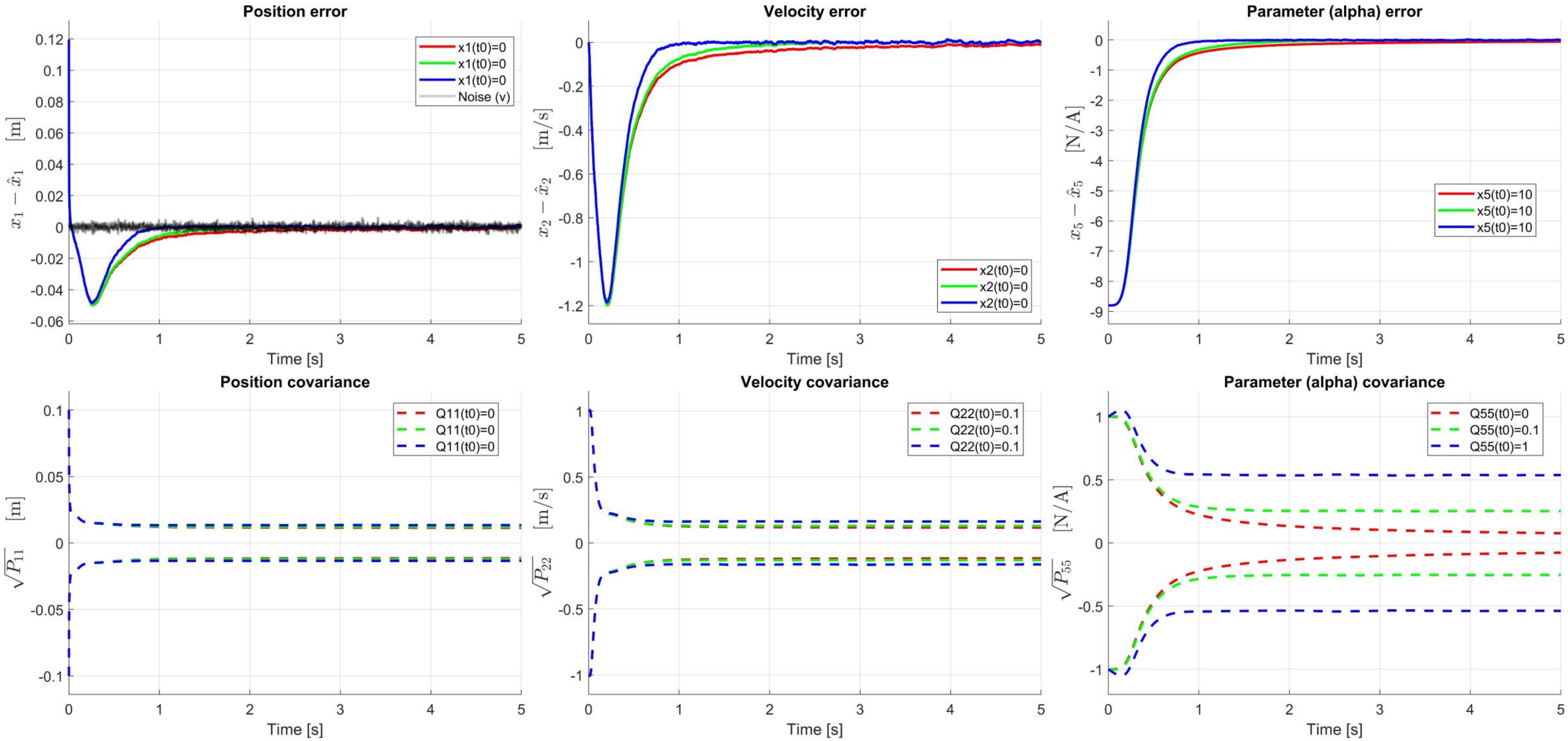
Influence of $P_0(5,5)$, keeping $Q(5,5) = 0$, $R = 10^{-5}$

Larger P_0 helps in reaching correct estimation in a shorter time. Too high values might lead to strong initial fluctuations.



Influence of $Q(5,5)$, keeping $P_0(5,5) = 1$, $R = 10^{-5}$

Larger Q helps to trust measurement more but leads to lower confidence in estimation.



Influence of R, keeping $P_0(5,5) = 1$, $Q(5,5) = 0$

Smaller R helps to trust measurement more but also reduces smoothing capabilities of the filter. On the other hand, larger R forces the filter to rely more on the model and thus also on the initial estimate, which may be wrong, imposing long times before a correct estimate is obtained.