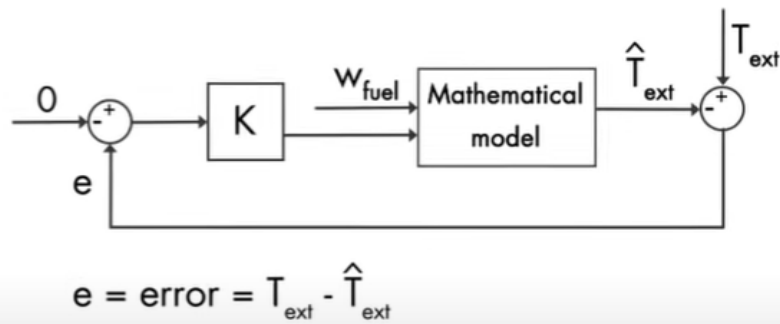
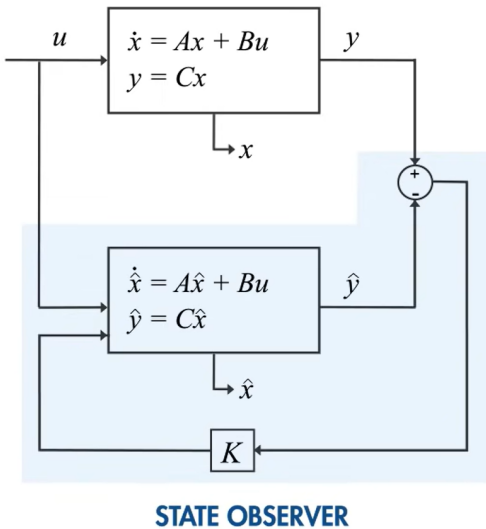


Kalman Filters

- Generally used to obtain the optimal estimate measurement after fusion of sensors when some sensors give uncertain or no value
- Algorithm generally used in applications like determining location speed etc
- State estimator- used to find quantities that are difficult or unable to find using mathematical model
- The methodology used in kalman filter is similar to feedback control mechanism where the difference between estimated and measured is minimised by using a controller K
- e here is the error of output.



Here is a typical example of how Kalman filters work



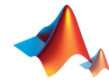
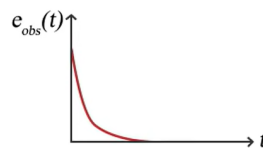
$$e_{obs} = x - \hat{x}$$

$$\begin{array}{ll} \dot{x} = Ax + Bu & y = Cx \\ \dot{\hat{x}} = A\hat{x} + Bu + K(y - \hat{y}) & \hat{y} = C\hat{x} \end{array}$$

$$\dot{e}_{obs} = (A - KC)e_{obs} \quad y - \hat{y} = Ce_{obs}$$

$$\hookrightarrow e_{obs}(t) = e^{(A - KC)t}e_{obs}(0)$$

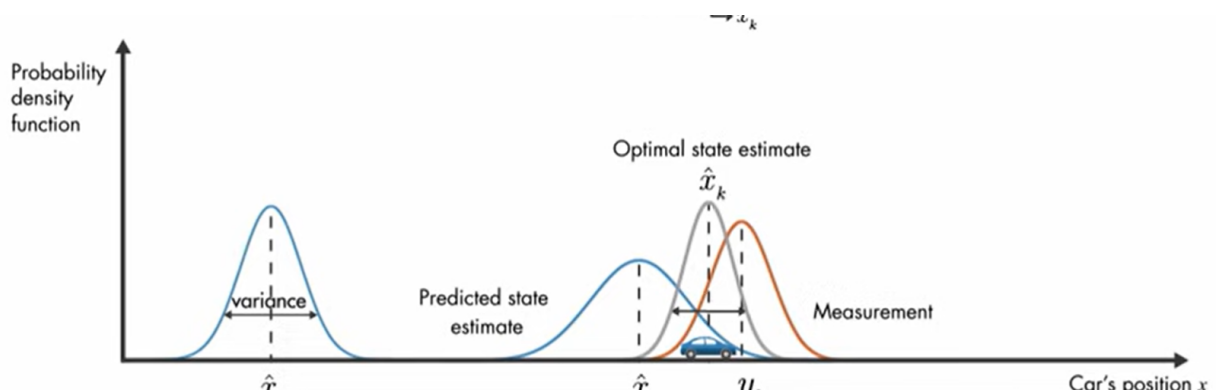
If $(A - KC) < 0$, then $e_{obs} \rightarrow 0$ as $t \rightarrow \infty$. So, $\hat{x} \rightarrow x$.



State estimator refers to the filter responsible for estimating the current state of a dynamic system

Kalman algorithm generally follows steps as follows

- Prediction- expected measurement
-



- Optimal state function(gaussian function) is obtained by multiplying the predicted and measured Probability Density Function and the mean of this gives the optimal estimate

- More the variance less the prediction is so our main aim is to reduce it so the probability density function value is high and we derive the optimal state estimate

- Variance and standard deviation

$$\sigma^2 = \frac{1}{N} \sum_{n=1}^N (x_n - \mu)^2$$

Kalman filter

$$\hat{x}_k = \underbrace{\hat{x}_k^-}_{\text{Predict}} + \underbrace{K_k (y_k - C \hat{x}_k^-)}_{\text{Update}}$$

- Posteriori estimate is the \hat{x}_k which refers to the previous value

Prediction
$\hat{x}_k^- = A \hat{x}_{k-1} + B u_k$ $P_k^- = A P_{k-1} A^T + Q$

Initial estimates for \hat{x}_{k-1} and P_{k-1} ↑

Update
$K_k = \frac{P_k^- C^T}{C P_k^- C^T + R}$ $\hat{x}_k = \hat{x}_k^- + K_k (y_k - C \hat{x}_k^-)$ $P_k = (I - K_k C) P_k^-$

- Distribution in graph
- Precision

Extended Kalman Filters

The Extended Kalman Filter (EKF) is an extension of the traditional Kalman Filter (KF) that allows it to handle nonlinear systems. But how's it different from extended kalman filters?

- Kalman filters assume that both the system's dynamics (state transition model) and measurement model (relationship between the state and measurements) are linear. But EKF is non linear
- Accuracy wise, KF is more accurate than the EKF in linear systems but in non linear terms EKF is very effective
- EKF uses Jacobian matrices and KF uses gaussian distributions for state and measurement noise.

Reminder: Jacobian

- It is a non-square matrix $m \times n$ in general
- Given a vector-valued function

$$g(x) = \begin{pmatrix} g_1(x) \\ g_2(x) \\ \vdots \\ g_m(x) \end{pmatrix}$$

- The Jacobian is defined as

$$G_x = \begin{pmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} & \cdots & \frac{\partial g_1}{\partial x_n} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} & \cdots & \frac{\partial g_2}{\partial x_n} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\partial g_m}{\partial x_1} & \frac{\partial g_m}{\partial x_2} & \cdots & \frac{\partial g_m}{\partial x_n} \end{pmatrix}$$

EKF Linearization: First Order Taylor Expansion

- Prediction:

$$g(u_t, x_{t-1}) \approx g(u_t, \mu_{t-1}) + \underbrace{\frac{\partial g(u_t, \mu_{t-1})}{\partial x_{t-1}}}_{=: G_t} (x_{t-1} - \mu_{t-1})$$

- Correction:

$$h(x_t) \approx h(\bar{\mu}_t) + \underbrace{\frac{\partial h(\bar{\mu}_t)}{\partial x_t}}_{=: H_t} (x_t - \bar{\mu}_t)$$

Jacobians

