State Estimation in the Automotive SCR DeNO\textsubscript{x} Process

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Abstract: Selective catalytic reduction (SCR) of nitrogen oxides (NO\textsubscript{x}) is a widely applied diesel engine exhaust gas after-treatment technology. For effective NO\textsubscript{x} removal in a transient operating automotive application, controlled dosing of urea can be used to meet the increasingly restrictive legislations on exhaust gas emissions. For advanced control, e.g. Model Predictive Control (MPC), of the SCR process, accurate state estimates are needed. We investigate the performance of the ordinary and the extended Kalman filters based on a simple first principle system model. The performance is tested through a series of simulation studies reflecting realistic challenges such as under-modelling and few gas composition sensors.

Keywords: State Estimation, Kalman Filtering, Nonlinear processes, SCR process

1. INTRODUCTION

Compared to gasoline engines, diesel engines are known for their better fuel efficiency and lower CO\textsubscript{2} emission [Hsieh and Wang, 2010a]. However, the diesel engines produce a higher level of particulate matter and NO\textsubscript{x} which are both harmful for the human respiratory system and contribute to smog formation, nitrogen oxides furthermore acts as a greenhouse gas and contribute to formation of acid rain ATSDR [2002]. Emissions of particulate matter are effectively reduced using particular filters while the conversion of the nitrogen oxides to nitrogen (N\textsubscript{2}) and water requires a reductant and a catalytic surface. Selective catalytic reduction (SCR) based on conversion of urea to ammonia is a promising DeNO\textsubscript{x} technology for heavy-duty diesel engines [Koebel et al., 2000, Willems et al., 2007]. Challenges still remain in meeting the increasingly stricter requirements on NO\textsubscript{x} and NH\textsubscript{3} emissions. In Europe, a stricter emission standard, EURO VI, is going to be valid from 2014. Compared to current emission standard, EURO V, it requires a reduction of the NO\textsubscript{x} emissions by 80%. Several control schemes for the urea SCR process have been proposed [Willems et al., 2007]. These studies conclude that feedback is necessary to achieve acceptable emission limits on both NO\textsubscript{x} and NH\textsubscript{3}. Thus in recent years, attentions are paid to application of advanced control strategies to the SCR process. Schär et al. [2006] proposed a model based feed forward and feedback controller. Devarakonda et al. [2009] implemented a linear model based estimator and an NH\textsubscript{3} sensor-based control strategy. McKinley and Alleyne [2010] were first to apply MPC for the SCR system. They based their MPC on a first principles model which was reduced to a first order linear model.

In the attempt to develop model based control strategies, several papers have been focused on development of state estimators for the SCR system [Devarakonda et al., 2009, Hsieh and Wang, 2009, 2010b]. A nonlinear estimator is motivated based on the different operating conditions in a diesel engine from different modes of driving. The SCR system will be exposed to changing flow rate, compositions and temperature from the engine exhaust gas. That affects the rate of the reactions on the catalyst surface. Hsieh and Wang use an extended Kalman filter for their three state first principle model and report good performance and robustness to measurement errors in simulations. Nonlinear input-output models for the control design have also been suggested. Meisami-Azad et al. [2011] apply a quasi linear parameter varying model and Zambrano et al. [2011] use a Hammerstein-Wiener model.

In this paper, we investigate linear and nonlinear Kalman filtering for state estimation in the SCR process. The simulations are based on a simple four state first principles model which we develop for control purposes. The filters are tested using different scenarios of gas analysis sensors and for the case of perfect model representation versus under modeling of the flow regimes through the SCR unit. These investigations are crucial elements in developing model predictive control for optimizing the DeNO\textsubscript{x} units performance and meet the future emission standards. The paper is organized as follows: An introduction to the SCR process and a simple nonlinear simulation model is presented in Sec 2. The formulation of the filters is given in Sec. 3 and simulation results demonstrating the performance of the filters are in Sec. 4. The main conclusions are given in Sec. 5.

2. THE AUTOMOTIVE SCR PROCESS

The urea-SCR system in Fig. 1 consists of a heavy duty diesel engine, a urea injecting system and the SCR catalyst. After the urea is sprayed into the hot exhaust gas stream, ammonia is formed from the urea in the initial part of the SCR catalyst. To
simplify the model, we adopt the strategy from Devarakonda et al. [2009] and Hsieh and Wang [2010a] and assume full urea to ammonia conversion before the catalyst. Furthermore, we choose to use the kinetic parameters reported by Olsson et al. [2008] which was proposed for the Cu-ZSM-5 catalyst. The considered reaction chemistry will be presented in the following subsections

2.1 Reversible ammonia adsorption

Ammonia can adsorb and desorb from sites on the catalyst surface

\[ \text{NH}_3 + (\ast) \rightarrow \text{NH}_3^* \]  
\[ r_{\text{ads}} = k_{\text{ads}} C_{\text{NH}_3} (1 - \theta_{\text{NH}_3}) \]  
\[ r_{\text{des}} = k_{\text{des}} \theta_{\text{NH}_3} \]  

where \((\ast)\) indicates an free site for adsorption and \(\text{NH}_3^*\) is the adsorbed ammonia to a catalyst site. \(\theta_{\text{NH}_3}\) is the coverage ratio of ammonia on the catalyst, i.e. the amount of adsorbed ammonia relative to the total ammonia adsorption capacity, \(\Theta\). \(C_i\) indicates the concentration of the species \(i\) in the gas phase. We will assume for simplicity that the kinetic constant \(k_{\text{des}}\) does not depend on the coverage ratio.

2.2 Reduction of NOx

The reduction of nitrogen oxides with adsorbed ammonia can occur through a number of reactions which are referred to as the standard, the fast and the slow SCR reactions [Conway et al., 2005, Olsson et al., 2008]. In this paper we will only include the first two which are the dominant reactions. The standard SCR reaction is

\[ 4\text{NH}_3^* + 4\text{NO} + \text{O}_2 \rightarrow 4\text{N}_2 + 6\text{H}_2\text{O} \]  
\[ r_{\text{red1}} = k_{\text{red1}} C_{\text{NO}} \theta_{\text{NH}_3} \]  

and the fast SCR reaction is

\[ 2\text{NH}_3^* + \text{NO} + \text{NO}_2 \rightarrow 2\text{N}_2 + 3\text{H}_2\text{O} \]  
\[ r_{\text{red2}} = k_{\text{red2}} C_{\text{NO}} C_{\text{NO}_2} \theta_{\text{NH}_3} \]  

2.3 Ammonia oxidation

Absorbed ammonia can react with oxygen and form nitrogen inside the catalyst

\[ 4\text{NH}_3^* + 3\text{O}_2 \rightarrow 2\text{N}_2 + 6\text{H}_2\text{O} \]  
\[ r_{\text{ox}} = k_{\text{ox}} C_{\text{O}_2} \theta_{\text{NH}_3} \]  

Other oxidation reactions may occur in the system but these are not significant and we exclude these [Devarakonda et al., 2009, Olsson et al., 2008].

### Table 1. The pre-exponential factor and the activation energy for calculation of rate constants Olsson et al. [2008].

<table>
<thead>
<tr>
<th>Reaction</th>
<th>(A)</th>
<th>(E_{\text{a}}) (kJ/mol)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adsorption</td>
<td>9.4 x 10^{-9} (mol/m²)</td>
<td>0</td>
</tr>
<tr>
<td>Desorption</td>
<td>1.0 x 10^{11} [1/s]</td>
<td>181.5</td>
</tr>
<tr>
<td>Standard SCR</td>
<td>2.3 x 10^{12} (mol²/m²/s)</td>
<td>84.9</td>
</tr>
<tr>
<td>Fast SCR</td>
<td>1.9 x 10^{12} (mol²/m²/s)</td>
<td>85.1</td>
</tr>
<tr>
<td>Oxidation</td>
<td>1.2 x 10^{11} (mol²/m²/s)</td>
<td>162.4</td>
</tr>
</tbody>
</table>

2.4 Kinetic and process parameters

The chemical reactions in the SCR system are temperature depended and we assume an Arrhenius expression for the kinetic constants

\[ k = A e^{-E_a/RT} \]  

where \(A\) is a pre-exponential constant, \(E_a\) is the activation energy for the reaction, \(R\) the gas constant, and \(T\) the temperature. Data for the \(A\) and \(E_a\) parameters given the reactions in the SCR catalyst are from Olsson et al. [2008] and presented in Table 1.

The SCR system is assumed to have a certain known volume and operate approximately at ambient pressure. Inputs to the system, containing the total flow rate, \(F\), exhaust gas temperature, \(T\), and the concentration of \(\text{NO}, \text{NO}_2\) and \(\text{O}_2\), depend on the operation of the engine. A control system will regulate the dosing of urea. The urea decomposes to ammonia which mix with the inlet gas to the SCR catalyst.

2.5 The SCR simulation model

When performing a mass balance for the system Lietti et al. [1998] and Tronconi et al. [2005] use a plug flow reactor description while Schär et al. [2006], Devarakonda et al. [2009], Hsieh and Wang [2010a] and Chiang et al. [2010] choose to use one or a series of stirred tanks i.e. a CSTR reactor model approach using one to four states in the model per compartment. We will apply the CSTR approach in our model derivation due to low model complexity and simplicity of the numerical scheme. A number of tanks in series is a good representation of the system in plug flow with a certain degree of back mixing. We chose to neglect transfer of mass and heat across the film layer which in reality covers the catalyst surface and energy balances as Olsson et al. [2008] report that the heat of reaction is minor. We assume that the catalyst temperature is equal to the exhaust gas temperature, that the ideal gas law applies and that the oxygen concentration remains constant. We will develop our model as if the reactor volume consists of just one compartment. In case we chose to use several units in series, we divide the volume equally and use the output of one tank as the inlet to the next. In that case the overall ammonia coverage ratio in the catalyst, \(\theta_{\text{NH}_3}\), will combine the contribution for the individual units.

Eq. (6) is mass balances for \(\text{NO}, \text{NO}_2, \text{NH}_3\) and \(\text{NH}_3\) using the reactor volume as system boundaries. The set of mass balances is a general nonlinear state space model of the form

\[ \dot{x} = f(x(t), u(t), d(t)) \]  

where the state, input and disturbance variables are

\[ x = \begin{bmatrix} C_{\text{NO}} \\ C_{\text{NO}_2} \\ C_{\text{NH}_3} \\ \theta_{\text{NH}_3} \end{bmatrix}, \quad u = C_{\text{NH}_3, \text{in}}, \quad d = \begin{bmatrix} F \\ T \end{bmatrix} \]  

\[ C_{\text{NO}, \text{in}}, C_{\text{NO}_2, \text{in}}, C_{\text{O}_2, \text{in}} \]
\[
\dot{\chi}_{NO} = \frac{F}{V} (C_{NO,in} - C_{NO}) - 4 \theta k_{red1} C_{NO} \theta_{NH_3} - \theta k_{red2} C_{NO} C_{NO} \theta_{NH_3}
\]
\[
\dot{\chi}_{NO_2} = \frac{F}{V} (C_{NO_2,in} - C_{NO_2}) - \theta k_{red1} C_{NO} C_{NO_2} \theta_{NH_3}
\]
\[
\dot{\chi}_{NH_3} = \frac{F}{V} (C_{NH_3,in} - C_{NH_3}) + \theta k_{deN} \theta_{NH_3} - \theta k_{add} C_{NH_3} (1 - \theta_{NH_3})
\]
\[
\dot{\theta}_{NH_3} = k_{add} C_{NH_3} (1 - \theta_{NH_3}) - k_{deN} \theta_{NH_3} - 4 k_{red1} C_{NO} \theta_{NH_3} - 2 k_{red2} C_{NO} C_{NO} \theta_{NH_3} - 2 k_{ov} C_{O_2} \theta_{NH_3}
\]

3. STATE ESTIMATION

In this section, we briefly present the approach used to compute state estimates for the SCR process. Full state information is needed to optimize the controlled ammonia dosing in a predictive control scheme. Not all states can be measured in the flue gas after treatment system. The estimation is computed at discrete time step based on the sample rate in the control loop. Consequently, the general system (7) is given in the following discrete time state space form

\[
x_k + 1 = F(x_k, u_k, d_k)
\]
\[
y_k = C x_k + v_k, \quad v_k \in \mathcal{N}_\text{prod}(0, R_v)
\]

where the matrices \(A\) and \(B\) come from a first order Taylor series expansion of (7) around the point \((\tilde{x}, \tilde{u}, \tilde{d})\) and subsequent discretization assuming constant inputs and disturbances between samples. The process noise is Gaussian distributed, \(w_k \in \mathcal{N}_\text{prod}(0, R_w)\), and can be used to tune the algorithm relative to the measurement noise. We assume that the two noise signals are not correlated.

The filter equations consist of a set of equations for updating the state estimate and its variance given the current measurement from the process and a set of equations predicting the state and the state variance in the future.

**Measurement update:**

\[
e_k = y_k - C x_k - I
\]
\[
K_{f,k} = P_{k|k-1} C^T (CP_{k|k-1} C^T + R_v)^{-1}
\]
\[
\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{f,k} e_k
\]
\[
P_{k|k} = P_{k|k-1} - K_{f,k} (CP_{k|k-1} C^T + R_v) K_{f,k}^T
\]

**Time update (one step ahead prediction):**

\[
\hat{x}_{k+1|k} = A \hat{x}_{k|k} + B u_k + E d_k
\]
\[
P_{k+1|k} = A P_{k|k} A^T + R_w
\]

3.1 The ordinary Kalman filter

State estimation using the ordinary linear Kalman filter is an well known and documented technique, see e.g. Kailath et al. [2000]. The algorithm uses a linear, discrete time, space model. We use the following equation for the state evolution in deviation variables

\[
x^d_{k+1} = Ax^d_k + Bu^d_k + Ed^d_k + w_k
\]

where the matrices \(A\) and \(B\) come from a first order Taylor series expansion of (7) around the point \((\tilde{x}, \tilde{u}, \tilde{d})\) and subsequent discretization assuming constant inputs and disturbances between samples. The process noise is Gaussian distributed, \(w_k \in \mathcal{N}_\text{prod}(0, R_w)\), and can be used to tune the algorithm relative to the measurement noise. We assume that the two noise signals are not correlated.

The filter equations consist of a set of equations for updating the state estimate and its variance given the current measurement from the process and a set of equations predicting the state and the state variance in the future.

**Measurement update:**

\[
e_k = y_k - C x^d_{k|k-1}
\]
\[
K_{f,k} = P_{k|k-1} C^T (CP_{k|k-1} C^T + R_v)^{-1}
\]
\[
\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{f,k} e_k
\]
\[
P_{k|k} = P_{k|k-1} - K_{f,k} (CP_{k|k-1} C^T + R_v) K_{f,k}^T
\]

**Time update (one step ahead prediction):**

\[
\hat{x}_{k+1|k} = A \hat{x}_{k|k} + B u_k + E d_k
\]
\[
P_{k+1|k} = A P_{k|k} A^T + R_w
\]

3.2 The extended Kalman filter

In contrast to the ordinary Kalman filter, the extended Kalman filter utilizes a nonlinear process model to compute the state estimate and its variance. We use a continuous-discrete time nonlinear Kalman filter formulation [Jazwinski, 1970, Jørgensen et al., 2007]. The model equation used for the discrete time state evolution, based on the continuous time process model, is

\[
x_{k+1} = f(x_k, u_k, d_k) + w_k
\]

where the distribution of the process noise term \(w_k\) can be chosen to tune the filter relative to the measurement noise. The filter equations are

**Measurement update:**

\[
e_k = y_k - C x^d_{k|k-1}
\]
\[
K_{f,k} = P_{k|k-1} C^T (CP_{k|k-1} C^T + R_v)^{-1}
\]
\[
\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_{f,k} e_k
\]
\[
P_{k|k} = P_{k|k-1} - K_{f,k} (CP_{k|k-1} C^T + R_v) K_{f,k}^T
\]

**Time update (one step ahead prediction):**

\[
\hat{x}_{k+1|k} = A \hat{x}_{k|k} + B u_k + E d_k
\]
\[
P_{k+1|k} = A P_{k|k} A^T + R_w
\]

4. SIMULATION RESULTS

The performance of the proposed Kalman filters will be tested simulating the behavior of the urea SCR process given a realistic scenario for a diesel engine. We will use a data set with gas compositions, flows and temperatures which come from simulation of an engine operating at the world harmonized transient driving cycle (WHTC). This 1800 seconds driving cycle specify engine speed and torque and is used to test engine emissions in the Euro V and VI emission standards. Furthermore, we will use data for the ammonia inlet concentration which comes from closed loop simulation of an industrial setup at Haldor Topsoe A/S. The industrial data are confidential. Therefore, to illustrate the performance of the filters on realistic data, all model outputs have been normalized. All gas concentrations are divided with a number which bring it in an interval between 0 and 1. Also the coverage ration varies between 0 and 1, where 1 correspond to full loading. This will not affect the conclusion related to
Table 2. Estimation statistics for the filters. The mean value and the standard deviation is reported for the estimation error on the individual states based on the normalized data. For the ordinary Kalman filter (KF) only data between times 400 to 1800 has been considered.

<table>
<thead>
<tr>
<th>Filter</th>
<th>Scenario</th>
<th>(\mu(C_{NO}))</th>
<th>(\sigma(C_{NO}))</th>
<th>(\mu(C_{NO_2}))</th>
<th>(\sigma(C_{NO_2}))</th>
<th>(\mu(C_{NH_3}))</th>
<th>(\sigma(C_{NH_3}))</th>
<th>(\mu(\theta))</th>
<th>(\sigma(\theta))</th>
</tr>
</thead>
<tbody>
<tr>
<td>KF case 1</td>
<td>1</td>
<td>1.8 \times 10^{-3}</td>
<td>9.5 \times 10^{-5}</td>
<td>8.1 \times 10^{-6}</td>
<td>3.8 \times 10^{-5}</td>
<td>2.0 \times 10^{-5}</td>
<td>8.4 \times 10^{-5}</td>
<td>9.0 \times 10^{-5}</td>
<td>2.4 \times 10^{-2}</td>
</tr>
<tr>
<td>KF case 2</td>
<td>1</td>
<td>2.3 \times 10^{-3}</td>
<td>1.1 \times 10^{-5}</td>
<td>2.3 \times 10^{-6}</td>
<td>1.1 \times 10^{-5}</td>
<td>2.2 \times 10^{-5}</td>
<td>8.3 \times 10^{-5}</td>
<td>1.1 \times 10^{-2}</td>
<td>2.3 \times 10^{-2}</td>
</tr>
<tr>
<td>EKF case 1</td>
<td>1</td>
<td>1.1 \times 10^{-3}</td>
<td>9.5 \times 10^{-4}</td>
<td>7.4 \times 10^{-6}</td>
<td>3.8 \times 10^{-5}</td>
<td>3.5 \times 10^{-6}</td>
<td>8.3 \times 10^{-4}</td>
<td>3.8 \times 10^{-5}</td>
<td>1.6 \times 10^{-4}</td>
</tr>
<tr>
<td>EKF case 2</td>
<td>2</td>
<td>3.0 \times 10^{-6}</td>
<td>9.3 \times 10^{-4}</td>
<td>7.4 \times 10^{-6}</td>
<td>1.4 \times 10^{-4}</td>
<td>1.9 \times 10^{-5}</td>
<td>8.2 \times 10^{-4}</td>
<td>3.4 \times 10^{-6}</td>
<td>1.7 \times 10^{-4}</td>
</tr>
<tr>
<td>EKF case 1</td>
<td>2</td>
<td>1.1 \times 10^{-5}</td>
<td>9.5 \times 10^{-5}</td>
<td>7.4 \times 10^{-6}</td>
<td>3.8 \times 10^{-4}</td>
<td>3.3 \times 10^{-6}</td>
<td>8.3 \times 10^{-4}</td>
<td>2.9 \times 10^{-2}</td>
<td>2.2 \times 10^{-4}</td>
</tr>
<tr>
<td>EKF case 2</td>
<td>2</td>
<td>3.7 \times 10^{-3}</td>
<td>6.8 \times 10^{-3}</td>
<td>6.7 \times 10^{-3}</td>
<td>1.9 \times 10^{-5}</td>
<td>8.2 \times 10^{-4}</td>
<td>3.0 \times 10^{-2}</td>
<td>2.3 \times 10^{-2}</td>
<td></td>
</tr>
</tbody>
</table>

The main issue under investigation, whether all the states of the SCR process can be estimated well based on limited output information and based on a simple system model.

In the simulations using the ordinary Kalman filter we need to linearize the process model (6) around a certain operating point. Since the system is constantly in a transient state it is most reasonable to choose an average value for all the process inputs over the driving cycle and calculate the corresponding steady state. We have done this neglecting the first 400 samples since the operation of the system in this initial phase is very different compared to the rest. This is due to low exhaust gas temperature when the engine starts up. When temperature is too low the control system will not dose urea since the low reaction rates will render an unnecessary large ammonia slip.

For both filters we will investigate their performance for two scenarios of the underlying process model and for two different cases of gas analyzing sensors. In the first scenario both the process model and the filter model are identical. It is the model (6) assuming that the SCR unit can be represented by one CSTR. In the second scenario the process model consists of four tanks in series while the filter is still based on just one CSTR. We have measurements of ammonia downstream of the catalyst and in one case both NO and NO\(_2\) are measured. In the second case only a measurement of the total concentration of nitrogen oxides is available. In all cases, we include measurement noise with a variance of 2% of the mean output level found from the operating point used in the linearization. We also include process noise with a variance of 5% of the corresponding state level in the filter equations (10) and (12). The simulation results are presented in Fig. 2 and 3. Some statistics on the estimation error is given in Table 2.

**4.1 Scenario 1 - Perfect model**

In the case where the system model and the filter model are identical, the simulations are performed using both the ordinary and the extended Kalman filter. It is seen from the simulation in Fig. 2 that the extended Kalman filter outperforms its linear counterpart and achieves very accurate estimations of both the gas composition but more importantly of the unmeasured coverage ratio of ammonia inside the catalyst. This superior performance is also true even if the first 400 seconds for the ordinary Kalman filter is neglected where performance was expected to be poor. The figure clearly shows that only the extended Kalman filter is able to provide reasonable estimates over the whole operating region of the process. In general, both filters provide good estimates on the state values which are also measured, but it is clearly seen from both the figure and the statistics in Table 2 that the nonlinear filter provides better estimates given more limited output information. The ordinary Kalman filter has a bias in the estimation of the coverage ratio and in the second case with one sensor for the total nitrogen oxide concentration the variation of the estimation error on these oxides are significantly increased. This is not observed for the extended Kalman filter which does not have a significant bias in any of the estimation errors and a moderate variation in both cases.

**4.2 Scenario 2 - Under-modelling**

In the second scenario, the process model has been changed to a four tanks in series model while the filters are still based on a model with only one CSTR. This scenario is very interesting since it is reasonable to assume that the SCR unit can be modelled using a tanks in series approach. However the number of compartments may be significant leading to a high number of states. Low complexity models are desired for fast computations in a model based control strategy and in the state estimators. Hence these models may be based on a reduced number of units in series compared to the actual flow path in the true system. The simulations presented here are based on the extended Kalman filter, only.

In Fig. 3 and Table 2 it is seen that the extended Kalman filter is still able to provide reasonable estimates of the gas compositions and the coverage over the operating region of the process. However, it should be observed that the filter now over estimates the ammonia coverage for a part of the driving cycle. This phenomenon is not difficult to explain from the difference between the model of the system and the model in the estimator. Since the estimator uses a one compartment model compared to the true four compartment system, it will predict a higher output of ammonia in the exhaust. Since the measured level of ammonia is less than predicted, the filter estimates a too high degree of adsorbed ammonia on the catalyst surface. In the case with reduced output information, the extended Kalman filter also produces a bias and an increased variance for the estimation errors on the nitrogen oxides compared to the case with perfect model information.

The performance of the state estimator can be improved further if the kinetic parameters used in estimation model are fitted to the dynamics of the true system. In this sense the reaction kinetics can be tuned to compensate for the error in the residence time distribution of the gas through the SCR unit. Despite the over estimation of the ammonia coverage ratio, the filter would still be useful in a model based controller strategy such as MPC. Since the SCR process has measurement of all important input variables it only need a reasonable estimate of the coverage ratio in order to optimize the urea dosing.

**5. CONCLUSION**

In this paper we present a simple four state first principle model of the automotive urea SCR process for diesel engine exhaust.

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It is clear that linear system description in the ordinary Kalman filter is a limitation in the state estimation for a process which we argued to be a good representation of the flow in the system. Both the algorithms for an ordinary Kalman filter and the extended Kalman filter are presented for this process. The filters are also evaluated using limited output information perfect model information and under-modelling, respectively. The filters are also evaluated using limited output information with respect to the nitrogen oxides.

It is clear that linear system description in the ordinary Kalman filter is a limitation in the state estimation for a process which...
covers such a large operating region. The extended Kalman filter, on the other hand, does an almost perfect job given full process information, even if only two of the four states are measured. In the scenario where the flow regime in the SCR unit is simplified to a one compartment model in the filter, the coverage ratio is overestimated due to too high output prediction of ammonia. The quality of the state estimate is nevertheless satisfactory. Further improvements would be possible if the kinetic parameters in the estimation model was tuned based of the dynamics of the true system.

This automotive urea SCR process is a very promising application for advances model based control such as MPC. The performance criteria is continuously getting tougher due to emission regulations. All main disturbances are available on line and the only missing key variable is the coverage of ammonia on the catalyst surface. This we have shown here can be effectively estimated using an extended Kalman filter.

REFERENCES


