Efficient on-line parameter estimation in TRANSCEND for nonlinear systems

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ABSTRACT

Prognosis and Health Management methodologies require efficient parameter estimation approaches to enable systematic system reconfiguration and adaptive control to accommodate faulty behaviors, and to predict future system states. However, accurate and timely on-line parameter estimation of complex, nonlinear systems is difficult and can be computationally expensive.

In this work, we propose a more efficient technique for on-line parameter estimation in TRANSCEND. This new approach is based on previous works on model decomposition and dependency compilation. We generate a set of smaller estimation tasks from the global estimation problem to reduce the computational burden. We tested the approach in a nonlinear three-tank system. Current results demonstrate that our method is more efficient and it does not compromise on the accuracy in the estimation.

1 INTRODUCTION

The need for increased performance, safety, and reliability in engineering systems provides the motivation for developing Integrated Systems Health Management (ISHM) methodologies that include efficient fault detection, diagnosis, and recovery mechanisms to reduce downtime and to increase system availability through the life of the system. Prognosis also requires efficient and accurate parameter estimation techniques as a starting point for predicting future system states under nominal and faulty conditions.

Our focus in this work is on model-based approaches to on-line fault isolation and identification (FII) in complex nonlinear systems. However, accurate and timely fault identification of complex, nonlinear systems is difficult and can be computationally expensive (Pouliezos and Stavrakakis, 1994; Isermann, 2006; Gertler, 1998).

Online methods for model-based diagnosis require the use of quick but robust fault detection methods to establish discrepancies between observed and expected system behavior. Discrepancies caused by faults trigger the fault isolation and identification processes that are responsible for determining the cause of the fault, and the change in the magnitude of the corresponding system parameter, respectively.

TRANSCEND (Mosterman and Biswas, 1999) combines qualitative fault isolation methods with quantitative parameter estimation techniques to isolate and to identify single faults in dynamic systems (Manders *et al.*, 2000). Its main problem is that the estimation process over the whole system is difficult and time consuming for complex, nonlinear systems, making the estimation process unsuitable for on-line applications.

System decomposition has been proposed to reduce complexity in the parameter estimations tasks. The goal of decomposition consists of generating a set of smaller estimation tasks from the global estimation problem. Williams and Millar (Williams and Millar, 1998) introduced the concept of $dissent$. A $dissent$ describes an overdetermined subsystem which can be used to estimate the parameters within the subsystem model.

Possible Conflicts, or PCs (Pulido and Alonso-Gonzalez, 2004) are conceptually equivalent to dissents, and can be used in the same way that dissents are used to generate smaller estimation tasks for fault identification. A structural approach based on possible conflicts is applied to derive the minimal set of overdetermined subsystems from the global system model. Each subsystem contains a minimal number of equations that suffice for fault parameters estimation.

In this work, we use the analogies between dissents and possible conflicts (Pulido and Alonso-Gonzalez, 2004), and the analogies between possible conflicts and temporal causal graphs (Biswas *et al.*, 2009; Bregon *et al.*, 2009) to propose a new fault isolation and identification approach for TRANSCEND. Our aim is to turn the global estimation problem in TRAN-

SCEND into a set of smaller estimation problems to improve efficiency for the localization and identification tasks.

We have tested the new identification strategy in a nonlinear simulation system. Experimental results demonstrate the computational improvement.

The rest of the article is organized as follows. Section 2 briefly introduces TRANSCEND and its current quantitative FII approach. Section 3 describes basic ideas of system decomposition using dissents and its relation with possible conflicts. Section 4 then briefly presents the possible conflicts approach. Section 5 presents the way to derive minimal parameter estimators using possible conflicts, and the new FII approach for TRANSCEND. Section 6 describes the experimental results obtained for a three tank system. And, finally, section 7 presents the discussion and conclusions.

2 THE TRANSCEND DIAGNOSIS APPROACH

TRANSCEND (Mosterman and Biswas, 1999; Manders *et al.*, 2000) uses a model-based diagnosis approach based on bond graphs that model the dynamic behavior of the system. The approach combines qualitative fault isolation methods with quantitative parameter estimation techniques to isolate and identify single faults in dynamic systems.

2.1 Qualitative Diagnosis from Transients

A *fault* (Blanke *et al.*, 2006) is a deviation of the system structure or the system parameters from the nominal situation. We can consider different kind of faults, but this paper focuses only in *abrupt faults*:

Definition 1 (Abrupt fault) *Abrupt faults are instantaneous and persistent changes in the parameter values that cause significant deviations from steady state operations (transients).*

Abrupt faults produce transients in system variables. The TRANSCEND diagnosis approach assumes the transients can only have discontinuities at the time of fault occurrence, t_f, that is, the behavior of the system is continuously differentiable before and after the occurrence of a fault. This implies that the transient response to a fault after the time of fault occurrence can be approximated by the Taylor series expansion:

$$\begin{aligned} y(t) &= y(t_f) + y'(t_f)\frac{(t-t_f)}{1!} \\ &+ y''(t_f)\frac{(t-t_f)^2}{2!} + \dots \\ &+ y^{(k)}(t_f)\frac{(t-t_f)^k}{k!} + \dots \end{aligned}$$

where t_f is the time of fault occurrence, and $t > t_f$.

If $\mid y^{(k+1)} \mid$ is bounded and t is close to t_f, then the Taylor series is a good approximation of the true signal $y(t)$. As t increases from t_f the Taylor series approximation is going to increasingly differ from the true signal $y(t)$, but higher order approximations follow the signal for a longer time interval. This analysis is done to describe the fault transient signal as a *fault signature* (Manders *et al.*, 2000; Roychoudhury *et al.*, 2009):

Definition 2 (Fault signature) *Given a fault, f, the time of fault occurrence, t_f, and a measurement, m, the fault signature, $FS(f,m)$, is the set of $k+1$ feature values consisting of the predicted magnitude and the 1^{st} through k^{th} order derivative values computed at t_f from the residual signal of measurement m.*

The problem within this approach is that when the fault occurs, the magnitude of change in the faulty parameter is unknown, so derivative values in the fault signature have to be computed from subsequent measurements. This is a difficult problem to solve for dynamic systems, and especially for systems that exhibit complex, nonlinear behaviors. To address this problem, qualitative constraint analysis techniques based on fault signatures have been developed for fault isolation.

The fault signatures are derived from a Temporal Causal Graph (TCG) that can be automatically derived from a bond graph model. The signatures are expressed in terms of qualitative values: below normal (-), normal (0) and above normal (+), for the measurements, and decreasing (-), steady (0) and increasing (+), for the derivatives of measurement deviations.

2.2 The TRANSCEND Fault Diagnosis Approach

Fig. 1 illustrates the architecture of the TRANSCEND fault diagnosis approach.

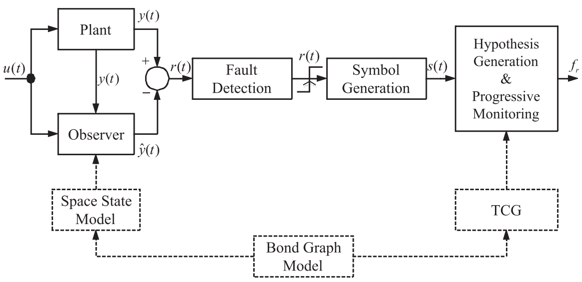

Figure 1: Block diagram of the TRANSCEND diagnosis approach.

The bond graph model of the system is used to generate both the state-space and the TCG models of the system. Using the state-space model, an Extended Kalman filter observer is designed for tracking nominal system behavior with noisy measurements. Using the estimation of the outputs given by the observer, $\hat{y}(t)$, and the measurements, $y(t)$, an statistical Z-test (Kirk, 1999) is employed for the fault detection task. A significant deviation in the residual, $r(t)$, triggers the symbol generation step. In this step, the measurement and slope values from the residuals are transformed into qualitative values $(+,-,0)$, $s(t)$.

The fault signature generation algorithm combines a backward propagation step to identify all possible parameter deviations (fault hypotheses) that are consistent with a deviated measurement, and a forward propagation step that generates the fault signature, i.e. the effect of each fault hypothesis on the available measurements (Mosterman and Biswas, 1999). As discussed earlier, the fault signature for the measurement residual is expressed in terms of the magnitude (zeroth order time-derivative), slope (first order time-derivative), and higher order effects. All deviation propagations start off as zeroth order effects (magnitude changes). When an integrating edge in the TCG is traversed, the magnitude change becomes a first order change, i.e. the first derivative of the affected quantity changes.

Even though this process is carried out online and triggered only when faults are detected, the prediction step can be done offline to each potential fault parameter to generate its fault signature (Mosterman and Biswas, 1999).

The last step in TRANSCEND is called progressive monitoring. In this step, the system compares signatures of the hypothesized faults against measurements as they change dynamically. This process tries to narrow down the number of fault candidates, generating a reduced set of fault candidates, f_r.

We will illustrate the significant issues in this paper with the well-known laboratory plant model of a three-tank system shown in Fig. 2. The plant is made up of three tanks $\{T_1, T_2, T_3\}$. A control loop defined by a function $f(x)$, where x is the pressure in tank T_1, determines the opening of valve V_0. Valves V_1, V_2, and V_3 are completely open. We assume four sensors: two, $\{P_1, P_2\}$, measure the fluid pressure in tanks T_1 and T_3, the third, $\{F_1\}$, measures the in-flow into tank T_1, and the fourth, $\{F_2\}$, measures the outflow from tank T_3. For this study, seven different parametric faults have been considered in the plant: change in tanks T_1, T_2, T_3 capacities, and partial blocks in valves V_1, V_2, V_3, and in the input pipe.

Fig. 3 shows the bond graph model for the plant. Measurement points shown as De and Df components are connected to junctions, and the faults appear as explicit parameters of the bond graph model. Fig. 4 shows the TCG for the plant.

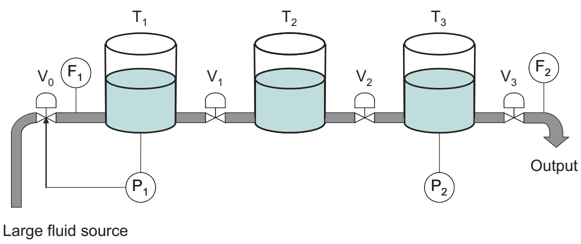

Figure 2: Diagram of the laboratory plant.

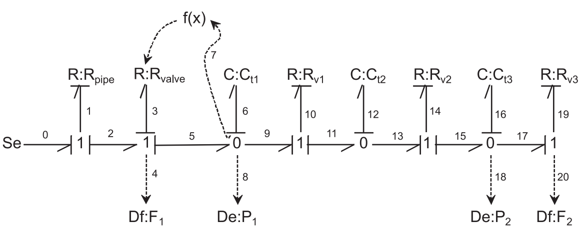

Figure 3: Bond graph model of the plant. $f(x)$ represents the control of R_{valve} resistance through V_0 aperture as a function of T_1 pressure (level).

Applying the fault signature generation process to all possible faults that can arise in the system shown in Fig. 2, we obtain the fault signature matrix for the system (see table 1). In this table, P_1, P_2, F_1, and F_2 columns represent the expected deviations (no change (0), increasing or decreasing (+/-), or indeterminate effect[1](*)) in the measurements, and in the slope or higher order effects, in the presence of faults. Column I shows isolation capabilities of this approach[2] (faults on parameters R_{v_1} and R_{v_2} cannot be completely isolated).

	P_1	P_2	F_1	F_2	I
C_{T_1}	$+*$	$0+$	$**$	$0+$	1
C_{T_2}	$0+$	$0+$	$0*$	$0+$	1
C_{T_3}	$0+$	$+-$	$0*$	$+-$	1
R_{V_1}	$0-$	$0+$	$0*$	$0+$	0
R_{V_2}	$0-$	$0+$	$0*$	$0+$	0
R_{V_3}	$0-$	$0-$	$0*$	$+-$	1
R_{pipe}	$0+$	$0+$	$+*$	$0+$	1

Table 1: Signature matrix for the temporal causal graph found for the laboratory plant.

2.3 Quantitative Fault Isolation and Identification (FII) in TRANSCEND

TRANSCEND avoids some of the computational difficulties associated with numerical schemes, but it lacks discriminative power due to qualitative constraints usage. For example, table 1 shows that the approach is unable to distinguish between fault hypotheses R_{V_1} and R_{V_2} for the three-tank system. In these cases, a parameter estimation procedure over the whole system is carried out (Manders *et al.*, 2000). The idea is to estimate the parameter for each one of the hypothesized faults from the available measurements. A separate parameter estimator (using standard least squares) will be initiated for each of the hypothesized faults in f_r using the measurements. Fault parameter with the smallest least squares error will then be considered as the faulty element. Moreover, the parameter estimator will provide the fault magnitude.

This combined qualitative/quantitative fault isolation scheme provides some advantages against the traditional numeric schemes, but it experiences computational problems when applied to on-line fault isolation/identification for complex, nonlinear systems. The problem is the complexity related to the real time estimation process over the whole system. It becomes more difficult and more time consuming as the dimension of the problem grows. This problem is even worse if we are dealing with complex, nonlinear systems. Our proposal consists of taking advantage of the strong analogies between model estimation and consistency-based diagnosis in the context of their respective de-

[1] An indeterminate effect means that there are at least two paths of the same order that propagate + and - effects, and the dominant effect is unknown.

[2] 1 means that the fault can be distinguished, during the isolation task, from the rest of the faults considered for the system; 0 means that it can not be isolated

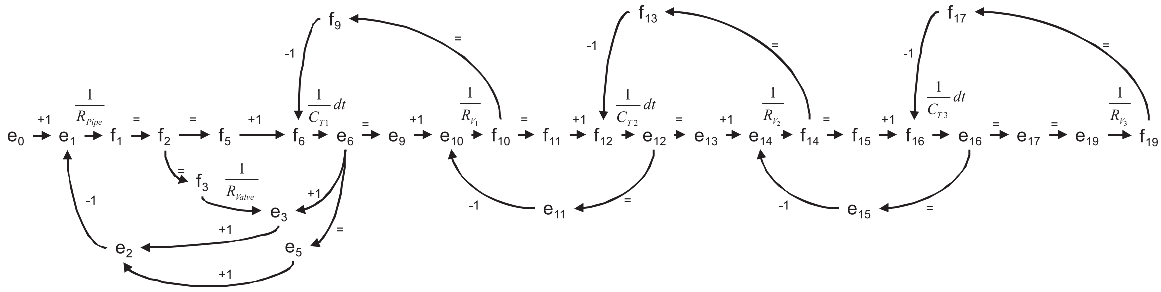

Figure 4: Temporal causal graph of the three-tank plant.

composition methods (Williams and Millar, 1998) to reduce problem complexity.

3 MODEL DECOMPOSITION

Given a continuous time state-space model of a nonlinear dynamic system:

$$\dot{x} = f(x, u, \theta)$$
$$y = g(x, u, \theta)$$

where f and g are nonlinear functions; x, u, and y are the vectors of the state, input, and output variables of the systems; and θ is the set of model parameters. We want to estimate an unknown parameter, $\theta_i \in \theta$. The estimation procedure consists of solving a nonlinear optimization problem:

Definition 3 (Nonlinear Optimization Problem) *Given a nonlinear system model and an estimator $e(u, \theta_i)$, we can estimate θ_i by solving the nonlinear optimization problem:*

$$\theta_i^* = \underset{\theta_i}{\operatorname{argmin}} \sum (y - e(u, \theta_i))^2 \qquad (1)$$

The goal of model *decomposition* consists of generating a set of smaller estimation tasks from the global estimation problem. Williams and Millar introduced the concept of *dissent* in their proposal of Decompositional Model-based Learning in Moriarty (Williams and Millar, 1998). A dissent is a minimal subset of equations from a system model which is over-determined given a set of measured variables. A dissent describes an over-determined subsystem which can be used to estimate the parameters within the subsystem model. Since we want to minimize the complexity of the estimation task, we are only interested in those subsystems that are *minimal* w.r.t. the number of equations.

Williams and Millar pointed out the analogy between model estimation using dissents and consistency-based diagnosis using minimal conflicts: conflicts are related to a discrepancy, and dissents signal a potential error in the estimation process. However, (minimal) conflicts are computed on-line using a dependency-recording engine, while dissents can be computed off-line. Therefore, dissents are also closely related to several methods in the Artificial Intelligence Diagnosis community to avoid on-line dependency-recording (such as possible conflicts (Pulido and Alonso-Gonzalez, 2004)), and they are also close to the structural approach employed in the System Dynamics and Control Engineering community to find Analytical Redundancy Relations (Blanke *et al.*, 2006).

We exploit this similarity and we focus on the Possible Conflict approach, which has been proved to be equivalent to conflict generation in the General Diagnostic Engine, GDE. In fact, Pulido and Alonso-Gonzalez (Pulido and Alonso-Gonzalez, 2004) have shown that both dissents and possible conflicts look for the whole set of minimal over-determined sets of equations in the model that can be solved using local propagation (solving one equation in one unknown). Their main difference comes from their use in model-based reasoning: while dissents are used for successive parameter estimation in Moriarty, Possible Conflicts have been used as an off-line dependency-recording for consistency-based diagnosis.

Summarizing, both approaches can be used to compute the potential error between a subset of estimations and a subset of measurements. Therefore, possible conflicts can be useful to decompose a system in order to reduce the complexity of the parameter estimation process.

The integration of possible conflicts in the fault isolation and identification task in TRANSCEND is rather straightforward. The structure of each PC defines a minimal subset of over-determined equations, which can be easily obtained from the TCG in TRANSCEND, i.e. PCs identify minimal over-determined structures in TCGs (Bregon *et al.*, 2009; Biswas *et al.*, 2009). Hence, our proposal is to use possible conflicts to identify off-line those minimal structures in TCGs, and then, use them as smaller estimation tasks for each of the hypothesized faults.

Before we develop this methodology, we review concepts related to possible conflicts in next section.

4 POSSIBLE CONFLICTS

Possible conflicts, PCs for short (Pulido and Alonso-Gonzalez, 2004), represent sub-systems that may become conflicts when faults occur within the Consistency Based Diagnosis framework (Reiter, 1987), i.e. *minimal subsets of equations containing the analytical redundancy necessary to perform fault diagnosis* (Pulido and Alonso-Gonzalez, 2004).

Computation of PCs is performed on an abstract model linked to the set of equations in the system description, i.e. a hypergraph including just the constrains in the model, and their related known and unknown variables. PCs are derived off-line using two core concepts: *minimal evaluation chains*, or MECs, and *minimal evaluation models*, or MEMs.

MECs are minimal over-constrained sets of relations, and they represent a necessary condition for a conflict to exist. MECs represent a partial subhypergraph from the original system description.

Each constraint in a MEC has one or more variables. We call an interpretation to each feasible causal assignment within a constraint, allowing to solve one variable assuming remaining variables are known. In the general case, not every interpretation is feasible for non-linear dynamic models.

The set of interpretations, seen as causal links among variables in each hyper-arc, define a causal graph for each MEC. A MEM is a global consistent causal interpretation for every constraint in a MEC. Hence, a MEM is a subgraph for each MEC. Using the whole set of available interpretations for each constraint in a MEC, algorithms used to compute PCs are able to find every possible causal interpretation which is globally consistent within a MEC, i.e., the whole set of MEMs for each MEC. Each MEM describes an executable model, which can be used to perform fault detection. Possible Conflicts are defined as the set of relations in a MEC that has, at least, one MEM.

If there is a discrepancy between predictions from these models and current observations, the PC must be responsible for such a discrepancy, and should be confirmed as a real conflict. Afterwards, diagnosis candidates are obtained from conflicts following Reiter's theory.

PCs calculation uses a minimality criterion in terms of sets of constraints. Nevertheless, it is straightforward to obtain candidates based on components. It has been demonstrated that the set of MEMs generated with this approach is equivalent to the set of conflicts computed by the GDE.

Moreover, if algorithms used to compute Analytical Redundancy Relations, or ARRs, through structural analysis use such a minimality criterion and provide a complete solution –explores every possible causal assignment for every minimal ARR–, the set of PCs has same detection and isolation capabilities as the set of minimal ARRs.

Finally, if every MEM in every PC provides the same solution–what is called the *Equivalence assumption* in (Pulido and Alonso-Gonzalez, 2004)–, then PCs, minimal ARRs, and minimal conflicts provide the same solution in terms of fault detection and isolation capabilities.

Cordier et al. (Cordier *et al.*, 2004) introduced the concept of *support* for an ARR (set of components whose models are used to derive an ARR). Based on such idea, off-line compiled conflicts and ARR's support can be considered as equivalent (the support for an ARR is a potential conflict, which is equivalent to a possible conflict).

As we showed in (Bregon *et al.*, 2009) the set of possible conflicts of a system can be automatically obtained from its bond graph model. For the three tank plant, we found four possible conflicts. Table 2 shows the components and the output variable estimated for each one of the possible conflicts.

	$Components$	$Estimate$
PC_1	R_{pipe}	F_1
PC_2	$C_{T_1}, R_{V_1}, C_{T_2}, R_{V_2}$	P_1
PC_3	$R_{V_1}, C_{T_2}, R_{V_2}, C_{T_3}$	P_2
PC_4	R_{V_3}	F_2

Table 2: PCs found for the laboratory plant.

5 AN EFFICIENT FII APPROACH FOR TRANSCEND

As we previously showed, our aim consists of making use of the strong analogies between model estimation and consistency-based diagnosis, and PCs and TCGs, to turn the global estimation problem in TRANSCEND into a set of smaller estimation problems. In this section we will show how to generate these smaller estimators from PCs, and how to integrate them into the TRANSCEND diagnosis approach.

5.1 Using PCs to Obtain Minimal Parameter Estimators

PCs have a set of equations, input variables, and one output variable which can be estimated using only observed variables. For a possible conflict PC_k, this estimation can be defined in state space form as follows:

$$\dot{\hat{x}}_{pc_k} = f_{pc_k}(x_{pc_k}, u_{pc_k}, \theta_{pc_k})$$

$$\hat{y}_{pc_k} = g_{pc_k}(x_{pc_k}, u_{pc_k}, \theta_{pc_k})$$

where f_{pc_k} and g_{pc_k} are nonlinear functions; $\hat{x}_{pc_k}$, and u_{pc_k} are vectors for the state and input variables; $\hat{y}_{pc_k}$ is the output variable; and θ_{pc_k} is the set of parameters for PC_k.

For linear systems, Gertler established (Gertler, 1998; 2002) that changes in the parameters can be directly obtained from the residuals of parity relations, and, consequently, parameter estimation can be performed through parity relations. As PCs are equivalent to ARRs (Pulido and Alonso-Gonzalez, 2004; Armengol *et al.*, 2009), PCs can be used to derive parameter estimators for linear systems.

That equivalence has been guaranteed for some classes of non-linear systems (Gertler, 2002), but can not be guaranteed in general. However, for those particular situations, PCs still can be used in the parameter estimation process, but in a different way: using PCs we can derive the structure of a parametrized estimator, e_{pc_k}, for a nonlinear system (involves parameters, θ_{pc_k}, and measured variables: u_{pc_k} and y_{pc_k}). Then, e_{pc_k} can be used as a minimal estimator to solve the nonlinear optimization problem defined in equation (1), as stated in the following proposition:

Proposition 1 *A possible conflict, PC_k, and a set of input variables for PC_k, u_{pc_k}, can be used as a parameter estimator, $\hat{y}_{pc_k} = e_{pc_k}(u_{pc_k}, \theta_i)$, by selecting the measured variable estimated by the possible conflict as $\hat{y}_{pc_k}$, and solving $\hat{y}_{pc_k}$ in terms of the remaining measured variables.*

Each estimator is uniquely related to one PC, hence it contains minimal redundancy required for parameter estimation. In this case, each PC has an executable

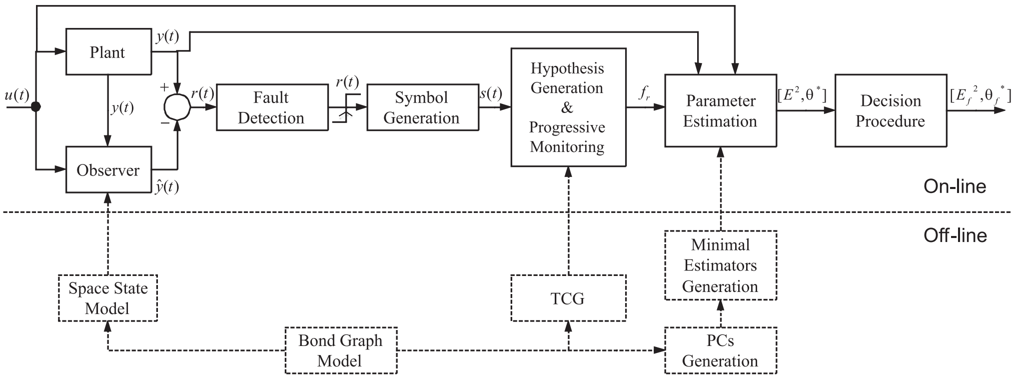

Figure 5: The new TRANSCEND FII approach.

model that can be used for simulation purposes. Access to parameters in the simulation models is straightforward, because these parameters come directly from the Bond-Graph model of the whole system. How these models are used for fault identification in TRANSCEND is shown in next section.

For the three tank system we have obtained four minimal parameter estimators shown in table 3, one for each possible conflict.

Table 3 shows that faults R_{pipe}, C_{T_1}, C_{T_3}, and R_{V_3} can be estimated using only e_1, e_2, e_3, and e_4 estimators, respectively. On the other hand, faults in R_{V_1}, C_{T_2}, and R_{V_2} can be estimated through both e_2 and e_3 estimators.

When a parameter can be estimated by two or more minimal estimators, it is possible to choose the preferred estimator in several ways (each estimator has different properties and provides different results). In this proposal we only provide the whole set of minimal estimators for each parameter, but we allow to choose as preferred estimator the one that better fits the requirements of the system. To select the preferred estimator, several options can be considered:

- Select the estimator that minimizes the number of equations needed for its computation.
- Select the estimator that maximizes the accuracy in the estimation (trade off between the number of equations and measurements involved in the PC). In this work, we selected this option.

5.2 New FII Approach for TRANSCEND

To integrate these ideas in TRANSCEND, we need to modify its current FII approach (Manders *et al.*, 2000).

Fig. 5 shows the new proposed FII approach for TRANSCEND. It relies upon four steps: (i), model decomposition by off-line computation of the set of minimal PCs from the bond graph model, (ii), off-line computation and selection of the better minimal estimator for each fault candidate, (iii), on-line quantitative parameter estimation procedure over the minimal estimators related with the set of isolated fault candidates, and (iv), decision procedure to select the faulty candidate.

The parameter estimation block is triggered on-line only after the progressive monitoring step. The output of the progressive monitoring (a narrowed down set of possible fault hypotheses, f_r), the inputs, and the outputs of the system, are used as the inputs for the parameter estimation. Within this block, a parameter estimation process is carried out for each one of the hypothesized faults, f, using its corresponding minimal estimator (obtained in step (ii)).

Fig. 6 shows the parameter estimation process using the minimal estimators. A parametrized minimal estimator, e_{pc_k}, uses the inputs of the system, u_{pc_k}, and a parameter value, θ_f, to generate an estimation of the output, $\hat{y}_{pc_k}$. This estimated output is compared against the observed output, y_{pc_k}, by the Least Squares, LS, error calculator block. This block computes the least square error between $\hat{y}_{pc_k}$ and y_{pc_k} for the fault candidate f, E_f^2. Then, the iteration engine block, that contains a nonlinear optimization algorithm, finds the minimum of the error surface $E_f^2(\theta_f)$, by iteratively invoking the estimator with different parameter values.

The value of the parameter and its minimum LS error will be the output of the parameter estimation block (and the input for the decision procedure block). Finally, for the decision procedure, a statistical test is used to discard the faulty candidates whose quadratic error, E^2, do not converge to zero.

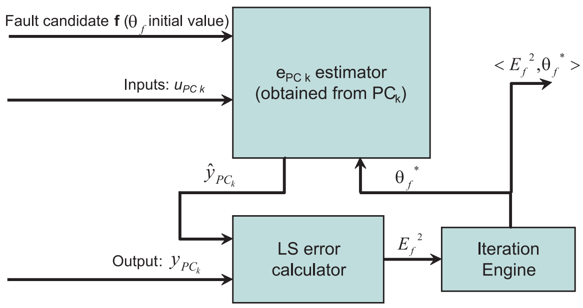

Figure 6: Parameter estimation using the minimal estimator from PCs.

It is important to point out that the big computational effort of the approach is made to generate the error surface by several estimations with different parameter values. The advantage of the new approach

$Estimator$	$Related$ PC	$Parameters$	$Inputs$	$Output$
e_1	PC_1	R_{pipe}	S_e, P_1	F_1
e_2	PC_2	$C_{T_1}, R_{V_1}, C_{T_2}, R_{V_2}$	F_1, P_2	P_1
e_3	PC_3	$R_{V_1}, C_{T_2}, R_{V_2}, C_{T_3}$	P_1, F_2	P_2
e_4	PC_4	R_{V_3}	P_2	F_2

Table 3: Minimal parameter estimators found for the three tank system, and their related Possible Conflicts.

against the previous one is that now, these estimations are carried out with minimal over-determined sets of equations, instead of using the whole model.

6 RESULTS ON THE CASE STUDY

The laboratory plant shown in Fig. 2 has been used for empirical studies for the proposed FII methodology. The study was made on a data-set containing examples obtained from several simulations for each fault mode in the plant.

Models and simulations were developed using the Simulink® environment. Simulations lasted 1000 time steps. White noise (mean = 0, variance = 5% of the measured signal) was added to the measurements. To test the consistency and accuracy of the approach, we carried out 10 experiments for each fault mode. Results shown in table 4 correspond with the mean values of the 10 experiments for each fault mode.

Abrupt faults with a 10% fault magnitude in the parameters were introduced at $t = 450$. We compared the results obtained using the new FII approach with the minimal estimators against the previous FII approach using the whole system model. Table 4 shows the results obtained for each one of the faulty parameters using 40 seconds (upper part), and 100 seconds (lower part) data sets for the estimation. Column $Fault\ candidate$ shows the output of the TRANSCEND progressive monitoring block, i.e., the reduced set of hypothesized faults for each faulty parameter. Column $PC\ used$ shows the possible conflict used for the estimation of each fault candidate. Column $Real\ value$ shows the current value of the faulty parameters. Columns $Estimated\ value$, $Confidence\ interval$, and $Elapsed\ Time$ show the estimated value, the 95% confidence interval, and the elapsed time for the parameter estimation, respectively, using the minimal estimators and the whole model.

For the sake of simplicity, a Nonlinear Least Squares algorithm was used for the parameter estimation task.

Possible conflicts isolate faults in R_{v_1} and R_{v_2} using in average half the time needed to isolate the same faults using the whole model. For example, using a 40 seconds data set for a fault in R_{v_1}, the minimal estimators are able to confirm R_{v_1} and discard R_{v_2} in 0.056 and 0.047 seconds, respectively. For the same example the whole system estimator lasted 0.104 and 0.106 seconds, respectively.

Regarding the identification results, table 4 shows that for all the faulty situations considered we obtained faster estimations without loosing accuracy in the estimation. Parameter values obtained with the minimal estimators are pretty similar to those obtained using the whole model. In some cases the estimation was even better while reducing the time consumed to carry out this estimation (see, for example, results obtained for faults in parameters C_{t_2}, C_{t_3}, and R_{v_3}). For example, using a 100 seconds data set of a fault in R_{v_3}, the minimal estimators are able to provide better estimation than the whole system, 109.98 vs. 109.89, while improving almost 80% the elapsed time for the estimation, 0.094 vs. 0.453.

To test the accuracy and validity of the parameters estimated with the possible conflicts, we computed the 95% confidence intervals for every faulty situation for the minimal estimators and the whole model. Intervals are rather similar in both cases. We also carried out more experiments using smaller and bigger data sets (20 seconds and 200 seconds) for the parameter estimation, obtaining similar results to those shown in table 4.

7 DISCUSSION AND CONCLUSIONS

This paper has presented a novel architecture for timely on-line parameter estimation in TRANSCEND, using system decomposition and possible conflicts. Our approach exploits the strong analogies between Decompositional Model-based Learning and Model-based Diagnosis to decompose the global estimation problem into smaller estimation tasks, thus reducing the computational problems for on-line parameter estimation. Based on these analogies, we have used possible conflicts to find minimal estimators derived from TCGs.

Simulation results obtained so far using the new approach show an improvement in the efficiency of TRANSCEND without compromising the accuracy on the estimation. This improvement comes from the reduced size of the estimation for the optimization task.

Several approaches have been proposed in the literature to solve the fault identification problem. Pure on-line quantitative parameter estimation for nonlinear models is usually very time consuming (Escobet and Travé-Massuyès, 2001) and have strong requirements for noise decoupling and input excitation (Patton *et al.*, 2000). To mitigate these factors, several authors have proposed the combination of different methods for fault detection and isolation, and fault identification (Pouliezos and Stavrakakis, 1994; Isermann, 2006; Gertler, 1998). Our proposal follows this trend.

The main task as we move forward is to test these ideas in a more complex nonlinear system, such as the reverse osmosis system that was developed for water recovery in long duration human space missions (Roychoudhury *et al.*, 2009). Our guess is that using possible conflicts for the parameter estimation task in a more complex model, computational effort will

40 seconds									
				Using PCs			Using the whole system		
Faulty parameter	Fault candidate	PC used	Real value	Estimated value	Confidence interval	Elapsed time	Estimated value	Confidence interval	Elapsed time
C_{T_1}	C_{T_1}	PC_2	11	11.03	[10.95 − 11.11]	0.063	11.03	[10.99 − 11.07]	0.096
C_{T_2}	C_{T_2}	PC_3	11	11.002	[10.94 − 11.05]	0.058	10.99	[10.86 − 11.12]	0.100
C_{T_3}	C_{T_3}	PC_3	11	11.11	[11.05 − 11.18]	0.055	11.13	[10.99 − 11.27]	0.092
R_{V_1}	R_{V_1}	PC_2	110	108.79	[108.15 − 109.43]	0.056	109.50	[108.78 − 110.22]	0.104
	R_{V_2}	PC_3	110	E^2 does not converge to zero		0.046	E^2 does not converge to zero		0.106
R_{V_2}	R_{V_1}	PC_2	110	E^2 does not converge to zero		0.047	E^2 does not converge to zero		0.116
	R_{V_2}	PC_3	110	110.21	[110.05 − 110.37]	0.053	109.93	[109.19 − 110.66]	0.112
R_{V_3}	R_{V_3}	PC_4	110	110.01	[109.71 − 110.30]	0.046	111.18	[110.52 − 111.84]	0.105
R_{pipe}	R_{pipe}	PC_1	110	110.20	[109.01 − 111.40]	0.056	110.60	[110.01 − 111.18]	0.103
100 seconds									
				Using PCs			Using the whole system		
Faulty parameter	Fault candidate	PC used	Real value	Estimated value	Confidence interval	Elapsed time	Estimated value	Confidence interval	Elapsed time
C_{T_1}	C_{T_1}	PC_2	11	11.04	[11.01 − 11.07]	0.122	11.04	[11.02 − 11.06]	0.339
C_{T_2}	C_{T_2}	PC_3	11	11.004	[10.98 − 11.01]	0.111	11.01	[10.96 − 11.05]	0.326
C_{T_3}	C_{T_3}	PC_3	11	11.02	[10.99 − 11.04]	0.145	11.02	[10.96 − 11.07]	0.314
R_{V_1}	R_{V_1}	PC_2	110	110.38	[110.22 − 110.55]	0.136	110.09	[109.78 − 110.41]	0.378
	R_{V_2}	PC_3	110	E^2 does not converge to zero		0.136	E^2 does not converge to zero		0.381
R_{V_2}	R_{V_1}	PC_2	110	E^2 does not converge to zero		0.166	E^2 does not converge to zero		0.441
	R_{V_2}	PC_3	110	110.06	[110.02 − 110.10]	0.179	109.93	[109.61 − 110.25]	0.422
R_{V_3}	R_{V_3}	PC_4	110	109.98	[109.83 − 110.13]	0.094	109.89	[109.68 − 110.09]	0.453
R_{pipe}	R_{pipe}	PC_1	110	109.96	[109.36 − 110.56]	0.141	110.04	[109.85 − 110.24]	0.396

Table 4: Estimation results (estimated value, 95 % confidence interval, and elapsed time) for each one of the faults considered using 40 seconds and 100 seconds data sets.

decrease due to the bigger complexity of the global model. We also plan to test the performance of the system with different optimization algorithms to improve computational effort, and decrease the possible negative effects of noise in the measurements in the parameter estimation process. Last task ahead will be to integrate this approach within the FACT architecture.

ACKNOWLEDGMENTS

Anibal Bregon and Belarmino Pulido's work has been partially supported by Spanish regional grant JCyL VA005B09. Gautam Biswas' work was partially supported by NASA grants NNX07AD12A and USRA 08020-013.

REFERENCES

(Armengol *et al.*, 2009) J. Armengol, A. Bregon, T. Escobet, E. Gelso, M. Krysander, M. Nyberg, X. Olive, B. Pulido, and L. Travé-Massuyès. Minimal structurally overdetermined sets for residual generation: A comparison of alternative approaches. In *Proceedings of the IFAC-Safeprocess 2009*, Barcelona, Spain, 2009.

(Biswas *et al.*, 2009) G. Biswas, X. Koutsoukos, A. Bregon, and B. Pulido. Analytic redundancy, possible conflicts, and TCG-based fault signature diagnosis applied to nonlinear dynamic systems. In *Proceedings of the IFAC-Safeprocess 2009*, Barcelona, Spain, 2009.

(Blanke *et al.*, 2006) M. Blanke, M. Kinnaert, J. Lunze, and M. Staroswiecki. *Diagnosis and Fault Tolerant Control*. Springer, 2006.

(Bregon *et al.*, 2009) A. Bregon, B. Pulido, G. Biswas, and X. Koutsoukos. Generating possible conflicts from bond graphs using temporal causal graphs. In *Proceeding of the 23rd European Conference on Modelling and Simulation, ECMS09*, Madrid, Spain, 2009.

(Cordier *et al.*, 2004) M.O. Cordier, P. Dague, F. Lévy, J. Montmain, M. Staroswiecki, and L. Travé-Massuyès. Conflicts versus analytical redundancy relations: a comparative analysis of the model-based diagnosis approach from the artificial intelligence and automatic control perspectives. *IEEE Trans. Syst. Man Cy. B.*, 34(5):2163–2177, 2004.

(Escobet and Travé-Massuyès, 2001) T. Escobet and L. Travé-Massuyès. Parameter estimation methods for fault detection and isolation. In *Proceedings of the 12th International Workshop on Principles of Diagnosis (The BRIDGE Workshop)*, 2001.

(Gertler, 1998) J.J. Gertler. *Fault detection and diagnosis in Engineering Systems*. Marcel Dekker, Inc., Basel, 1998.

(Gertler, 2002) J.J. Gertler. All linear methods are equal - and extendible to (some) nonlinearities. *International Journal of Robust and Nonlinear Control*, pages 629–648, 2002.

(Isermann, 2006) R. Isermann. *Fault-Diagnosis System. An Introduction from Fault Detection to Fault Tolerance*. Springer, 2006.

(Kirk, 1999) R. E. Kirk. *Statistics: An Introduction*. Fort Worth: Harcourt Brace, 1999.

(Manders *et al.*, 2000) E. J. Manders, S. Narasimhan, G. Biswas, and P. J. Mosterman. A combined qualitative/quantitative approach for fault isolation in continuous dynamic systems. In *Proceedings of the 4th Symposium on Fault Detection, Supervision, and Safety for Technical Processes*, pages 1074–1079, 2000.

(Mosterman and Biswas, 1999) P. Mosterman and G. Biswas. Diagnosis of continuous valued systems in transient operating regions. *IEEE Trans. Syst. Man Cy. A.*, 29(6):554–565, 1999.

(Patton *et al.*, 2000) R. J. Patton, P. M. Frank, and R. N. Clark. *Issues in fault diagnosis for dynamic systems*. Springer Verlag, New York, 2000.

(Pouliezos and Stavrakakis, 1994) A.D. Pouliezos and G.S. Stavrakakis. *Real time fault monitoring of industrial processes*. Microprocessor-based systems engineering. Kluwer Academic Publishers, Dordrecht, 1994.

(Pulido and Alonso-Gonzalez, 2004) B. Pulido and C. Alonso-Gonzalez. Possible conflicts: a compilation technique for consistency-based diagnosis. *IEEE Trans. Syst. Man Cy. B.*, 34(5):2192–2206, 2004.

(Reiter, 1987) R. Reiter. A theory of diagnosis from first principles. *Artificial Intelligence*, 32:57–95, 1987.

(Roychoudhury *et al.*, 2009) I. Roychoudhury, G. Biswas, and X. Koutsoukos. Designing distributed diagnosers for complex continuous systems. *IEEE Transactions on Automated Sciences and Engineering (T-ASE)*, 6, (to appear) 2009.

(Williams and Millar, 1998) B.C. Williams and B. Millar. Decompositional model-based learning and its analogy to diagnosis. In *Proceedings of (AAAI-98)*, 1998.

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