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FTC Based on Data Driven FDI for a Dearomatisation Process

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Abstract—**In this paper, a fault tolerant control (FTC) system based on data driven fault detection (FDI) is presented. The behaviour of the system with proactive and reactive FTC strategies is studied in the presence of faults in an online product quality analyser with a simulated dearomatisation process operated under model predictive control (MPC). The performance of the system is validated onsite at the Neste Oil Oyj Naantali refinery. It is shown, that the inherent accommodation properties and model information in the studied MPC provide means to realise the proposed types of FTC strategies as confirmed both by simulation and the real process results. It is also shown that similar results are achieved within a simulated and the real process environments.**

I. Introduction

IN the highly competitive petroleum oil refining industry, continuous optimisation of the production processes is a crucial factor for the operation economy. Increasing the plant availability by improving the equipment fault detection and by more efficient handling of the consequent process disturbances is one way for optimising the production. Traditionally industrial fault detection systems have been designed using model-based approaches, but currently several data driven methods have become real alternatives to the first principles modelling due to the recent development of the methods and improved model identification tools. Dynamic versions partial least squares regression (PLS) have been developed for continuous processes by Ku et al. (1995), Chen et al. (1998), as well as recursive variants of PLS by Qin (1998) and Li et al. (2000). Different approaches to augment PLS with nonlinear characteristics have been proposed by Wold et al. (1989), Qin and McAvoy (1992), Malthouse et al. (1996), Wold (1992), Walczak and Massart (1996) and Bang et al. (2003). State-space models that capture the dynamic properties of processes can now be created with the recently developed subspace model identification method (SMI) that identifies the system matrices from the process history data. During the last decade a number of different algorithms for SMI have been proposed; canonical variate analysis (Larimore, 1990), N4SID (van Overschee and de Moor, 1994), MOESP (Verhaegen 1994) and, more recently, a PCA based method by Wang and Qin (2002). Nonlinear process behaviour is commonly modelled with artificial neural networks (ANN) e.g. multilayer perceptron network (MLP), which is a commonly accepted and widely used feedforward network. A large number of industrial applications of these data-based monitoring methods with successful results have been reported (e.g. Komulainen et al. 2004 and Jämsä-Jounela et al. (2003) and Kämpjärvi et al. 2007) and reviewed, e.g. by Isermann and Ballé (1997) and Meireles et al. 2003. However, in spite of the rapid development of the monitoring methods, only few studies have been published about exploiting the information provided by them in process control. FTC strategies utilising model predictive control (MPC) have been studied by e.g. Maciejowski (1999), Pranatyasto & Qin (2001) and Prakash et al. (2002). More recently Järvinen et al. (2006) have shown that the inherent accommodation properties of model predictive control (MPC) can readily be exploited to implement different types of FTC strategies providing the necessary FDI information is available. The concept has been elaborated further in Sourander et al. (2006).

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In this paper, a method for utilizing FDI information in fault tolerant process control is introduced for a dearomatisation process. The proposed system is tested offline with a simulated process and validated online in real process environment at the Neste Oil Oyj Naantali refinery. Results of similar fault cases in simulated and real process are presented and discussed. The paper is organised as follows: Section 2 is dedicated to introducing the dearomatisation process. In section 3, the structure of the implemented FDI/FTC system is presented. In the section, also descriptions of the proposed FDI algorithms and models are discussed. Section 4 is dedicated to present the FTC. Testing and validation results of the FTC system are given and discussed in section 5. The paper ends with a conclusion in section 6.

II. Dearomatisation Process

Dearomatisation processes are widely used in the petroleum oil refining industry. These processes are used to remove aromatic compounds in the feedstock by hydrogenation. The process studied in this paper consists of two trickle-bed reactors with packed beds of catalyst, a distillation column, a side stripper, several heat exchangers and separation drums, and other unit operations. The quality of the cooled product is measured online by a flash point and

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a distillation curve analyser having operation cycles of 2 min and 40 min. The MPC quality control relies on analyser values and thus this study concentrates on detecting faults in the analysers. A simplified process diagram of the studied Neste Oil Naantali Refinery dearomatisation process is presented in Fig. 1. Challenges of the fault detection are the infrequent outputs of the analysers, the clearly separate operating points related to different product grades and the slow dynamics and long delays of the nonlinear process. The long delays between the distillation analysis results also provide challenges for the FTC, since the corrective actions often have to be made before the faults are detected with full confidence. For this reason the FTC actions must be such that their effects on the process are reversible in case a fault indication later turns out to be false.

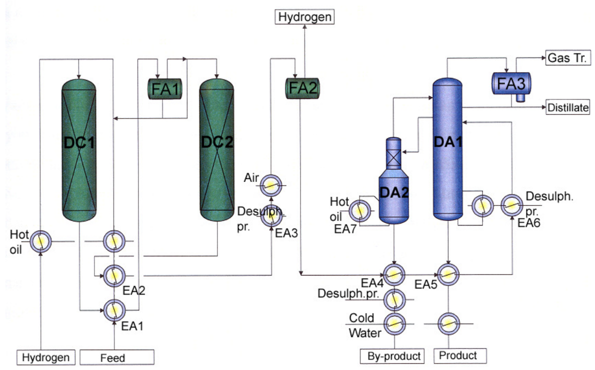

Fig. 1. The Naantali dearomatisation process.

III. FAULT DETECTION

The aim of the process monitoring is to detect faults in the bottom product flashpoint and distillation curve analysers. The fault tolerant control system functions using the FDI/FTC system with both FDI and FTC modules and acts upon the process MPC. The FDI module is based on FDI models identified from the plant data with the following methods; PLS, MLP and subspace identification. The structure of the FDI/FTC system is presented in Fig. 2. Process data used in the modelling has been acquired from the Naantali refinery dearomatisation process during winter 2007. As the dearomatisation process exhibits substantial transport delays and slow dynamical behaviour, it is necessary to take the process delays into account. The delays have been studied with correlation analysis and the measurements in training data have been time shifted to compensate for the delays.

A. *Dearomatisation process models*

The input variable set (IVS) for the initial boiling point (IBP) of the distillation curve model consists of 6 variables. The input variables and the corresponding delays are presented in Table 1. Five major latent variables (LVs) were used in the model. The flash point (FP) model was created with 5 variables in IVS reduced to 3 latent variables. Two of the input variables were calculated variables, i.e. variables whose values are not measured directly, but are derived using the measured quantities. During the modeling phase several models with different IVSs and different number of LVs were created and the ones with best estimation capabilities, described before, were chosen. To improve the applicability of the linear PLS algorithm to the nonlinear dearomatisation process, models were augmented with non-linear components, namely MLPs. First, normal PLS models were created and then a residual signal between the measured and estimated analyser outputs was calculated. The residual signal was then bounded in order to remove the occasional large absolute values and make the signal better describe systematic errors in the PLS model. Next, an MLP model was trained with the same inputs as the PLS model, but instead of using the analyser measurements, the residual signal was used as the target output. The PLS models are the same as described above and the MLP models use the same input variable sets. In the IBP case the MLP has 5 neurons in the hidden layer and in the FP case it has 4 neurons. The state-space models have been identified with a subspace method that uses PCA to reduce the dimension of the input variable set. Both models have two states and the IBP model an IVS of five process variables and FP model of six variables, two of which are calculated variables. In addition, the FP model has been augmented with an MLP model that has 3 neurons in the hidden layer. The input variables and corresponding delays of the state-space and MLP models are presented in Table 1.

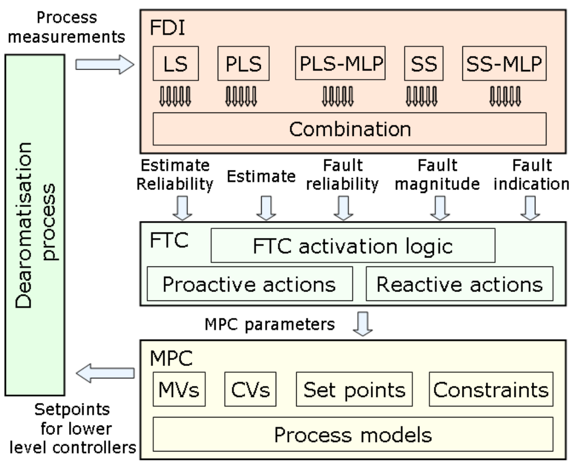

Fig. 2. Structure of the FDI/FTC system

B. *Fault detection information*

To provide all the necessary information for the FTC, the fault detection system is required to produce other information besides the estimated output values. These additional pieces of information are: reliability of the estimate (RE), fault indicator (FAULT), reliability of fault indicator (RELF) and estimated magnitude of the fault (FAULTE). The reliabilities of the estimates of the PLS models are based on the Hotelling T^2 and SPE indices. The values are modified by a sigmoid function:

$$y = \frac{1}{1 + e^{-a(x-b)}} \qquad (1)$$

where y is the scaled value, x the original value and a and b are tuning parameters. The final value for the reliability is determined by (2)

$$R_E = \frac{y_{HT^2} + y_{SPE}}{2} \qquad (2)$$

where R_E is the final estimate reliability value and y_{HT2} and y_{SPE} are the scaled reliabilities related to the Hotelling T^2 and SPE indices. Fault detection is based on comparing the estimated and real analyser outputs. The residual signal is analysed with a modified version of the Page-Hinkley algorithm. The original equations for detecting a positive deviation are given in (3)-(5). Similar equations are used for detecting negative deviations.

$$U_0 = 0 \qquad (3)$$

$$U_n = \sum_{k=1}^{n} (y_k - \mu_0 - \frac{\nu}{2}) \qquad (4)$$

$$m_n = \min_{0 \le k \le n}(U_k) \qquad (5)$$

Where U is the cumulative error sum, y_k the analysed signal, n is the total number of sample in the signal, μ_0 the mean of y, $v/2$ is the minimum size of a fault that is possible to detect with this algorithm, m is the minimum cumulative sum over the analysed period and k a time index. A fault in the analysed signal is detected when

$$U_n - m_n \ge \lambda \qquad (6)$$

where λ is the threshold for fault detection. The minimum size of the detected fault (v/2) and the detection threshold (λ) are tuning parameters, whose values were determined based on knowledge about the analysers' characteristics. The first modification to the original algorithm is to keep the m_n values at zero. The original algorithm will increase and decrease the values of m_n in detecting positive and negative jumps during normal operation. After long periods of normal operation the values may become so large in absolute value, that they will cause problems with computers. The second modification is to clear the cumulative sums after the analyzer readings agree with the corresponding estimations for three consecutive analyser cycles. With the original algorithm, the cumulative sums can become very large during the periods when faults are present and thus the algorithm will indicate a fault long after it has been removed. The reliability of a fault is determined based on the ratio of cumulative sums and the threshold limits according to the (7) where δ is a tuning parameter. If the reliability of the fault is greater than 1, it is set to 1.

RELF = (U/λ- 1)/δ (7)

The estimated magnitude of a fault is the residual between the estimated and the true value of the analyser outputs.

TABLE I

VARIABLE DELAYS FOR PLS MODELS (MIN) DELAYS FOR STATE-SPACE MODELS (MIN)

Variable	Delays for PLS models (min)		Delays for state-space models (min)	
	IBP	FP	IBP	FP
Column 1 tray 39 pressure compensated temperature [°C]	-66	NU*	-66	-53
Column 1 tray 39 temperature, [°C]	-71	-60	NU	NU
Column 1 reboiling temperature, [°C]	-79	NU	-79	NU
Colunm 1 tray 22 temperature, [°C]	-75	NU	-75	NU
Colunm 1 tray 14 temperature, [°C]	-61	NU	NU	NU
Column 1 top pressure [kPa]	-40	-39	-40	-39
Colunm 2 top pressure, [kPa]	NU	NU	-41	NU
Side product flow, [t/h]	NU	NU	NU	-53
Column 1 reboiler hot oil flow [t/h]	NU	NU	NU	-44
Feed type switch	NU	-206	NU	NU
Column 1 tray 39 - tray 22 temperature, [°C]	NU	U**	NU	U
Colunm 1 tray 14 - tray 6 temperature, [°C]	NU	U	NU	NU
Colunm 1 tray 41 - tray 39 temperature, [°C]	NU	NU	NU	U

* NU stands for 'Variable not used in the model'

** U stands for 'Undetermined'

IV. FAULT TOLERANT CONTROL SCHEME

The fault tolerant control strategy was selected based on the properties of the dearomatization process, such that they could be tested in both offline simulation and used in the real plant without any changes in the strategy. Also, it was important that the strategy was simple enough to be verified at the refinery in the relatively short time of one calendar month. Based on the strategy studies by (Järvinen et al., 2006) on the dearomatization process the minimum necessary FTC functions were defined. The developed FTC scheme consists of two types of strategies: proactive and reactive. These strategies make intensive use of the fault detection reliability information produced by the FDI-module. Reactive FTC trategies are triggered when the fault has already occurred, as measured by both the cumulative sum and the high reliability index. The reactive FTC strategies are powerful in disabling any further faults effects on process. Temporary feedback deactivation is therefore performed to prevent the faulty measurement from affecting control. Once the MPC feedback parameter is deactivated for a controlled variable, the variable uses exclusively its internal models disregarding the new faulty feedbacks. In case the analyzer fault produces higher than true values, there is a risk of off-specification product due to the feedback action and another strategy, target manipulation, is applied. In the target manipulation strategy, the controlled variable target value is modified by the estimated size of a detected fault. This is necessary in order to counteract the cumulated effects of the faulty feedback, produced at time after the fault but preceding the fault detection. Proactive FTC strategies are used to mitigate the control move effects when the fault detection is still unsure, as measured by low fault detection reliability. These FTC strategies aim at the same time to minimise the loss of control performance for cases where the fault detection later turns out to be false. The appropriate MPC parameters are automatically retuned, so that the control relies less on the analyzer measurements when a fault is detected with low reliability. For example, for the distillation analyser a simple feedback filter factor was retuned while for the flashpoint the deadband was used instead. Although the retuning can be a continuous function of the reliability index, in this application three threshold levels; I, II and III, with III being the most severe, were used for easier interpretability of the alarms. Retuning is automatically cancelled if the fault detection turns out to be false. The FTC logic is checked each minute and the actions are automatically activated or deactivated as required. If a reactive FTC strategy is triggered, all retuning actions are removed and cannot be reactivated before the fault has been corrected.

V. FTC SYSTEM PERFORMANCE

A. *Offline evaluation of FDI model performance with real plant data*

The FDI models' performances were dynamically evaluated using measurement data from the refinery process. The real IBP and FP temperatures and the corresponding estimation errors for the evaluation period of about 30 days are shown in Figs 3 and 4. All models perform well and the occasional large estimation errors are related to the transitions after feed stock changes. When the cumulative distribution of the estimation errors are analysed (see Fig. 5), it can be noted that, on the average, the combined PLS-MLP model produces estimates with smaller error than the other methods. In the IBP case, 90.7 % of the estimations are inside the acceptable error limit of 3 °C. For the FP the fraction is 94.3 %. The root mean squared errors (RMSE) of estimation shown in Table 2, show that with all methods, the estimation errors are significantly larger for IBP than for FP.

TABLE II
ROOT MEAN SQUARED ERROR OF PREDICTION

RMSE [°C]	PLS	SS	SS-MLP	PLS-MLP
IBP	5.550	5.644	-	5.4832
FP	4.780	-	2.6315	2.4958

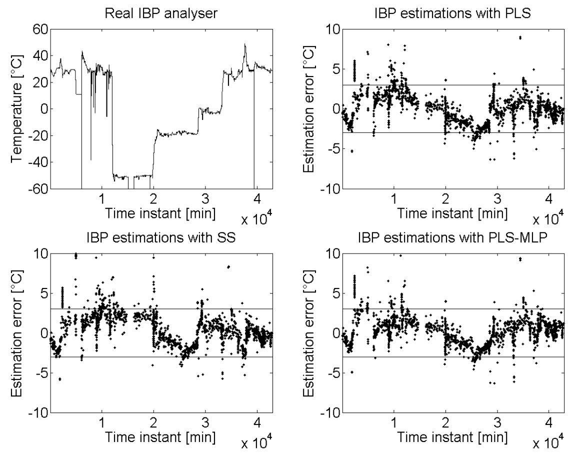

Fig. 3. Real IBP temperatures and estimation errors with an evaluation data set.

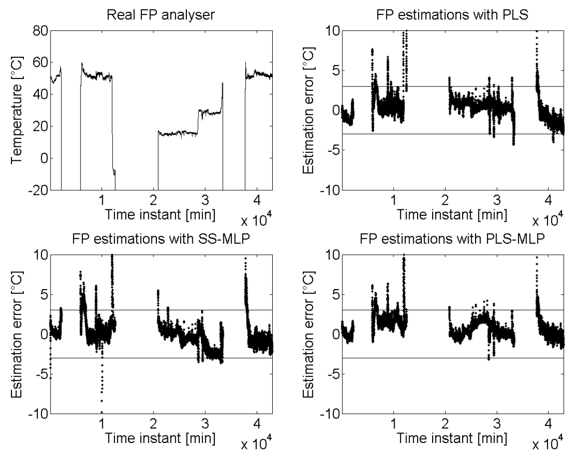

Fig. 4. Real FP temperatures and estimation errors with an evaluation data set.

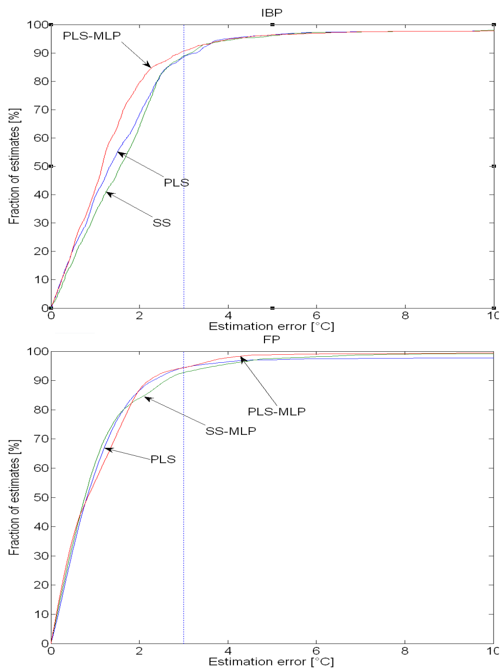

Fig. 5. Cumulative distribution of estimation errors of PLS, SS and PLS-MLP models in IBP (top) FP (bottom) temperature estimation.

B. Evaluation of FTC performance with simulated and real process

The performance of the whole FTC system was tested both with simulated and real process. The simulations were performed on an offline test platform consisting of several proprietary software products all of which run on an MS Windows PC. The most important part of the test platform is the Neste Jacobs NAPCON MPC that is used to control the simulated process in a similar way it controls the real process. Concurrently, the dearomatisation process was dynamically simulated by the Neste Jacobs PROSimulator software in the same real-time testing system. A large number of simulation tests were performed during 6 months. During those tests, the simulated process was running normally with both the basic level controllers and the higher level quality controller active. To simulate the faults present in the real analysers, the results of the simulated analysers were modified. The behaviour of the whole FDI/FTC system was analysed both during normal operation and during the faults. In this paper, a typical distillation analyser fault scenario example is discussed: a slow upward drift fault in the distillation analyser result. Throughout the dynamic simulation the MPC was controlling the initial boiling point of the solvent product and the model providing the fault detection information was the PLS model. A fault progressing at a rate of 1.8 °C/h was simulated starting at time 66. Proactive and reactive FTC strategies were triggered as the FDI system detected the progressing incipient fault at time 150. MPC retuning III was triggered first skipping the levels I and II as the reliability of the fault was already considerably high at the moment the fault was detected. Upon a new analyser result around 40 minutes later, the fault detection reliability index increased to a value large enough to trigger the MPC feedback deactivation. Simultaneously the MPC target manipulation was also triggered since the fault was upwards. During the simulation, the real IBP did not drop significantly as would have happened without the FTC. The target shift was adequate to cancel the effects of the erroneous measurement caused before its detection. The progresses of all relevant variables of this test case are illustrated in Fig. 6.

The one month validation period at the Neste Oil Naantali refinery was May 2007. In general, the FTC results acquired during the onsite validation period correspond to those of the offline testing. To illustrate typical behaviour of the FTC system in the real industrial environment, a case similar to the previously described simulated case is presented. In this case the analyser result for IBP is artificially cumulatively increased by 4.5 °C in 4 steps in a period of three hours. The resulting elevation in the faulty IBP remained relatively small as the MPC controls the process keeping it close to the desired level. The controller uses the distillation column

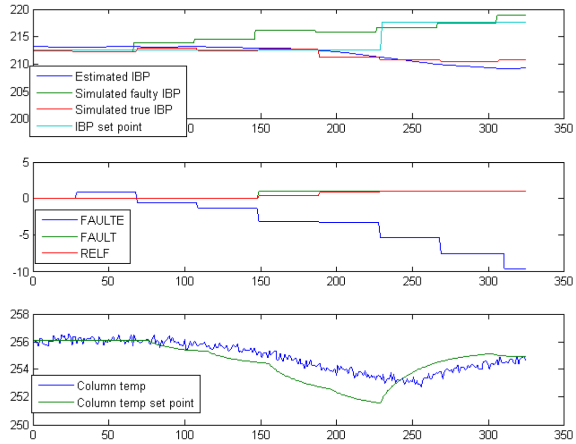

Fig. 6. Offline example of an incipient fault in the distillation analyser result. IBP temperatures (on top), FDI information (on middle) and the pressure compensated temperature in column with corresponding MPC set point value (on bottom)

temperature to control the initial boiling point and under closed loop operation, a fault in the initial boiling point result is most prominently reflected in the value of this MV. 72 min after the fault is introduced, the FDI gives a fault indication with moderate reliability and a proactive FTC strategy of MPC retuning I is triggered. After the first retuning action, the reliability of the fault increases rapidly and as the next distillation analyser result for IBP becomes available, the proactive levels II and III are skipped and instead the reactive FTC strategies of MPC feedback deactivation and CV target manipulation are triggered. As a result of these FTC actions, the drop in the value of the column temperature MV caused by the faulty analyser feedback is almost completely cancelled as in the simulated case. The progress of the relevant process measurements and the outputs of the FDI system during the upward incipient fault are illustrated in Fig. 7. In the figure, the IBP and column temperature (MV) are shown in addition to the information provided by the FDI, the estimated IBP, the fault

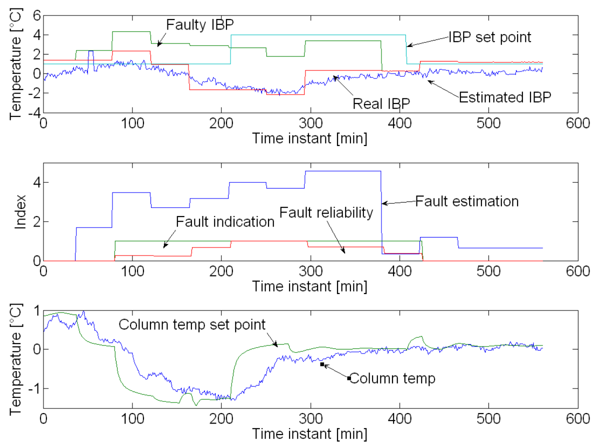

Fig. 7. Onsite example of an incipient fault in the distillation analyser result. IBP temperatures (on top), FDI information (on middle) and the pressure compensated temperature in column with corresponding MPC set point value (on bottom)

indication and the reliability of the fault indication. compensated temperature in column with corresponding MPC set point value (on bottom)

VI. CONCLUSION

An FTC strategy has been developed for Naantali refinery dearomatization process. The implemented system has been validated both with simulated and real process. All four tested data driven FDI methods were found to be effective in detecting faults in the online quality analysers. Most accurate results were given by the combined PLS-MLP method. The effectiveness of the FTC, using both proactive and reactive strategies, has been demonstrated with two similar fault cases using simulated and real process. The results indicate that the FTC works in both environments very similarly as the effects of the faults are efficiently mitigated in both cases. Analysis of the almost identical results of the cases also indicate that systems like the proposed FTC can be tested and to some degree validated with simulated processes provided an accurate simulator is available.

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