

Chemical Process Disturbance Compensation as a Fault Tolerant Control Problem

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Abstract: In general, the control of chemical processes that involve unknown disturbances presents interesting challenges. Research issues have been focused on detailed modelling of the involved phenomena in order to use *e.g.* robust on-line disturbance compensation procedures or attempting to cancel out the disturbance effect in the feedback control of the chemical system. However, the chemical modelling problem can remain a very difficult challenge due to the unknown or partially-known dynamics occurring in the process under investigation. Therefore, this article proposes a new approach to the disturbance compensation, which is recasted into the theory of robust fault estimation. The disturbances acting in the system can be thus viewed as faults with time-varying characteristics to be estimated and compensated within an output feedback fault-tolerant control scheme. In this way, the limitations arising from the use of model-based approaches are obviated. The unknown input estimation problem is hence embedded inside a control system with required stability and performance robustness. This can be a significant advantage over model-based unknown input compensation methods, in which the detailed modelling of the disturbance term can be essential, and for which robustness with respect to its characteristics is difficult to achieve using purely nonlinear modelling strategies.

Keywords: Fault tolerant control system; fuzzy modelling and identification; data-driven scheme; disturbance estimation; chemical process.

1. INTRODUCTION

The maintenance and the control of chemical processes can be challenging, since their reliability must be high to avoid safety problems and minimise production cost, which could be expensive. Some chemical processes are also planned to work with quite tight control requirements, in spite of uncertainty and disturbances affecting the controlled plants (Russell et al. (2000)). If the unknown terms are considered as fault effects, these key features can be achieved by designing control solutions that are able to manage possible fault situations. Therefore, the disturbance compensation issue is recasted into the problem of the development fault tolerant control (FTC) systems, as they possess the ability to accommodate faults automatically. In general, FTC methods are classified into two types, *i.e.* Passive Fault Tolerant Control (PFTCS) and Active Fault Tolerant Control schemes (AFTCS).

In general, the control of chemical processes can involve unknown disturbances, thus presenting interesting challenges. Research issues have been focused on detailed modelling of the involved phenomena in order to use *e.g.* robust on-line disturbance compensation procedures, or

attempting to cancel out the disturbance effect in the feedback control of the chemical system, see *e.g.* (Russell et al. (2000)). However, the chemical modelling problem can represent the key issue due to the unknown or partially-known dynamics occurring in the process under investigation. Therefore, this work suggests a possible approach to disturbance compensation, which relies on the robust fault estimation framework. The disturbances acting on the system, and the most important in this case, the impurity of the chemical process, are considered as faults with time-varying characteristics to be estimated and compensated within a suitable fault-tolerant control strategy. In this way, the limitations arising from the use of model-based approaches can be obviated. The uncertainty estimation issue is thus embedded inside a fault control tolerant design problem with required stability and performance robustness. This can have a significant advantage over classic model-based unknown input compensation methods, in which the detailed description of the disturbance model can be essential, and for which robustness with respect to unknown input characteristics is difficult to achieve using purely nonlinear descriptions.

In more detail, this paper addresses the development of a FTC system, which integrates a disturbance estimation scheme with the design of a controller accommodation

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system. In particular, the methodology for on-line disturbance/fault estimation relies on fuzzy models derived via the data acquired from the process under diagnosis. The controller accommodation exploiting further control loops depends on the on-line estimate of the unknown signals themselves. Note that fuzzy approaches exploited for the design of FTC strategies were successfully applied to wind turbine systems *e.g.* in (Shaker and Patton (2014); Simani et al. (2014, 2015)). The design of the overall FTC for the chemical process and based on fuzzy FDD modules represents the novel contribution of this paper. The chemical process addressed in this work was already considered for the development of model-based FDD strategies, as shown *e.g.* in (Patton et al. (2001); Simani (2002)). Moreover, the disturbance compensation principle recasted into a FTC problem was proposed in (Patton et al. (2010)) but applied to mechanical systems.

2. CHEMICAL PROCESS DESCRIPTION

The aim of the study presented in this paper is to develop a general procedure for the estimation of the disturbance in a chemical process by means of the development of a FTC procedure applied to the process under investigation. In particular, the monitored process is a real Continuous Stirring Tank Reactor (CSTR), where the reaction between reactant and product is exothermic.

The main input variables ($r = 3$) are: the reactor jacket inlet temperature $T_{in}(t)$ [K], the reactor temperature $T(t)$ [K], and the reactor cooling water rate $q(t)$ [$\frac{m^3}{min}$]. The main output ($m = 4$) measurements are: the reactor jacket outlet temperature $T_{out}(t)$ [K], the product percentage conversion $C(t)$ [%], the number average molecular weight $N_m(t)$ [$\frac{g}{mol}$], and weight average molecular weight $W_m(t)$ [$\frac{g}{mol}$].

As it will be shown in Section 4, the main control objective is to maintain constant the reactor polymer production by controlling the process variables in despite of the unmeasurable disturbance, *i.e.*, the reactor impurity concentration and fouling. On the other hand, other sources of uncertainty can affect the CSTR control performances, and they will be represented by the generic signal $d(t)$. The importance of this case study is that there are many examples of reactors in industry like polymerisation reactor (Russell et al. (2000)). The CSTR scheme is shown in Fig. 1.

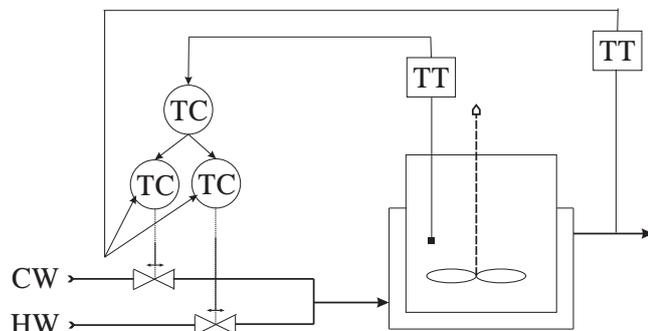


Fig. 1. Schematic of the CSTR process.

Hence, the process has $r = 3$ control inputs, $\mathbf{u}(t) = [T_{in}(t), T(t), q(t)]$, while the output measurements ($m = 4$)

are $\mathbf{y}(t) = [T_{out}(t), C(t), N_m(t), W_m(t)]$. These signals can be acquired from the plant depicted in Fig. 1.

The generic disturbance $d(t)$ will be considered as a fault $f(t)$ acting on the controlled system. Constant physical properties and constant boundary pressures of all input and output streams are assumed. Both process normal operating time series and data with different amount of impurities and fouling have been measured from the real process. A sampling rate of 0.1s was used to acquire a number of $N = 7500$ actual data sequences. More details of the considered chemical process, which was already used as benchmark for the FDD design but via linear model-based approaches, can be found in (Simani (2002)). Note that realistic faults can affect the considered process, as described in (Patton et al. (2001); Simani (2002)), but they will not be considered in this paper, since the attention is focused on the disturbance estimation. Further works will consider the FTC design in the presence of these faults.

Finally, the process FDD and FTC methods presented in this work has been tested on the data collected from the process simulation for the CSTR process. The plant has been widely used by the process monitoring community as a benchmark or source of data for comparing various FDD approaches (Russell et al. (2000)). The system was also considered to provide a realistic industrial process for evaluating process control and monitoring methods.

3. FUZZY IDENTIFICATION FOR DISTURBANCE ESTIMATION

The proposed disturbance estimation method consists of two phases. The first stage requires the identification of the nonlinear dynamic filter, which is required for disturbance estimation. From this FDD module, the disturbance reconstruction is thus exploited by the control scheme for compensating the alteration of the measured signals and used by the controller.

The nonlinear identification approach suggested in this work employs fuzzy clustering techniques to partition the available data into subsets characterised by linear behaviours. Relationships between clusters and linear regression are exploited, thus allowing for the combination of fuzzy logic techniques with system identification tools. In addition, an implementation in the Matlab[®] Toolbox of the Fuzzy Modelling and IDentification (FMID) technique recalled in the following is available (Babuška (1998)). In this study, Takagi-Sugeno (TS) fuzzy models are exploited as they are able to provide the nonlinear function between measurements and the unknown input. The switching and the scheduling between the submodels is achieved through a smooth function of the system state, the behaviour of which is defined using fuzzy set theory (Babuška (1998)).

3.1 Fuzzy Modelling via Data Clustering

The fuzzy modelling methodology is based on a two-step procedure, in which at first, the operating regions are determined using the data clustering technique, and in particular, the Gustafson-Kessel (GK) algorithm, since already available in (Babuška (1998)). Then, in the second stage, the estimation of the fuzzy model parameters is

achieved using the identification algorithm already proposed in (Simani et al. (1999)), which can be seen as a generalisation of classical least-squares. The TS fuzzy prototype has the form of:

$$y(k+1) = \frac{\sum_{i=1}^M \mu_i(\mathbf{x}(k)) y_i}{\sum_{i=1}^M \mu_i(\mathbf{x}(k))} \quad (1)$$

where $y_i = \mathbf{a}_i \mathbf{x} + b_i$, with \mathbf{a}_i the parameter vector (regressand), and b_i is the scalar offset. M is the number of clusters. $\mathbf{x} = \mathbf{x}(k)$ represents the regressor vector, which can contain delayed samples of $u(k)$ and $y(k)$. The *antecedent* fuzzy sets μ_i are extracted from the fuzzy partition matrix (Babuška (1998)). The *consequent parameters* \mathbf{a}_i and b_i are estimated from the data using the procedure developed in (Simani et al. (1999)).

This section represents the main point of the work and addresses the identification of the disturbance estimator structure. Once a reasonably accurate fuzzy description of the considered benchmark has been available, it is used to directly estimate the nonlinear function between the input-output measurements and the disturbance signals. In particular for this study, the proposed design methodology relies on the unknown input reconstruction principle, solved within the fuzzy identification framework. It is well-known that for stable fuzzy systems, whose inverted dynamics are stable, a nonlinear estimator for the unknown input can be simply designed by inverting the fuzzy model of the process under investigation. Moreover, in the ideal situation of no modelling errors and disturbances, this estimator provides perfect reconstruction of the unknown input signal with zero steady-state errors. However, in practice, one has to deal with the model-reality mismatch, which can be tackled with an arbitrary degree of accuracy by exploiting the fuzzy modelling strategy.

It is worth noting that fuzzy identification is proposed in this paper since it is able to accurately approximate any nonlinear functions. Therefore, this section explains how the nonlinear function exploited as disturbance estimator can be directly identified again by exploiting a fuzzy identification scheme, inspired by the unknown input reconstruction. In fact, the nonlinear estimator based on a fuzzy inverse process model takes into account the process nonlinearities, including the inherent saturation (level) constraints of the control inputs and other process variables.

First, it is assumed that the rule-based model (1) has been identified for describing the continuous-time behaviour of the chemical system recalled in Section 2 in the discrete-time form (2):

$$y(k+1) = F(\mathbf{x}(k), f(k)) \quad (2)$$

where $\mathbf{x}(k)$ represents the generic system state and $f(k)$ the unknown input (disturbance or fault) signal. Its TS fuzzy prototype has the form of (3):

$$y(k+1) = \frac{\sum_{i=1}^M \mu_i^{(m)}(\mathbf{x}^{(m)}(k)) (\mathbf{a}_i^{(m)} \mathbf{x}^{(m)}(k) + b_i^{(m)})}{\sum_{i=1}^M \mu_i^{(m)}(\mathbf{x}^{(m)}(k))} \quad (3)$$

The input of the model is the current state $\mathbf{x}^{(m)}(k)$ that collects the lagged inputs $u(k)$ and outputs $y(k)$, as well

as the unknown input $f(k)$. The model output is the prediction of the process measurement at the next sample $k+1$. In (3) the estimated membership functions $\mu_i^{(m)}$, the state $\mathbf{x}^{(m)}$, and the parameters $\mathbf{a}_i^{(m)}$, $b_i^{(m)}$ of the monitored system are denoted by the superscript (m) . A proper choice of the model parameters in (3) allows to obtain the approximation of the monitored system (2) with arbitrary accuracy.

3.2 Disturbance Estimation for FTC Design

The objective of the fuzzy estimator is to provide the reconstruction of the unknown input $d(t)$, which can be considered as the problem of the estimation of an equivalent fault signal $\hat{f}(k)$, such that the system output $y(k)$ at the next sampling instant is equal to the desired output or reference. In principle, this can be achieved by inverting the model of the process (3). Given the generic current state $\mathbf{x}(k)$ and the output $y(k)$, the unknown input $\hat{f}(k)$ can be expressed as:

$$\hat{f}(k+1) = F^{-1}(\mathbf{x}(k), y(k)) \quad (4)$$

Generally, it is difficult to find the *analytical inverse* function $F^{-1}(\cdot)$ (4) of $F(\cdot)$ (2). Therefore, the method exploited in this paper relies on the identified fuzzy TS model of the process under investigation (3) for providing the particular state $\mathbf{x}^{(m)}(k)$ at each time step k . From this mapping, the inverse relation $\hat{f}(k+1) = F^{-1}(\mathbf{x}(k), y(k))$ is easily identified again as a TS fuzzy prototype again in the form (1), if the whole system is stable. In particular, this expression is described in the form (5):

$$\hat{f}(k+1) = \frac{\sum_{i=1}^M \mu_i^{(r)}(\mathbf{x}^{(r)}(k)) (\mathbf{a}_i^{(r)} \mathbf{x}^{(r)}(k) + b_i^{(r)})}{\sum_{i=1}^M \mu_i^{(r)}(\mathbf{x}^{(r)}(k))} \quad (5)$$

where the inputs of the identified disturbance estimator (5) are the state $\mathbf{x}^{(r)}(k)$ and the current process output $y(k)$. In (5), the estimated membership functions $\mu_i^{(r)}$ and the parameters $\mathbf{a}_i^{(r)}$, $b_i^{(r)}$ of the identified TS fuzzy model are denoted now by the superscript (r) . Therefore, the series connection of the fault estimator and the identified inverse model should yield to an identity mapping, when $\hat{f}(k)$ exists such that $y(k+1) = F(\mathbf{x}^{(m)}(k), \hat{f}(k))$. On the other hand, due to model-reality mismatch, by means of the fuzzy identification procedure described in this paper, the difference $|y(k+1) - F(\mathbf{x}(k), \hat{f}(k))|$ can be made arbitrarily small by an appropriate choice of the prototype parameters (5), *i.e.* the membership functions $\mu_i^{(r)}$, the number of clusters M , and the regressand $\mathbf{a}_i^{(r)}$, $b_i^{(r)}$. The fuzzy model of the process (3) is required for the recursive prediction of the state vector $\mathbf{x}^{(m)}(k)$. Therefore, the state of the fuzzy estimator $\mathbf{x}^{(r)}(k)$ in (5) is updated using the process model state $\mathbf{x}^{(m)}(k)$ and the output $y(k)$. Apart from the computation of the membership degrees $\mu_i^{(r)}$, both the process model (3) and the estimator (5) are estimated using standard matrix operations and linear interpolations, which makes the algorithm suitable for real-time implementation.

Note that the nonlinear disturbance estimator and the unknown input reconstruction $\hat{f}(k)$ are derived on-line, thus representing nonlinear adaptive schemes. The disturbance estimation is therefore exploited for the compensation of the measured signals used by the chemical controller affected by the uncertainty $d(t)$. In particular, in order to compute the simulation results described in Section 4, the overall disturbance (fault) accommodation scheme has been completed by means of the process controller described in (Patton et al. (2001); Simani (2002)) and shown in Fig. 1. In this way, the signals from the chemical process controllers can be compensated by the disturbance estimation module providing the $\hat{f}(k)$ additive signals cancelling out the disturbance $d(t)$ effects. After these corrections, the nominal chemical process controller provides the tracking of the reference signal. Note that these identified nonlinear filters are also able to perform the estimation of multiple disturbance terms.

Note that the overall strategy proposed in this paper can be considered as an equivalent FTC problem, if the disturbance is seen as the unknown fault, and the FDD module represent the fuzzy disturbance estimator. This fault accommodation scheme is thus summarised in Fig. 2.

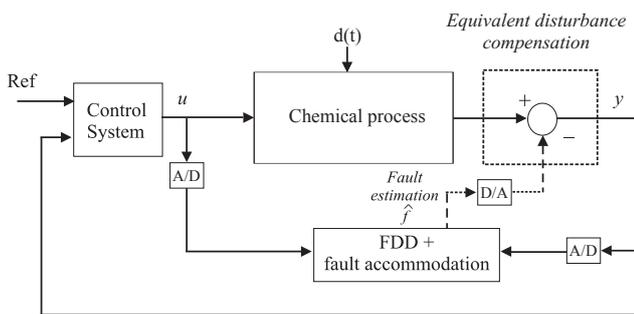


Fig. 2. Diagram of the equivalent FDD and FTC strategy.

Fig. 2 describes the structure of the FTC system where u are the controller outputs, y and Ref are the process measurements and the reference signals, respectively. Within this framework, the term \hat{f} represent the estimated fault, *i.e.* the reconstructed equivalent disturbance signals d . Therefore, Fig. 2 shows that the FTC system is obtained by integrating the fuzzy FDD module with the original control system. Analog-to-Digital (A/D) and Digital-to-Analog (D/A) converters are also reported. Note that the FDD module is also able to provide the correct estimation of multiple fault signals. In fact, in case of multiple faults (disturbances), the FDD module consists of a bank of fuzzy estimators, which gives the correct reconstruction of the corresponding signals. These estimated signals are injected into the control loop in order to compensate the effect of the disturbances. Thanks to this fault estimation feedback, the controller can be easily designed considering the nominal plant. For the case of the analytical design of the FTC scheme, it can be shown that the fault feedback is able to improve the estimation of the unknown signal itself.

Finally, regarding the stability analysis of the overall FTC system, the simulation results shown in Section 4 highlight that the model variables remain bounded in

a set, which assures control performance, even in the presence of disturbances. Moreover, it is assumed that the considered disturbance conditions do not modify the system structure, thus guaranteeing the global stability. However, a few more issues can be considered here. It should be clear that in steady-state conditions, when the fault effect is completely eliminated, the performances of the FTC method are the same of the nominal situation. Therefore, the performances of the complete system are the same of the nominal controller. The stability properties of the FTC scheme should be considered only in transient conditions, when the fault is not compensated. However, it is possible to show that the fault estimation error is limited and convergent to zero, thus the stability of the complete system is maintained.

4. SIMULATED RESULTS

In order to show the capabilities of the proposed FTC strategy, the system has been simulated as described in (Patton et al. (2001); Simani (2002)). The designed nonlinear filters provide the estimates of the signals $d(t)$, which represent the disturbances acting on the chemical process, as shown in Section 2.

Therefore, according to Section 3, the TS fuzzy prototype of the chemical process in the form of (1) has been identified by using a batch sequence of normal operating data. In general, the process model (1) is driven by the measured inputs and outputs \mathbf{x} and provides the one-step-ahead prediction of the four process outputs $\mathbf{y}(k)$, for $k = 1, \dots, N$, with $N = 7500$ and a sampling rate of 0.1s (Patton et al. (2001)).

Table 1 shows the performances of the different Multiple-Input Single-Output (MISO) identified TS fuzzy process models in the form (3) by reporting the values of the percent Normalised Sum of Square Errors ($NSSE\%$) with respect to the *identification* data. Each model provides the reconstruction of the i -th output ($i = 1, \dots, 4$) and it has been tested also in different operating conditions. The corresponding output reconstruction errors in terms of $NSSE\%$ are compared in Table 1. Several time series of batch data from the CSTR in different working conditions (*i.e.* the validation data) have been also exploited in order to validate the fuzzy TS models (3).

Table 1. Fuzzy model performances J with identification and validation data.

Output	M	n	$NSSE\%$ (Ident.)	$NSSE\%$ (Valid.)
$T_{out}(t)$	4	3	0.22%	0.38%
$C(t)$	4	4	0.35%	0.43%
$N_m(t)$	4	3	0.004%	0.007%
$W_m(t)$	4	4	0.005%	0.008%

The simulation results summarised in Table 1 highlight also the optimal number of clusters M and the local linear model order n chosen to describe with the best accuracy the chemical process dynamics and actual outputs.

After the identification of the TS fuzzy process models (3), the estimated nonlinear fuzzy filters providing the reconstruction of the signals $\hat{f}(k)$ are used by the fault accommodation module of Fig. 2. In order to compute the simulation results described below, the FTC scheme has

been completed by means of the CSTR controller recalled in (Patton et al. (2001); Simani (2002)). The following results refer to the simulation of the CSTR system, where the performances of the CSTR controller of Fig. 1 are compared with and without the proposed FTC solution. Hence, after the proper choice of the parameters in (5), the nonlinear fuzzy estimators in the form (5) provide the reconstruction of the disturbance signals with arbitrary accuracy.

As an example, Figures 3 and 4 compare the controlled $C(t)$ and $T_{out}(t)$ outputs, y_1 and y_2 , respectively, when the effects of the disturbances are not compensated by the FDD module of Figure 2.

For the case of the output C , a second order ($n = 2$) MISO TS fuzzy model with $M = 4$ clusters described by (5) provided the correct estimation of the disturbance, and therefore the accurate tracking of the signal reference, *i.e.* the product concentration. This is the most important process output that has to be monitored, and the estimated fault $\hat{f}(k)$ corresponds to the CSTR impurities and fouling $d(t)$ of the polymerisation process, which can alter the required chemical production.

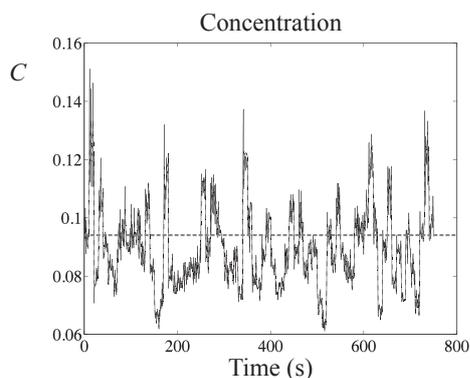


Fig. 3. Controlled (continuous line) and reference (dashed line) concentration C output y_1 without FTC.

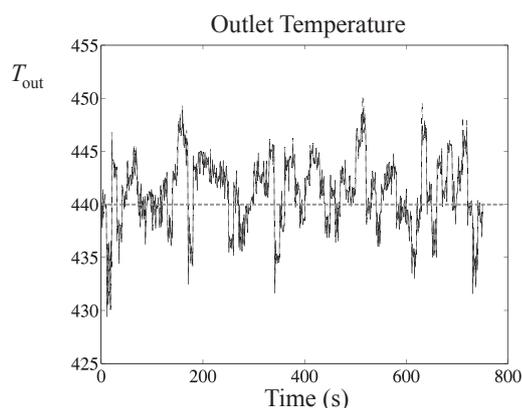


Fig. 4. Controlled (continuous line) and reference (dashed line) output temperature T_{out} outlet output y_2 without FTC.

For these examples, when the FTC scheme is not exploited, the tracking error between the controlled and the reference outputs was approximately 15.92% for the first output $y_1(t)$ and about 2.72% for the second one, $y_2(t)$. These

values are quite high, and the accurate control of the CSTR process cannot be achieved.

In order to highlight the importance of the disturbance compensation for this chemical process, Fig. 5 shows the tracking performance with and without FTC, provided by the FDD module in Fig. 2. This disturbance compensation has been removed from the feedback after $t = 350$ s. Fig. 5 can also represent the sensitivity of the nonlinear TS fuzzy filter (5) used for disturbance reconstruction. In fact, the minimum disturbance $d \approx \hat{f}$ affecting the signal C that can be estimated depends on the TS fuzzy model (3) accuracy, summarised in Table 1.

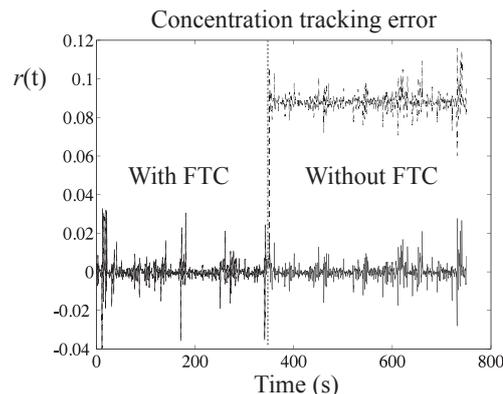


Fig. 5. Tracking error $r(t)$ with and without disturbance compensation of the C controlled output y_1 .

From a physical point of view, after $t = 350$ s, the presence of the un-compensated disturbance $d(t)$ induces a step change in the reactor concentration C . However, by means of the FDD module, the FTC strategy control compensates for the change, and the concentration C in the reactor tends to return to its desired setpoint, before $t = 350$ s. Detecting and estimating such a disturbance could be a challenging task, due to the process complexity and the model-reality mismatch.

In order to summarise the advantages of the proposed strategy, the performance of the integrated FDD and FTC schemes applied to the chemical process has been evaluated again in terms of $NSSE\%$ and considering different data sequences. In this case, the performance index refers to the tracking error accuracy. Therefore, the simulations were performed by exploiting the CSTR simulator, followed by a Matlab[®] Monte-Carlo analysis. As recalled in Section 2, it was assumed that the input-output signals u and y were affected by errors, expressed as per-cent standard deviations of the corresponding nominal values summarised in Table 2.

Table 2. Process measurement accuracy.

Variable	Standard Deviation
$T_{in}(t)$	0.12%
$T(t)$	0.12%
$q(t)$	3%
$T_{out}(t)$	0.12%
$C(t)$	0.5%
$N_m(t)$	0.01%
$W_m(t)$	0.01%

Therefore, for performance evaluation of the control schemes, the average values of the $NSSE\%$ index were

computed, and experimentally evaluated with 500 Monte-Carlo runs. The value of $NSSE\%$ is computed for the signal variations reported in Table 2. It is worth noting that Table 2 describes the uncertain signals that have been simulated in order to analyse the robustness of the proposed FTC scheme. In fact, the FTC approach for disturbance compensation has been proposed for removing the uncertainty $d(t)$ effect, and not for handling the signal variations in Table 2.

Table 3 summarises the results obtained by considering the FTC scheme integrating the original CSTR controllers, and compared with the control strategy without disturbance compensation from the FDD module, for each output, in terms of average $NSSE\%$ values.

Table 3. Comparison of the achievable performance in terms of $NSSE\%$.

Output	Benchmark Controller	FDD + FTC
$T_{out}(t)$	15.92%	0.51%
$C(t)$	2.72%	0.53%
$N_m(t)$	2.02%	0.013%
$W_m(t)$	1.96%	0.014%

It is worth noting that, regarding the method proposed in this paper, Table 3 highlights how this scheme allows to achieve better performances in terms of tracking error with respect to the nominal control methodology, in spite of the presence of disturbances affecting the chemical process. As already remarked, the proposed FTC approach was considered in this paper only for disturbance compensation. Fault conditions affecting the chemical process and described in (Patton et al. (2001); Simani (2002)) were not considered in this paper. However, this issue will be investigated in future works. Note also that the most important controlled variable is $C(t)$, even if the monitoring of the CSTR temperature is also essential. Moreover, the results reported in Table 3 highlight that the FTC scheme is able to enhance the estimation of the uncertain process variables, such as $N_m(t)$ and $W_m(t)$. However, the disturbance $d(t)$ affecting the CSTR temperature control can depend on the model-reality mismatch, whilst the correct estimation of the chemical variables heavily derives from the reactor impurities and fouling. Moreover, it is possible to show that the compensation strategy of Fig. 2, which is based on the feedback of the estimated signal, improves the reconstruction of the unknown input itself.

From a general point of view, in order to compensate also the effect of possible sensor and actuator faults, and not only the process disturbances, the FDD module should be designed in order to predict the faults affecting the inputs and output measurements. Moreover, the TS fuzzy prototypes for disturbance reconstruction proposed in this paper can solve also the fault isolation task. In fact, with a proper selection of the inputs and outputs feeding the TS fuzzy filters, they can be designed to be selectively sensitive to a specific fault signal. However, these issues that were not investigated in this paper, will be considered in further studies.

Finally, the achieved features of the proposed strategy for FDD and FTC relying on identified fuzzy models appear to be promising for applications to real chemical processes.

5. CONCLUSION

This paper proposed a data-driven approach to the disturbance compensation, which was based on the theory of robust fault estimation. The disturbances acting in the system were viewed as faults with time-varying characteristics to be estimated and compensated within a fault-tolerant control scheme. In this way, the limitations arising from the use of model-based approaches can be obviated. The disturbance estimation problem was embedded inside the design of a fault tolerant control scheme with required stability and performance robustness. This can be an advantage over classic model-based unknown input compensation methods, in which detailed modelling of the disturbance structure can be essential, and for which robustness with respect to its characteristics is difficult to achieve using purely nonlinear descriptions. The achieved simulated results seem to be promising for applications to real chemical processes.

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