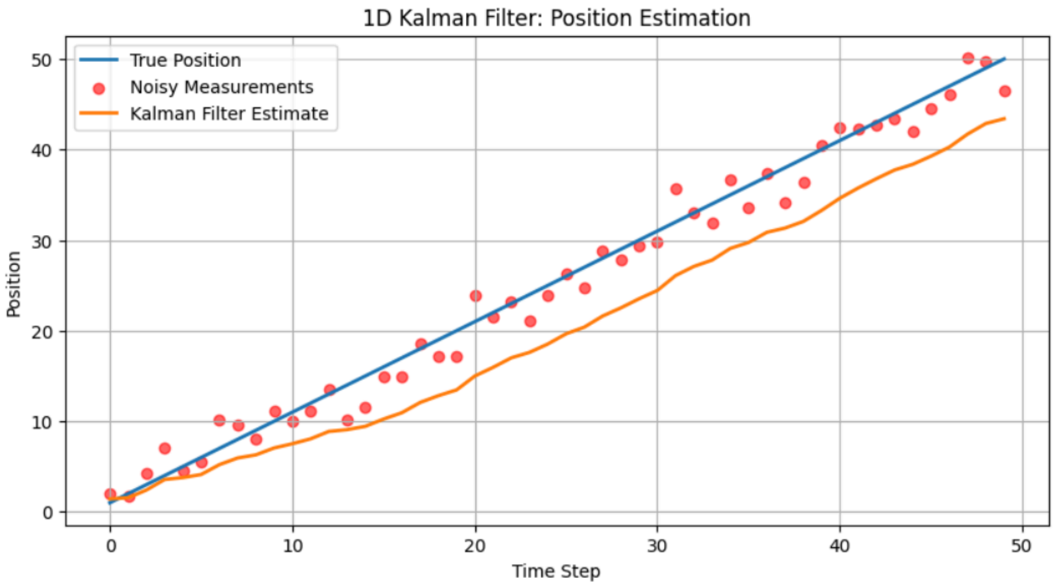
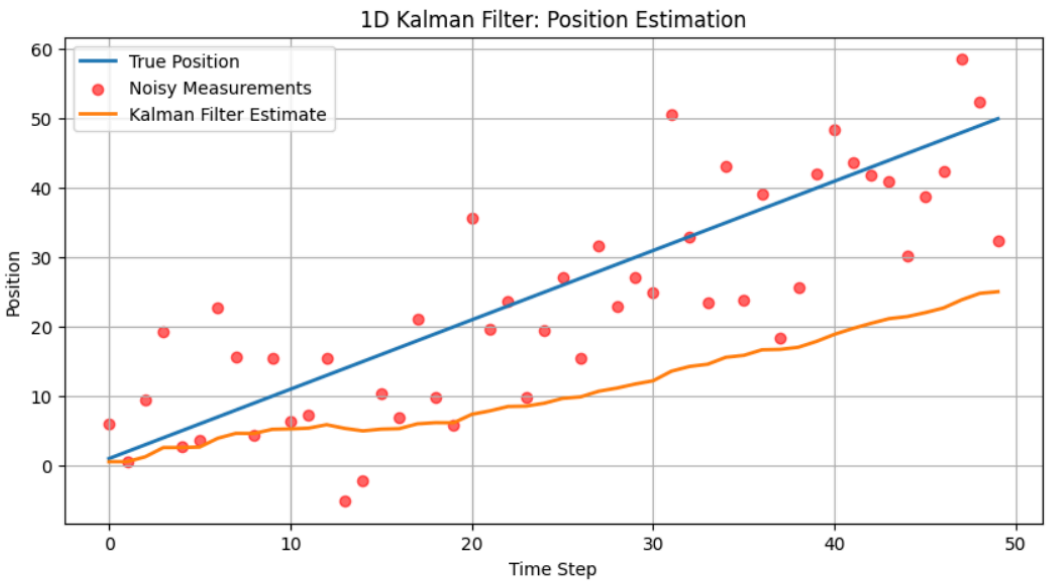
Without any change in parameters , we observe the following

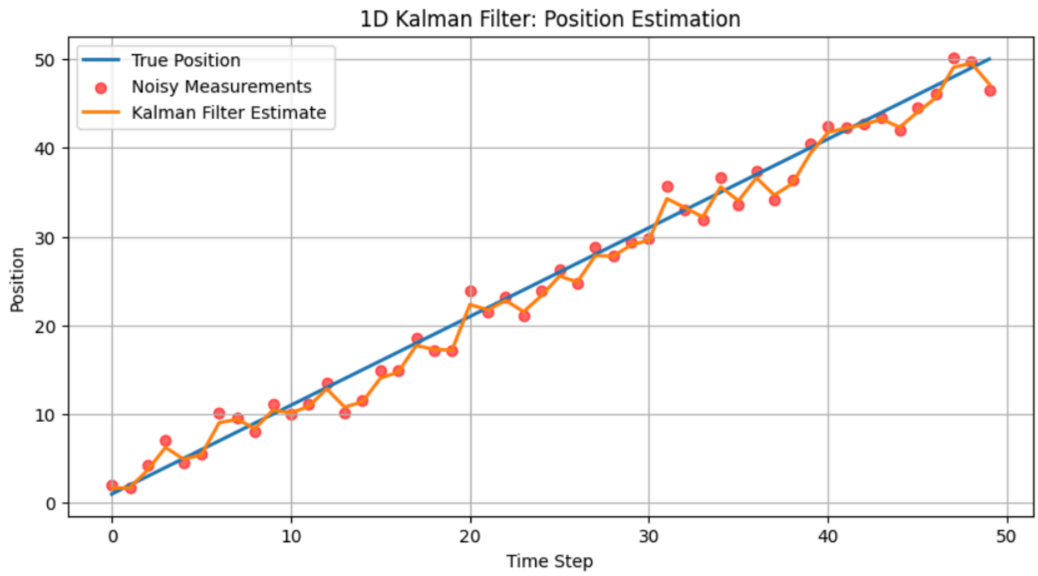


Now , when we increase R (from 2.0 to 8.0) , the measurement noise , we observe the following.



We see that the Kalman gain has reduced , thereby making the filter rely more on the previous estimates it made rather than the sensor measurements for making predictions.

Now, when we increase Q (from 0.1 to 10) , the process noise, we observe the following



We see that the Kalman gain has increased, thereby making the filter rely more on the sensor measurements than its previous estimates for making predictions.

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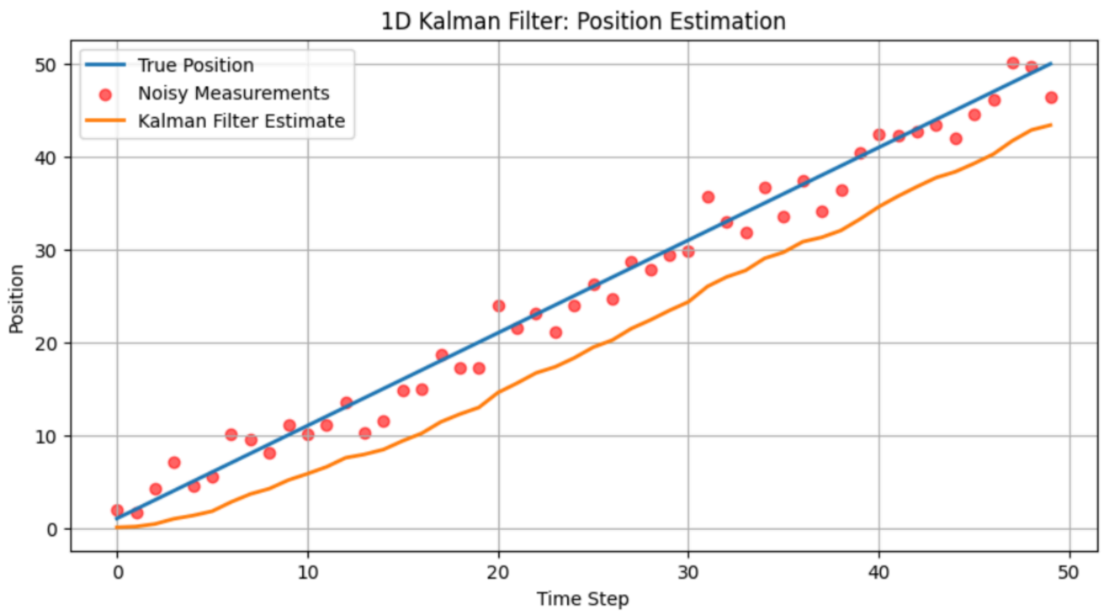
Now , when we start with a very small uncertainty P (10^-6) , let us see what happens.



So , initially , the Kalman gain is very small , thus the filter relies more on its initial estimate rather than the sensor measurements , so the change in state by the filter is gradual towards the true trajectory , as expected due to a small initial gain/covariance.

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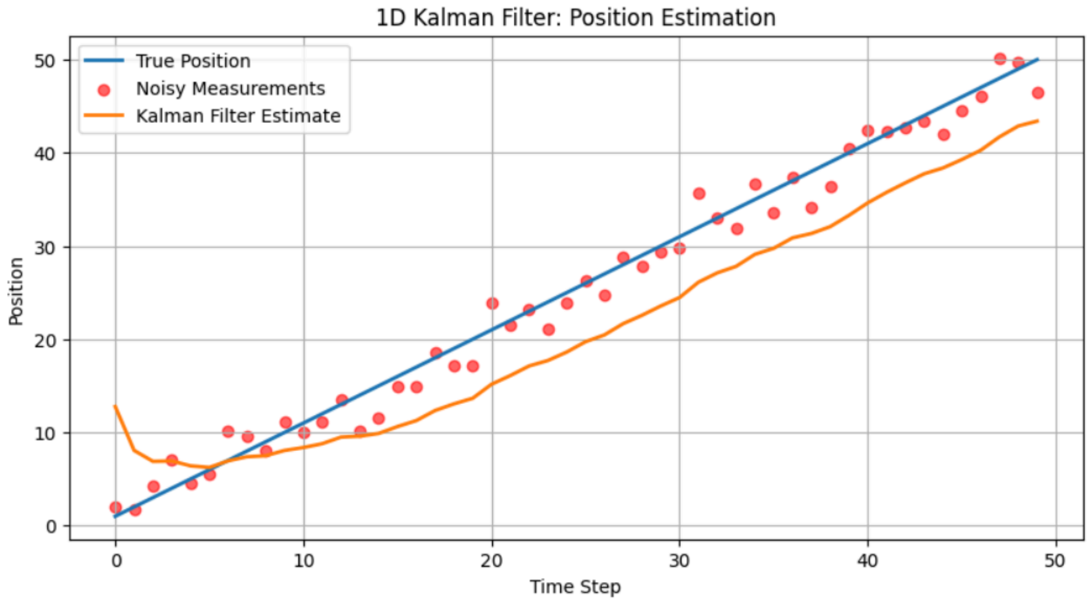
Now , when we start with a very wrong state initially (0) ,



Now, because the initial state is way off , we see that the Kalman gain is high enough such that the sensor measurements guide the filter rather than its initial estimate (way off so following this would throw the filter off track). Hence , a rapid descent is observed in the estimates leading to a fast convergence along the true trajectory. (high gain)

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