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Fault Tolerant Adaptive Estimation of Nonlinear Processes Using Redundant Measurements

M. Miranda† and A. Edelmayer‡ *Member IEEE*

***Abstract*— This paper presents a dual layer approach for robust fault tolerant estimation of nonlinear processes using a combined adaptive extended Kalman filter and fault detection and filter reconfiguration. From the one hand, the filter is made robust in face of environment uncertainty using adaptive filtering. To this end, the filter identifies the measurement covariance by means of recursive estimation, upon which the adaptation relies, to suppress the effect of sporadic variations in the quality of measurements as well as compensates for incipient sensor faults. From the other hand, fault monitoring is continuously applied to the filter's innovation in an attempt to initiate filter reconfiguration when the adaptation mechanism alone is not able to overcome the failure situation. The discussion of the results is embedded in the application framework of state estimation of a batch distillation process.**

I. INTRODUCTION

An impressive number of references in the literature has been devoted to state and parameter estimation techniques for linear and nonlinear systems. When selecting from the range of feasible estimation methods to the solution of a particular estimation problem, at least two fundamental properties of the dynamical system at hand have to be properly appreciated. They are the phenomena of modeling uncertainty and the nature of the exogenous disturbances. These properties, in the most cases, may determine whether one can formulate the estimation problem in linear or nonlinear and in deterministic or stochastic settings. Different approaches provide different answers to the treatment of the problems.

Based on the simplifying assumptions that (i) modeling uncertainty can be safely disregarded and (ii) the disturbance statistics of the system is reliably known (i.e., it can be modeled as a Gaussian random process with known mean and covariance), for state estimation in linear systems the traditional Kalman filter (KF) has been unrivaled for decades. This is because of its optimality and robustness and the relatively simple model of implementation that makes it a feasible solution on many platforms.

When it came to state estimation for nonlinear systems, the corresponding nonlinear filter is obtained by straightforward extension of the linear solution, resulting in the formulation of the extended Kalman filter (EKF) [1], [2]. Beyond doubts, in spite of its varying performance in terms of estimation accuracy, ease of implementation, robustness, and computational burden, the EKF still dominates the nonlinear state and parameter estimation techniques [3]. There are two discerned application domains where EKF attracts distinguished attention. *Process control* and chemical engineering are motivated by the simple implementation and the favoring behavior of EKF in the presence of smooth nonlinear dynamics. *Localization and mapping*, including dynamic map building technologies, to estimate the state vector containing both the pose (position and orientation) of a mobile unit and the landmark locations of the infrastructure, is another area where EKF has become ultimately popular in the past years, see [4], [5], [6], [7].

Quite interestingly, the most successful applications of the above characterized target fields reveal that the EKF solutions are unsustainable in certain areas. EKF approximates the state distribution as Gaussian random variable (GRV) and can handle only a limited amount of nonlinearity. This is one of the well-known limitations of the traditional EKF that it linearizes the nonlinear model in a way that the traditional linear KF can be applied. The linearization is based on first-order Taylor method, which approximate, at every time step, the nonlinear state transition and observation equations about the estimated state trajectory, with a linear time varying (LTV) system. This approach is problematic from not a single point of view. First, the linearization tends to introduce large errors and even cause instability of the filter.

Not paying attention to rudimentary system variations, moreover, stability issues may potentially happen when the noise covariances increase and/or change, as compared to the dynamics of the system. Sporadically changing intensity of measurement noise due to communication nonperformance of the sensor network, e.g., is an issue both in advanced process control and localization applications [7], which are increasingly implemented as distributed operations.

Another distinctive attribute is that the filter is required to converge to the actual state even when it is initialized with partially known initial conditions. This is an important feature (both in process control and localization), because the filter's operation, more or less frequently, is subject to reset and resume, regularly. Reset mode, sometimes, is an inherent feature of the operational strategy of the filters [7]. This is to be done in a process environment where the initial conditions are rarely known. In these situations traditional EKF is difficult to tune, its convergence time may be varied, the resetting conditions and the Jacobian can be hard to derive.

There have been a few innovations of the EKF in the past decade. Though particle filters (PFs), (i.e., another nonlinear derivative of the KF), can handle arbitrary distributions and

†M. Miranda is with Laboratory of Unit Operations, Department of Chemical Engineering, Faculty of Engineering, University of Los Andes, 5101, Mérida, Venezuela. E-mail: moira@ula.ve

‡A. Edelmayer is with Systems and Control Laboratory, Computer and Automation Research Institute, Hungarian Academy of Sciences, H-1111, Budapest, Kende u. 13-17, Hungary. E-mail: edelmayer@sztaki.hu

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nonlinearities reportedly providing better performance than EKF in general, they are computationally very complex to derive and as such, there is no chance to apply them in resource constrained embedded applications. Unscented filtering (UF) solutions [8], that approximate Gaussian type distributions over a fixed number of deterministic parameters, try to achieve a performance tradeoff between PF and EKF.

In a current laboratory work program we aim to collect experience with the design, implementation and operation of other, alternative filtering methods in an attempt to eliminate the shortcomings of the traditional EKF solution especially in distributed filtering applications, resembling to [7]. The objective is to select implementation candidates of filters amenable to embedded system applications. In a series of laboratory experiments, therefore, we investigated a number of applications that pose challenging problems substantially similar to the ones occurring in high-accuracy state estimation in nonlinear systems. The work with real, non-simulated process data and access to real plant measurements got priority in this project.

In a previous work [9], the performance of EKF and UF implementations have been compared with each other. The experiments showed convincingly that the UF can be successful in getting rid of the performance degradation caused by the linearization, and as such, it can be seen a promising method in solving filter's stability problems attributable to the computation of the derivatives of the state and measurement variables. Better estimation accuracy in steady state is also on the plus side of the unscented solution. The increased robustness of the UF against changing and varying intensity noise and unmatched initial conditions, however, could not be substantiated in comparison to the standard EKF.

In this paper, the experimental work to finding solutions of the latter problem is continued. In order to develop robustness to changing noise statistics and occasionally disrupting measurement signals, an EKF is derived, which relies on an *adaptive* policy. This is done in an application to a nonlinear system estimation problem in an attempt to robustly handle uncertainty in the sensor noise statistic that identifies the value of the covariance R in the filter's equations. The objective is to explore and verify the capabilities of adaptive filtering to enhance state estimation in process environments where the application of the standard EKF is prevented, or at least severely restricted, by one of the above mentioned circumstances.

In a recent project a pilot plant of batch distillation process was rendered at our disposal for experimentation. Embedding the concept of adaptive estimation in a real industrial problem like this, beyond performance and accuracy of estimation, poses further arguments to the idea, namely sensor fault tolerance. It will be shown how the instrumentation specificity of batch distillation processes, such as the availability of multiple redundant measurements, together with the application of adaptive filtering create the potential for enhanced fault tolerant process estimation.

The basic idea of the adopted approach is to adaptively estimate the covariance of the measurement processes based on the filter's residual and using the innovation for sensor fault detection. Then, based on the decision of the existence of the fault a filter reconfiguration is initiated in an attempt to restore the normal operational conditions of the filter. In fact, the development of this dual layered fault tolerant operational policy of the filter is the main contribution of this paper.

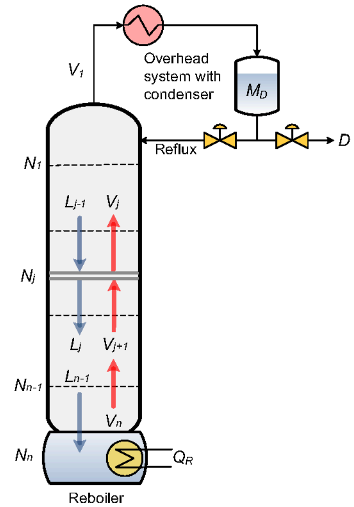

Fig. 1. *Distillation column schematic.*

II. Estimation for batch distillation

Batch distillation is a popular unit operation widely used in fine chemistry, pharmaceutical, cosmetics and biochemical industries to process small amounts of chemical materials with high added value. Batch distillation is a precious technology, capable of separating components of a multi-component mixture in a single operation, with great accuracy. The need for preciseness calls for control methods capable to ensure quality requirements of products and processes. Because of the ever increasing demand for low volume specialty chemicals, batch distillation is becoming an increasingly important technology [10], [11].

Operation management and control of batch distillation require knowledge of products compositions during the entire duration of the process. Some of these systems, for instance, are controlled by Model Predictive Controls (MPCs) that necessitate the availability of accurate data obtained from state estimation.

A traditional way of obtaining this knowledge is by means of the use of composition analyzers. Though very accurate, they are expensive instrumentation, and the measurement process is fully manual. This, besides introducing additional delays in the control loop, necessitates direct supervision from the operational personnel. For the state-of-the-art of batch distillation technologies, see [12], [13] and [14], this manual interaction is highly undesirable.

The most popular alternative to composition controllers is the utilization of standard temperature feedback controllers. Temperature measurements, however, are not accurate indicators of composition variation [12]. Another alternative is

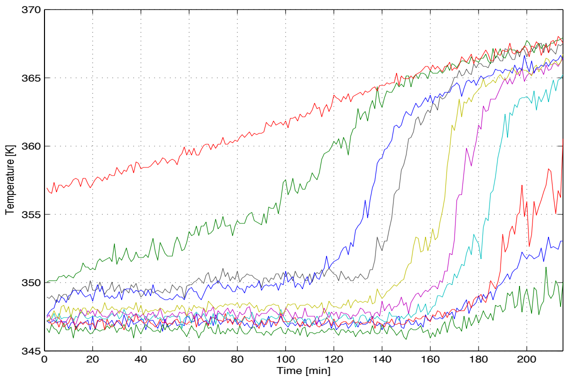

Fig. 2. *Temperature measurements available at individual column trays provide analytically redundant set of measurements.*

the use of state estimators, which are based on secondary temperature measurements.

Batch distillation, as well as continuous distillation, is a complex, high-order nonlinear process, whose dynamics varies over time. There have been deterministic [15] and probabilistic modeling approaches [13], [16] used to state estimator design for batch columns.

A. Formulation of the filtering problem

The batch distillation process and its sensory system, in their nominal representations, are modeled as a nonlinear dynamical system described by ordinary differential equations

$$\dot{x}(t) = \phi(x(t), u(t)), \tag{1}$$
$$\varphi(t) = h(x(t)). \tag{2}$$

For a special case this can be written in state space form by means of the set of state and observation equations affected by additive noise

$$\dot{x} = \sum_{i=1}^{m} g_i(x)u_i + w_i, \tag{3}$$
$$\varphi_i = h_i(x) + v_i, \qquad 1 \leq i \leq p, \tag{4}$$

where $x \in \mathbb{R}^n$, $u \in \mathbb{R}^m$, $\varphi \in \mathbb{R}^p$ denote the state, the input and the output of the system. The noise $w(t)$ and $v(t)$, which affect the system and measurement equations, respectively, are considered zero-mean Gaussian white noise independent of each other as well as of $x(0)$. Let Q_i and R_i denote the covariance matrix of v_i and w_i for all i, respectively,

$$Q_i = \mathbf{E}\{v_k v_k^T\}, \quad R_i = \mathbf{E}\{w_k w_k^T\}. \tag{5}$$

Our objective is to construct a statistical filter, which is robust to the variations and changes of $v_i(t)$, in an attempt to give an estimate $\hat{x}$ of the state x, which is a GRV of (3), assuming the process is observable by all, or by some combination of the available measurements.

B. Column models and model validation

High definition nonlinear models for batch distillation processes have been available in the literature from many sources for years, see e.g., [17]. They typically consist of a large number of coupled nonlinear differential equations describing the variation of compositions along individual column trays based on the tray's thermodynamics and hydraulics, and models of the condenser and the reboiler behaviour by taking energy and material balances, liquid hold-ups, vapor and liquid flow-rates etc. into consideration. High definition models are indispensable tools for the analysis, however, they are overly complicated for controller and filter synthesis because of the implied computational complexity of the implementation. Therefore, filter design necessitates a simpler representation, which still captures the essential parts of the dynamics of (3).

Though, a high definition model, similar to the one published in [17] was used for validation purposes, a simple representation of (3) for two components mixtures of batch distillation was developed for filter synthesis. In the following part the simplified model is given, the more complex high definition model is not detailed. The interested reader is directed to [17].

The state variables are the liquid compositions of the individual stages (stills and trays), i.e., $x_i = {c^\ell}_i$. Since, for a system of n_c components $\sum_i^{n_c} {c^\ell}_i = 1$, it suffices to consider $n_c - 1$ state variables at each stage, because the composition of the n_c^{th} component can always be obtained by simple subtraction. In modeling we relies on the following simplifying assumptions.

The process is driven by the reflux rate as input, which is given as

$$u = \begin{bmatrix} L \\ V \end{bmatrix},$$

where L and V are the liquid and the vapor flow rates, respectively. We consider equimolal overflow (i.e., $L_j = L$ for $1 \leq j \leq n$ and $V_j = V$ for $2 \leq j \leq n$) and theoretical stages with negligible vapor and constant liquid hold-up M_j for $1 \leq j \leq n-1$, moreover, constant pressure and negligible drum reflux hold-up.

Then, the simplified nonlinear state space representation of (3) with $x \in \mathbb{R}^n$ and $n_c = 2$ subject to noise is written as

$$\begin{bmatrix} \dot{x}_1 \\ \vdots \\ \dot{x}_j \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} \frac{V}{M_1}(y_2 - x_1) \\ \vdots \\ \frac{V}{M_j}(y_{j+1} - y_j) + \frac{u\,V}{M_j}(x_{j-1} - x_j) \\ \vdots \\ \frac{u\,V}{M_n}(x_{n-1} - x_n) + \frac{V}{M_n}(y_n - x_n) \end{bmatrix} + \begin{bmatrix} w_1 \\ \vdots \\ w_j \\ \vdots \\ w_n \end{bmatrix}, \tag{6}$$

where the section index $j = 1$ stands for the *condenser*, $j = n$ for the *reboiler* and ($j = 2 \dots n-1$), for the *column trays* dynamics.

The mole fraction (composition) of component c_i in the liquid and vapor of stage j is denoted by x_j and y_j, respectively. The system state is not directly observable. The observed process variables are the tray temperatures

($\varphi_i = T_i$). The measurement system, similarly to (7), is modeled as the function $h(x)$ of the state vector corrupted by measurement noise, i.e.,

$$T = h(x) + v. \quad (7)$$

The nonlinear relationship $h(x)$ between temperature and composition can be obtained from the vapor-liquid equilibrium (VLE) equations. Since the system pressure and the a priori composition estimates are known, this can be given by solving the bubble-point temperature problem for each stage in the following way. The mole fractions x_j, y_j of component c_i in stage j, in equilibrium, can be represented by the thermodynamic model described by the modified Rault's law

$$y_j = \gamma_j \, x_j \left(\frac{p_j^V}{p} \right), \quad (8)$$

where γ_j are the activity coefficients calculated from the Wilson equation, see [18], and p is the column pressure which is assumed constant in our case (i.e., atmospheric distillation). The tray vapor pressure p_j^V is defined by the Antoine vapor-pressure correlation equation $T_j = \psi \, p_j^V$, see [18]. Realize that the thermodynamics of (8), together with the VLE condition $\sum_{i=1}^{n_c} y_i = 1$, give the equilibrium temperatures in (7) as the function $h(x)$ for every tray. The accuracy of process model (6) was validated against the high definition model.

C. Filter synthesis

The process, depicted on Fig. 1, consists of ten separate distillation stages, i.e., 8 column trays plus the reboiler and a total condenser as usual. Trays are identified by the parameter NT, which has the value $1 \ldots n$. The control-input is the reflux of liquid flow rate which acts on the plant. The sensor outputs used for control and estimation purposes are the temperature data of the column trays. There is one temperature measurement available for each tray.

The instrumentation includes temperature sensors of varying quality. The reliability of individual sensors is frequently inadequate to satisfy the reliability requirements of this type of industrial processes. Due to the coupled nature of the nonlinear dynamics, however, these sensors provide a redundant set of measurements upon which the estimation and control of the process can be based. It is known from the literature that the n-component distillation process is considered observable if at least n temperature measurements along column trays are available for filter synthesis. For the proof of this condition, see [19]. In cases when more than n measurements may be used, the performance of the estimator may improve. In this paper the case of using the minimum necessary number of measurements is taken into consideration, i.e., two of the 10 available temperature measurements are used for filter synthesis. Due to the availability of redundant sensors, the estimation of a particular state of the global state vector of the system can be accomplished relying on various different measurements.

In the following part of the paper the core filtering algorithm is considered as the extension of the standard linear (Kalman) filter, which can be characterized briefly as follows. Let the estimate and its covariance provided by the filter be represented with $\hat{x}$ and P. Since the system is not linear, the Riccati matrices that attempt to approximate the *a priori* and the *a posteriori* covariances are defined, respectively, as

$$P_{k|k-1} \approx \mathbf{E}\{e_{k|k-1} \, e_{k|k-1}^T\}, \text{ and } P_{k|k} \approx \mathbf{E}\{e_{k|k} \, e_{k|k}^T\}.$$

The filter is initialized with $x_{o|o} = x_o$ and $P_{o|o} = P_o$, and then operated recursively performing a single cycle each time a new set of measurements becomes available. Each iteration propagates the estimate from the time the last measurement was obtained to the current time. The propagation process consists of two stages: update and prediction as usual. The update equations are responsible for the feedback, i.e., for incorporating a new measurement set into the *a priori* estimate to obtain an improved *a posteriori* estimate. The *a posteriori* state estimate $\hat{x}_{k|k}$ is computed as a linear combination of an *a priori* estimate $\hat{x}_{k|k-1}$ and a weighted difference between an actual measurement φ_k and a measurement prediction:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left[\varphi_k - \bar{h}(\hat{x}_{k|k-1}) \right], \quad (9)$$

$$K_k = P_{k|k-1} \bar{H}_k^T \left(\bar{H}_k P_{k|k-1} \bar{H}_k^T + R_k \right)^{-1}, \quad (10)$$

where $\bar{H}_k$ is the Jacobian matrix of partial derivatives of $h(x)$ with respect to x. The covariance matrix is updated by

$$P_{k|k} = (I - K_k \bar{H}_k) P_{k|k-1.} \quad (11)$$

The prediction equations are responsible for projecting the current state and error covariance estimates forward to obtain *a priori* estimates for the next time step. The state and covariance matrix in the next sampling instant are estimated by

$$\hat{x}_{k+1|k} = \bar{f}(\hat{x}_{k|k}, u_k), \quad (12)$$
$$P_{k|k+1} = \bar{F}_k P_{k|k} \bar{F}_k^T + Q_k,$$

where $\bar{F}_k$ is the Jacobian matrix of partial derivatives of $\bar{f}(x)$ w.r.t. x.

III. Fault tolerant filter synthesis

Fault tolerant filtering in this paper is approximated in a dual layer approach, meaning that, from the one hand, the filter is attempted to make robust against measurement drop-outs and excessive variations in the input signals by means of recursive estimation of the noise covariance. To this effect, real-time correction of the filter gain, based on the actual characteristics of the noise, suppresses the effect of sporadic variations in the quality of the measurements as well as compensates for slowly worsening sensory conditions and incipient sensor faults. From the other hand, fault monitoring is continuously applied to the filter's innovation in an attempt to initiate a filter reconfiguration action when the adaptation mechanism alone is not able to overcome the failure situation.

A. Estimation of the noise covariance

The idea of using adaptively tuned EKF to increase estimation accuracy and robustness against system modeling errors and variations in the driving noise by means of real-time estimation of the covariances R and Q is not new. There have been many different adaptation schemes developed in the past years. The idea in a classical approach was presented in [20] and [21], which is known as the Maximum Likelihood Estimation (MLE) that have been used in various forms in many applications. Another variants are the multiple model and the covariance matching method that try to make the elements of the online estimates of the innovation (or residual) covariances consistent with their reference values as calculated by the state estimator. The idea is that the innovations (residual) covariance should correspond to its reference form by modifying Q and R until they matches. For further details of the adaptation techniques, see [2].

The method adopted in this work relies on the evaluation of the *residual* sequence $r_k = \varphi_k - H_k \hat{x}_{k|k}$ that can be derived from (9) in a straightforward way. One difficulty of the residual-based approach is that positive definitiveness of R is to be additionally ensured. One method to achieve it is through the application of the side condition presented in [22]. Application of a similar approach for the enhancement of GPS-signal based navigation was reported in [23] and [24]. Using the above considerations the estimated value of the covariance R at time k is given as

$$\hat{R}_k = \hat{C}_{\bar{\nu}} + H_k \hat{P}_k H_k^T, \tag{13}$$

where the estimated variance of the residual covariance in a moving window of size m is calculated as

$$\hat{C}_{\bar{\nu}} = \frac{1}{m} \sum_{i=1}^{m} r_{k-i}\, r_{k-i}^T. \tag{14}$$

Then, the estimated value of R is used in the measurement update (9) at time $k+1$ by adaptively recalculating the filter gain K according to the varying noise conditions.

B. Fault detection and filter reconfiguration

The idea of fault tolerance is based on the detection of the abnormal signal behavior and the proper selection of the measurement signals. In case a particular measurement gets faulty and the fault is detected the faulty sensor is replaced with a healthy one in real-time in an attempt to restore the unaffected operational mode of the filter, instantaneously.

In contrast to filter adaptation, which is a residual-based method as seen in (13)-(14), the idea of fault detection relies on the filter's innovation as follows. The innovation $\rho_k = \varphi_k - H_k \hat{x}_{k|k-1}$ is known to be a white sequence if the linear Gaussian condition for the measurement noise is reasonably true. Detection of the abnormal (faulty) behavior of the measurements, therefore, can be based on standard whiteness tests carried out on the innovation $\rho(t)$. In this paper the Normalized Innovation Squared (NIS) statistic is applied for this purpose that was defined in [25] in the form

$$\Psi = \rho_k^T\, S_k^{-1}\, \rho_k, \tag{15}$$

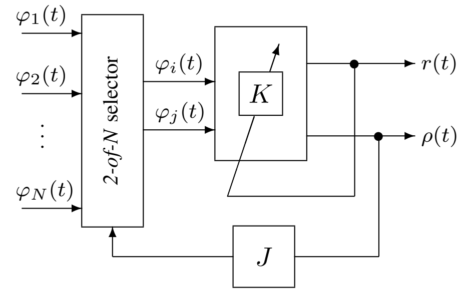

Fig. 3. *Dual layer fault tolerance scheme based on (i) adaptive tuning of the filter gain and (ii) sensor fault detection and filter reconfiguration.*

where the innovations covariance matrix is calculated as

$$S_k = H_k\, P_{k|k-1}\, K_k^T + R. \tag{16}$$

Since the statistic of (15) generated by the white nose driven filter's innovation follows a χ^2 distribution the test if Ψ falls outside a confidence region for a χ^2 random variable provides an indication of a fault in the sensory system when its value is compared to a threshold. In order to minimize false alarm rate of the detector, on account of the overly sensitivity to outliers and non-consistent measurement data, the test is evaluated along a sliding window over the values of (15) that results in the test statistic calculated in the particular time k as

$$J_k = \sum_{i=k-\ell}^{k} \frac{\Psi_i}{\omega} \quad \text{with} \quad \ell = \omega - 1, \tag{17}$$

where ω is the length of the moving evaluation window. Then, the windowed variable J_k is used as a means for triggering filter reconfiguration, i.e., for deciding whether the current filter applied during time k should be further used for time $k+1$, or to choose an alternative filter that can be obtained by the replacement of the erroneous measurement.

During measurement switching, the information, i.e., the current state and covariance estimates contained by the filter in the last time step is forwarded to the new filtering setup. For measurement replacement a 2-of-the-N selection algorithm is applied, which, quite intelligibly, prefers opting the least neighboring healthy signal from the set of available N redundant measurements.

IV. Experimental results

A. Pilot plant and experimental scenario

The laboratory equipment G.U.N.T. CE-600 distillation column unit, used for engineering education, served for the purposes of the pilot. Temperature measurements were available at 10 different locations of the column, see Fig. 2 (eight at the trays and two at the condenser). The column was equipped with pressure transducers to measure the relative pressure between the top and the bottom of the column. The reflux ratio was controlled by means of the actuation of an electromagnetic valve. Two additional actuators, one for controlling the water flow-rate at the condenser and the other for controlling the absolute pressure, were also part of the plant. A flow meter gave access to the water flow-rate

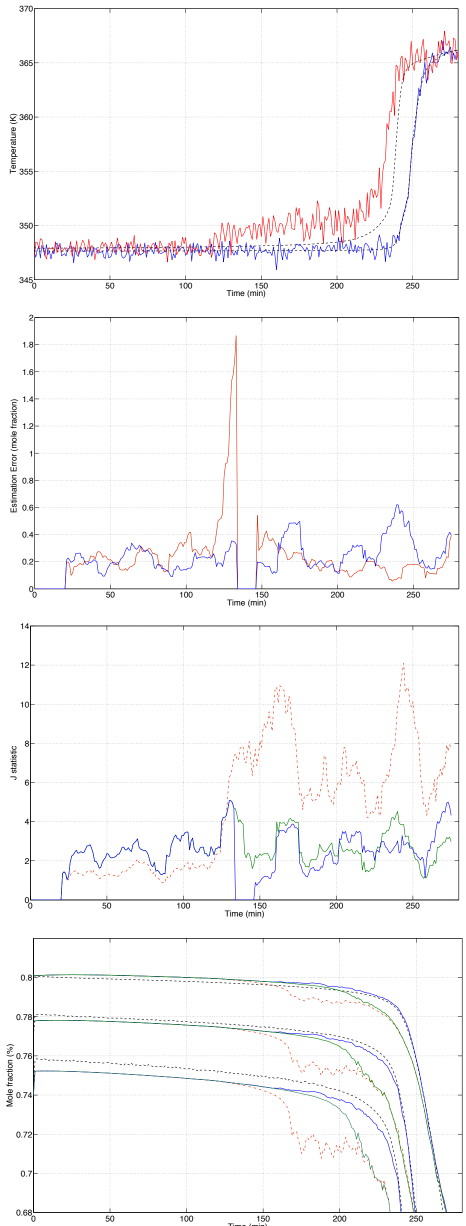

Fig. 4. *From top to bottom: a) Filter temperature measurements subject to nuisance variation of the input noise cropping up at time 120. b) Residual errors of the EKF. c) J statistic of individual filters when triggered by the violated threshold of the residual error. d) Estimations' accuracy. (red: EKF, green: adaptive EKF, blue: adaptive EKF with filter reconfiguration, dotted black: simulated fault free process behavior).*

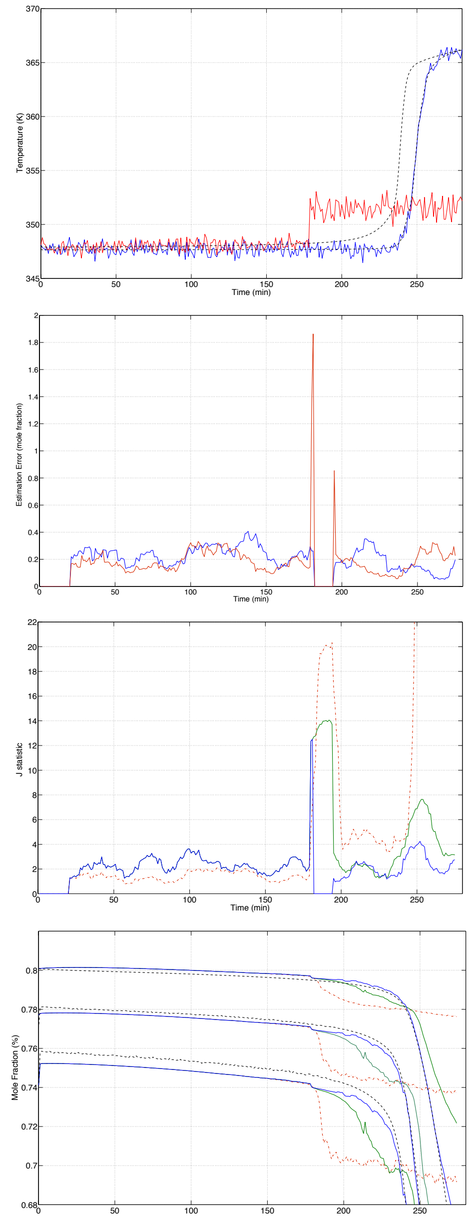

Fig. 5. *From top to bottom: a) Temperature measurements of the filter, which is subject to a measurement bias appearing at time 150. b) Residual error of the EKF. c) J statistic of individual filters when triggered by the violated threshold of the residual error. d) Estimations' accuracy. (red: EKF, green: adaptive EKF, blue: adaptive EKF with filter reconfiguration, dotted black: simulated fault free process behavior).*

at the condenser. The plant instrumentation was connected with a computer and controlled by a process supervision and data acquisition software.

Distillation experiments with ethanol and water mixtures have been performed. Relying on [19], which concluded that the composition variables of the distillation (7) are observable from the measurement system if the number of temperature measurements is at least equal to $n_c - 1$, the two component observation matrix was composed of the measurements T_5 and T_7.

B. Simulation results

Based on time series data obtained from real plant measurements the filter calculations were performed in Matlab. The filter behavior in the incidents of abnormal input signals was investigated in various experimental scenarios. In this paper the performance of three different filtering solutions, namely, (i) the normal EKF, (ii) the adaptive EKF and (iii) the fault tolerant adaptive EKF in response to two typical sensor flaw scenarios are illustrated by the simulation results in a comparative way. In Scenario 1 the effect of nuisance input signal variations and incipient sensor faults is studied. To this end, moderate increase in the measurement noise covariance was applied to one of the filter's input at time 120 in the simulations. In Scenario 2 a continuous bias, as another typical abnormality of the sensory system, was formed by adding a constant term to the measurement, which entered the system at time 150. Simulation results comparing the performance characteristics of the three filtering solutions are shown in Figs. 4 and 5. It can be seen how the particular filtering approaches affect estimation accuracy in the presence of the two fault scenarios. While the standard EKF estimate fails to follow the real state almost inmediately subsequent to the fault injection time the adaptive filter is capable to compensate the fault effect very nicely and the adaptive filter extended with the fault tolerant mechanism become nearly insensitive to the introduced abnormalities.

V. Conclusions

In this paper a dual layer approach to the robust fault tolerant estimation of nonlinear processes is presented. The implementation and performance of the standard EKF solution in comparison with the adaptive and a fault tolerant adaptive EKF schemes, which make up the two operational modes of the filter in a complementary way, were comparatively studied. The filter algorithms were applied to state estimation of a pilot plant of batch distillation process based on the column time series data. The results confirmed convincingly that the adaptive EKF is capable to increase robustness of the filter against nuisance variation of the measurement signals and, extended with a fault reconfiguration mechanism, enhance estimation accuracy, significantly.

References

[1] A. Gelb, J. F. Kasper, R. A. Nash, C. F. Price, and A. A. Sutherland, *Applied optimal estimation*. MIT Press, MA, 1974.

[2] P. S. Maybeck, *Stochastic Models, Estimation, and Control, Volume 2*. Academic Press, 1982, New York.

[3] H. W. Sorenson, *Kalman Filtering: Theory and Application*. IEEE Press, NY, 1985.

[4] S. J. Julier and J. K. Uhlmann, "A counter example for the theory of simultaneous localization and map building," in *Proc. of the IEEE Conf. on Robotics and Automation*, 2001, pp. 4238–4243.

[5] U. Frese, "A discussion of simultaneous localization and mapping," *Autonomous Robots*, vol. 20, pp. 25–42, 2006.

[6] T. Bailey, J. Nieto, J. Guivant, M. Stevens, and E. Nebot, "Consistency of the EKF-SLAM algorithm," in *Proc. of the IEEE/RSJ Int. Conf. on Intelligent Robots and Syst.*, 2006, pp. 3562–3568, Beijing, China.

[7] A. Edelmayer, M. Miranda, and V. Nebehaj, "A cooperative federated filtering approach for enhanced position estimation and sensor fault tolerance in ad-hoc vehicle networks," *IET Intell. Transp. Syst.,*, vol. 4(1), pp. 82–92, 2010.

[8] S. J. Julier, J. K. Uhlmann, and H. F. Durrant-Whyte, "A new approach for filtering nonlinear systems," in *Proc. IEEE American Control Conference, ACC'95*, 1995, pp. 1628–1632.

[9] M. Miranda, A. Edelmayer, and A. Encinoza, "Case study of unscented state estimation for batch distillation processes," in *Proc. IEEE Int. Conf. Cont. Aut, ICCA'11*, 2011, pp. 919–924, Santiago, Chile.

[10] M. Barolo and P. D. Cengio, "Closed-loop optimal operation of batch distillation columns," *Computers and Chemical Engineering*, vol. 25, pp. 561–569, 2001.

[11] J. K. Kim and D. P. Ju, "Shortcut procedure for multicomponent batch distillation with distillate reciever," *Industrial & Engineering Chemistry Research*, vol. 38, pp. 1024–1031, 1999.

[12] T. Mejdell and S. Skogestad, "Estimation of distillation compositions from multiple temperature measurements using partial-least-squares regression," *Industrial & Engineering Chemistry Research*, vol. 30(12), pp. 2543–2555, 1991.

[13] R. M. Oisiovici and S. L. Cruz, "State estimation of batch distillation columns using and extended Kalman filter," *Chemical Engineering Science*, vol. 55, pp. 4667–4680, 2000.

[14] C. Venkateswarlu and S. Avantika, "Optimal state estimation of multicomponent batch distillation," *Chemical Engineering Science*, vol. 56, pp. 5771–5786, 2001.

[15] E. Quintero-Marmol, W. L. Luyben, and C. Georgakis, "Application of an extended luenberger observer to the control of multicomponent batch distillation," *Industrial & Engineering Chemistry Research*, vol. 30, pp. 1870–1880, 1991.

[16] R. M. Oisiovici and S. L. Cruz, "Inferential control of high-purity multicomponent batch distillation columns using an extended Kalman filter," *Industrial and Engineering Chemistry Research*, vol. 40, pp. 2628–2639, 2001.

[17] I. M. Mujtaba, *Batch Distillation: Design and Operation*. Series on Chemical Engineering, Vol. 3, Imperial College Press, 2004, London.

[18] N. P. Chopey (Ed.), *Handbook of Chemical Engineering Calculations (3rd Edition)*. McGraw-Hill, 2004, iSBN 978-0-07-136262-7.

[19] C. C. Yu and W. L. Luyben, "Control of multicomponent distillation columns using rigorous composition estimators," *Int. Chem. Eng. Symp. Series*, vol. 104, pp. A29–A69, 1987.

[20] R. Mehra, "On the identification of variance and adaptive kalman filtering," *IEEE Trans. Aut. Cont.*, vol. 15(2), pp. 175–184, 1970.

[21] ——, "On-line identification of linear dynamic systems with applications to Kalman filtering," *IEEE Trans. Aut. Cont.*, vol. 16(1), pp. 12–21, 1971.

[22] J. Wang, "Stochastic modeling for real-time kinematic GPS/GLONASS positioning," *Navigation*, vol. 46(4), pp. 297–305, 2000.

[23] R. Campana and L. Marradi, "GPS-based space navigation: Comparison of kalman filtering schemes," in *Proc. of Institute of Navigation GPS Meeting*, 2000, Salt Lake City, UT.

[24] F. D. Busse, J. P. How, and J. Simpson, "Demonstration of adaptive extended Kalman filter for low earth orbit formation estimation using CDGPS," in *Proc. of Institute of Navigation GPS Meeting*, 2002, Portland, OR.

[25] M. Scalzo, G. Horvath, E. Jones, A. Bubalo, M. Alford, R. Niu, and P. K. Varshney, "Adaptive filtering for single target tracking," in *Proc. of the SPIE: Defense & Security Symposium*, vol. 4336, 2009, Orlando, FL.