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Parameter fault diagnosis in heat exchange networks with distributed time delay

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Abstract: This paper deals with parameter fault diagnosis in heat exchange networks (HENs) with joining and splitting connections where the change in the heat transfer coefficient is considered as fault. The fault diagnosis oriented model of the HEN elements was developed based on the equivalent LTI realization of distributed delay models. The Signed Directed Graph (SDG) method is used to derive the fault observability conditions. The presence of faults induces bi-linear fault-input terms into the system model. Thus, a nonlinear adaptive observer was proposed for fault diagnosis. To verify and validate the proposed method, a case study is presented. The simulation results show that the observers are successfully detecting and estimating the faults and unknown system states.

Keywords: Fault diagnosis; Heat Exchange Networks, Distributed delay, Process systems

1. INTRODUCTION

Heat exchange units form an important class of operating elements in process systems (see e.g. Hangos and Cameron [2001]). They are used for dynamic modelling of industrial heat exchanger networks or household heating systems, to mention only the most important ones. The dynamic models of heat exchange units can be derived from first engineering principles, in particular from energy balances, and they are in the simplest lumped parameter case linear or bi-linear state space models depending on the chosen/available input variables (see Hangos et al. [2004]).

In most cases, heat exchange units are used in multiple instances forming a heat exchange network (HEN), which is a networked dynamic system. A recent book of Leitold et al. [2020] describes network-based methods for analysing structural properties of dynamic systems in general, and heat exchanger networks in particular.

Generally, the fault diagnosis design in networks of dynamic systems represents a hard problem due to the fault effect propagation through the network connections. In particular cases, the specifics of the interconnections and the subsystems have to be explored to design fault diagnosis methods with guaranteed performances (see e.g. Keliris et al. [2015] or Ferrari et al. [2009]). Some also tried to use heuristic approaches such as fuzzy neural network (see Liu et al. [2009]) or machine learning (see Sargolzaei et al. [2016]) to handle it. A recent study by Li et al. [2020] has also proposed a dissipation based distributed fault diagnosis that can detect and isolate actuator faults in HENs as the case study.

In this present study, a common fault in heat exchange networks which is the change in the heat transfer coefficient caused by e.g. the deterioration of the heat transfer surface by ageing (see Weyer et al. [2000]) or by degradation of the isolation of the heat transferring tubes are considered. As the heat transfer coefficient is a parameter of the dynamic model, a parametric fault diagnosis method is proposed that is built upon a simple specific model of HENs.

2. FAULT DIAGNOSIS ORIENTED MODELING OF HENS

Heat exchange systems form a well known and well investigated sub-class in process systems (see Hangos and Cameron [2001]). They appear in both industrial and household environments with slightly different properties. This paper is concerned with domestic heat exchange networks (HENs), that form heating systems of buildings, for example.

In domestic heat exchange systems one can distinguish two types of basic elements: *heating devices* and *consumers* (e.g. room radiators). These elements are connected by *isolated pipes* where the heating fluid (most often water) circulates. Consider a HEN composed of $j = 1 \dots N$ such elements and pipes.

The basic heat exchange unit (CL unit) A simple way of describing a unit (heating devices, consumers and pipes)

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of a HEN is applied here. Assume a tube with a heat transferring wall that contains incompressible liquid phase in it, that is surrounded by the environment of different temperatures T_{EXT}. The tube is well-mixed in its cross-section and has a spatially distributed temperature along its length. There is a plug flow along the tube. The inlet temperature is considered the first input of the system $u_1^{(j)}$. We also consider that there is an irreversible exchange term to or from the environment. Thus, the second input $u_2^{(j)} = T_{EXT}$ of the model is the temperature of the environment. The measured output of the system ($y^{(j)}$) is represented by the outlet temperature.

Interconnections in HEN To construct a realistic network topology, splitting and joining connections are assumed. A *joining connection* represents a real joining of tubes while a *splitting connection* represents a real branching of tubes. The connections affect the flow rates along the tubes. Let $v^{(i)}$ be the flow rate in the ith unit.

The input neighbour set ($\mathcal{N}_I^{(j)}$) of the jth unit is represented by such units that are connected to this unit through a joining connection. The input flow rate can be written as:

$$v^{(j)} = \sum_{\ell \in \mathcal{N}_I^{(j)}} v^{(\ell)} \quad (1)$$

The output neighbour set ($\mathcal{N}_O^{(j)}$) of the jth unit is represented by such units that are connected to this unit through a splitting connection:

$$v^{(i)} = \beta_i v^{(j)}, \quad \sum_{i \in \mathcal{N}_O^{(j)}} \beta_i = 1, \quad (2)$$

where $\beta_i \in (0, 1]$ are positive constant coefficients.

Distributed delay in the connections Between the inlet temperature and outlet temperature of a connecting pipe, a delay will occur that can be described using a kernel function g in the general case (see Smith [2011]). This general case is called *distributed delay* and the model of the connection with distributed delay is in the form of:

$$y^{(j)}(t) = \int_{-\tau}^{0} g_j(s) u_1^{(j)}(t+s) ds \quad , \quad \int_{-\tau}^{0} g_j(s) ds = 1 \quad (3)$$

where $g_j : [-\tau, 0] \to [0, \infty)$ is the distributed delay kernel or distribution function. However, networked system with distributed delayed connections can be described by delay differential equations (DDEs). As DDEs are difficult to handle, one can associate an *equivalent ordinary differential equation (ODE) model* to a DDE in special cases using the well known linear chain trick (see Krasznai et al. [2010]) in the simplest case. This equivalent ODE model can be used for dynamic model analysis (stability or observability, for example) or for observer design.

In our earlier work (see Lipták et al. [2019]), it was shown that the lumped model of convective and/or diffusive transport coupled with transfer through the environment results in a distributed time delay of the connection with an appropriate kernel function. So, one can realize a distributed time delay connection using a simple LTI model.

This means, that the basic heat exchange units can be equivalently represented as simple distributed delayed connections or a dynamic unit in the network, depending on our purpose.

Basic heat exchange unit model Generally, the complete dynamic model of a heat exchange unit can be built from the energy conservation equations (see Hangos and Cameron [2001]) in their lumped model form.

In this study, to obtain the model of a heat exchange unit (the CL unit), we considered a plug flow convection model with flow-rate $v^{(j)}$ extended with a heat transfer term $k_E^{(j)}(T_{EXT} - x_i^{(j)})$ where T_{EXT} is the external temperature and $k_E^{(j)} > 0$ is the heat transfer coefficient. The resulting two input one output (2ISO) model of a heat exchange unit has the form of:

$$CL_j := \begin{cases} \dot{\boldsymbol{x}}^{(j)} = A^{(j)}\boldsymbol{x}^{(j)} + B^{(j)}\boldsymbol{u}^{(j)} \\ y^{(j)} = C\boldsymbol{x}^{(j)} \end{cases}$$

$$A^{(j)} = \begin{bmatrix} -v^{(j)} - k_E^{(j)} & 0 & \dots & 0 \\ v^{(j)} & -v^{(j)} - k_E^{(j)} & \dots & 0 \\ 0 & v^{(j)} & \dots & 0 \\ 0 & \dots & \dots & 0 \\ 0 & \dots & \dots & -v^{(j)} - k_E^{(j)} \end{bmatrix} \quad (4)$$

$$B^{(j)} = \begin{bmatrix} v^{(j)} & 0 & \dots & 0 \\ k_E^{(j)} & k_E^{(j)} & \dots & k_E^{(j)} \end{bmatrix}^T, \quad C = \begin{bmatrix} 0 & 0 & 0 & \dots & 1 \end{bmatrix}$$

where $\boldsymbol{u}^{(j)} = [u_1^{(j)} \; T_{EXT}]^T$ and the state vector $\boldsymbol{x}^{(j)} \in \mathbb{R}^n$ contains the temperatures x_i along the tube of the jth subsystem where $i = 1 \dots n$ represents the position of a flow element in the tube. The measured output of the system is the last state variable $x_n^{(j)}$, i.e. $y^{(j)}(t) = x_n^{(j)}(t)$.

Note that in the case of heating devices, T_{EXT} represents the temperature of an external heat source in which heat is transferred to the HENs.

3. THE FAULT DIAGNOSIS PROBLEM

The heaters and consumers of HENs could be connected by such transmitting elements (pipes) that can hardly be monitored e.g. due to the unfavourable spatial placements or excessive lengths. In these cases, it is important to estimate the internal states and operating conditions of these elements based only on measurements performed at their terminals.

The fault model A critical parameter in the elements of a heat exchange network is represented by the heat transfer coefficient $k_E^{(j)}$. Its decrease leads to heat loss and consequently to the performance degradation of the HEN. The slackening of the heat transfer coefficient is treated as a fault event in the network. The fault is modelled as a multiplicative parameter uncertainty in the system:

$$k_{Ef}^{(j)} = (1 - f_j) k_E^{(j)} \quad (5)$$

where $k_{Ef}^{(j)}$ is the modified heat transfer parameter and $f_j \in [0, 1)$ is a piece-wise continuous fault signal with sparse changes.

The fault signal can be incorporated into the state space model (4) as follows:

$$\dot{\boldsymbol{x}}^{(j)} = A^{(j)}\boldsymbol{x}^{(j)} + B^{(j)}\boldsymbol{u}^{(j)} + f_j\boldsymbol{h}^{(j)}(\boldsymbol{x}^{(j)}) \ , \ y^{(j)} = C\boldsymbol{x}^{(j)} \quad (6)$$

where the ith entry of $\boldsymbol{h} \in \mathbb{R}^n$ is $h_i^{(j)} = k_E^{(j)}(x_i^{(j)} - T_{EXT})$.

The fault diagnosis problem Design a dynamic system which generates the estimates of the internal states of the system (6) and the fault as

$$\begin{aligned} \widehat{f}_j &= \mathcal{O}_f^{(j)}\left\{\boldsymbol{u}^{(j)}, y^{(j)}, \widehat{f}_j, \widehat{\boldsymbol{x}}^{(j)}\right\} \\ \widehat{\boldsymbol{x}}^{(j)} &= \mathcal{O}_{\boldsymbol{x}}^{(j)}\left\{\boldsymbol{u}^{(j)}, y^{(j)}, \widehat{f}_j, \widehat{\boldsymbol{x}}^{(j)}\right\} \end{aligned} \quad (7)$$

such that the estimated state vector $\widehat{\boldsymbol{x}}$ and the estimated fault $\widehat{f}_j$ satisfy:

$$\lim_{t\to\infty} |\widehat{f}_j - f_j| = 0 \ \text{ and } \ \lim_{t\to\infty} \|\widehat{\boldsymbol{x}}^{(j)} - \boldsymbol{x}^{(j)}\| = 0 \quad (8)$$

Special case: Faulty model with splitting connection Consider two interconnected CL type connections where the first (j) is before the split while the second (k) is one of the split elements after the split. The state vector of this system is $\boldsymbol{x}^{(j,k)} = [\boldsymbol{x}^{(j)T} \ \boldsymbol{x}^{(k)T}]^T \in \mathbb{R}^{2n}$. Assume that the fault can only happen either before or after the split so that it will not affect all of the states.

The fault diagnosis oriented model (6) in this case can be extended by adding a fault distribution matrix $F^{(j,k)}$ to the last term of the model:

$$\begin{aligned} \dot{\boldsymbol{x}}^{(j,k)} &= A^{(j,k)}\boldsymbol{x}^{(j,k)} + B^{(j,k)}\boldsymbol{u}^{(j,k)} + F^{(j,k)}\boldsymbol{h}^{(j,k)}(\boldsymbol{x}^{(j,k)}) \\ y^{(j,k)} &= C^{(j,k)}\boldsymbol{x}^{(j,k)} \end{aligned} \quad (9)$$

where

$$\begin{aligned} F^{(j,k)} &= \begin{bmatrix} f_j I & O \\ O & O \end{bmatrix} \text{ if the fault happen before the split} \\ F^{(j,k)} &= \begin{bmatrix} O & O \\ O & f_k I \end{bmatrix} \text{ if the fault happen after the split} \end{aligned} \quad (10)$$

Here, $I \in \mathbb{R}^{n\times n}$ is the identity matrix and $O \in \mathbb{R}^{n\times n}$ is the zero matrix.

4. STRUCTURAL OBSERVABILITY ANALYSIS

In this section, we investigate the sensors placement problem in joining and splitting connections by using observability analysis from a graph theoretic approach. To do this, a Signed Directed Graph (SDG) is drawn from the structural state-space of the related system (see Bhushan and Rengaswamy [2000] or Varga et al. [1995]). The observability analysis is done by checking the fulfilment of the following two conditions (see Reinschke [1988]):

(1) There is at least one path from every state vertices to at least one of the outputs vertices.
(2) There is at least one cycle family which touches every state vertices.

A "cycle family" means a set of vertices with disjoint cycles. If both of those conditions are satisfied, then it is called "structurally observable" or "s-observable".

In the CL type connection (see Eq. (4)), each state affects its successive state. The last state is measured by a sensor so that it is directly connected to the output vertex. The fault representing the change in $k_E^{(j)}$ parameter is influencing all of the states. Thus, we can make a *condensed graph* where all of the states are represented by just one vertex except the fault because we want to investigate whether that fault is observable or not concerning the sensors placement. Moreover, it implies that the first condition is already satisfied so we only need to check the fulfilment of the second condition.

As an example, consider three CL type connections CL_1, CL_2, and CL_3 which are joined into one CL type connection CL and then it is split into three CL type connections CL_a, CL_b, and CL_c as shown in Fig 1. The y vertices are representing the possibility of sensors placement in the joining and splitting connections.

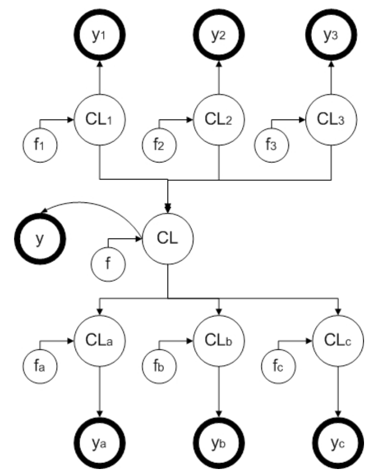


Fig. 1. SDG of Joining and Splitting CL Type Connections

For *joining connection*, it is seen that (f_1, CL_1, CL, y, f_1) is not in a disjoint cycle family with (f_2, CL_2, CL, y, f_2) because it has 2 common vertices CL and y. This is also valid for the other cycles (f_3, CL_3, CL, y, f_3), and so on. Thus, with only one sensor put at the end of the CL type connection after the join, a single observer to isolate all the faults can not be constructed because the second observability condition is not fulfilled. However, a *bank of observers* can be built by which each observer is constructed specifically just to detect a single specific fault. For each observer, we treat the output of the remaining CL type connections as an additional disturbance. The drawback of this approach is that a disturbance decoupling must be designed to compensate for the additional disturbances from the remaining CL type connections other than the one that we build a specific observer to estimate the fault happening there.

One other way to make the *joining connection* be s-observable for the whole fault vertices is *by adding a sensor at each CL type connection output in addition to the one at the joining connection output*. With this treatment, it will have exactly one cycle family for each fault vertex in the interconnected subsystems which are (f, CL, y, f), (f_1, CL_1, y_1, f_1), (f_2, CL_2, y_2, f_2), (f_3, CL_3, y_3, f_3), and so on.

For *splitting connection*, it can be seen that each output vertex has 2 cycle families. One cycle touches the fault and state vertices of the CL type connection before it is split, while the other one touches the fault and states vertices of its related CL type connection after the split. Thus, *with just one sensor put at the output of a specific CL type connection after the split, an observer can always be constructed to estimate a fault happening at the CL type connection before the split.* Moreover, based on that same sensor, another observer to estimate a specific fault that occurs in the related CL type connection after a split can also be constructed. It should also be remarked that for this splitting connection, only some of the states are affected by the fault depending on whether it happened before or after the splits (see Eq (9) and Eq (10)).

5. OBSERVER FOR FAULT ESTIMATION

A critical issue in the formulated fault diagnosis problem is that there are unmeasurable states in the system. Jiang and Chowdhury [2005] has developed a fault observer based method where a nonlinear fault distribution function depends not only on the inputs and outputs but also on estimated states. By taking the basic idea from this previous research, we modified it to suit our case.

The dynamics of the CL type connections with fault is as shown in the Eq (6). Define the estimation errors as:

$$\begin{aligned} \boldsymbol{e}_x^{(j)} &= \boldsymbol{x}^{(j)} - \hat{\boldsymbol{x}}^{(j)}\ ,\ e_y^{(j)} = y^{(j)} - \hat{y}^{(j)} = C\boldsymbol{e}_x^{(j)} \\ e_f^{(j)} &= f_j - \hat{f}_j \end{aligned} \tag{11}$$

where $\hat{f}_j$ is the estimated fault.

Consider an observer for faulty case as follows:

$$\begin{aligned} \dot{\hat{\boldsymbol{x}}}^{(j)} &= A^{(j)}\hat{\boldsymbol{x}}^{(j)} + B^{(j)}\boldsymbol{u}^{(j)} + \hat{f}_j\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)}) + K_x^{(j)}e_y^{(j)} \\ \hat{\boldsymbol{y}}^{(j)} &= C\hat{\boldsymbol{x}}^{(j)} \end{aligned} \tag{12}$$

along with the following parameter adaptation equation:

$$\dot{\hat{f}}_j = K_f^{(j)}\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)})e_y^{(j)} \tag{13}$$

Here $K_x^{(j)}, K_f^{(j)T} \in \mathbb{R}^n$ are the observer and adaptation gain vectors.

By assuming piece-wise constant fault signal, we can derive the state and fault estimation error as follows:

$$\begin{aligned} \dot{\boldsymbol{e}}_x^{(j)} &= A^{(j)}\boldsymbol{e}_x^{(j)} + f_j\boldsymbol{h}^{(j)}(\boldsymbol{x}^{(j)}) - \hat{f}_j\boldsymbol{h}^{(j)}(\hat{x}^{(j)}) - K_x^{(j)}C\boldsymbol{e}_x^{(j)} \\ \dot{e}_f^{(j)} &= -\dot{\hat{f}}_j = -K_f^{(j)}\boldsymbol{h}(\hat{\boldsymbol{x}}^{(j)})C\boldsymbol{e}_x^{(j)} \end{aligned} \tag{14}$$

As $f_j\boldsymbol{h}^{(j)}(\boldsymbol{x}^{(j)}) - \hat{f}_j\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)}) = e_f\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)}) + f_jk_E^{(j)}\boldsymbol{e}_x^{(j)}$, the state estimation error yields as

$$\dot{\boldsymbol{e}}_x^{(j)} = (A^{(j)} - K_x^{(j)}C)\boldsymbol{e}_x^{(j)} + e_f^{(j)}\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}^{(j)}}) + f_jk_E^{(j)}\boldsymbol{e}_x^{(j)} \tag{15}$$

Hence, the state and fault estimation error dynamics in the faulty case is:

$$\begin{bmatrix} \dot{\boldsymbol{e}}_x^{(j)} \\ \dot{e}_f^{(j)} \end{bmatrix} = \underbrace{\begin{bmatrix} A^{(j)} - K_x^{(j)}C + f_jk_E^{(j)}I & \boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)}) \\ -K_f^{(j)}\boldsymbol{h}^{(j)}(\hat{\boldsymbol{x}}^{(j)})C & 0 \end{bmatrix}}_{A_e} \begin{bmatrix} \boldsymbol{e}_x^{(j)} \\ e_f^{(j)} \end{bmatrix} \tag{16}$$

According to Gershgorin's Circle Theorem, if $A^{(j)} - K_x^{(j)}C$ is stable, then $A^{(j)} - K_x^{(j)}C + f_jk_E^{(j)}I$ is also stable as long as $k_E^{(j)}f_j \geq 0$ has small norm ($f_j \in [0,1)$). Furthermore, the estimation error $\boldsymbol{e}_x^{(j)}$ and $e_f^{(j)}$ will converge to zero if A_e is stable for all $\hat{\boldsymbol{x}}^{(j)}$ and f_j. This stability can be checked online during the adaptation process. Thus, an observer described by Eq (12) along with its adaptation as in Eq (13) can be used to estimate the fault and it is called a fault estimator.

Special case: Fault detector and fault estimator for splitting connection As concluded in the previous section, for splitting connection, we can put the sensors only at the end of each element after the split. With this configuration, there will be one specific sensor that is used as an input to two observers for fault estimation either before or after the split. However, by *assuming no simultaneous fault*, the difference in fault distribution matrix (see Eq (10)) causes the need of a *fault detector* to determine where the fault is happened before fault estimation can be carried out.

Consider a bank of linear observers:

$$FD_k := \begin{cases} \dot{\hat{\boldsymbol{x}}}^{(j,k)} &= A^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} + B^{(j,k)}\boldsymbol{u}^{(j,k)} + K_xe_y^{(j,k)} \\ \hat{y}^{(j,k)} &= C^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} \end{cases} \tag{17}$$

where $e_y^{(j,k)} = y^{(j,k)} - \hat{y}^{(j,k)}$ and FD_k is a fault detector based on the measurement at the end of the kth split elements (elements after the split).

If K_x is chosen such that $A^{(j,k)} - K_xC^{(j,k)}$ is stable, then $\lim_{t\to\infty}\boldsymbol{e}_{\boldsymbol{x}}^{(\boldsymbol{j},\boldsymbol{k})} = 0$ and $\lim_{t\to\infty}e_y^{(j,k)} = 0$ for non-faulty condition. It is also easily inferred that when a fault occurs before the split, it will propagate to all of the split elements. Thus, the following algorithm can be used to determine where the fault is happening in the splitting connection (fault isolation logic):

$$e_y^{(j,k)} \begin{cases} = 0\ \forall\ FD_k, & \text{no fault} \\ \neq 0\ \forall\ FD_k, & \text{a fault has occured before the split} \\ \neq 0\ \exists\ FD_k, & \text{a fault has occured at the } k\text{th split element} \end{cases} \tag{18}$$

Then, after a fault has been detected, a specific nonlinear observer is activated to estimate the related fault. For this purpose, a bank of nonlinear observers is constructed as follows:

$$\begin{aligned} FE_j &:= \begin{cases} \dot{\hat{\boldsymbol{x}}}^{(j,k)} &= A^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} + B^{(j,k)}\boldsymbol{u}^{(j,k)} \\ & \quad + \hat{F}_j^{(j,k)}\boldsymbol{h}^{(j,k)}(\hat{\boldsymbol{x}}^{(j,k)}) + K_xe_y^{(j,k)} \\ y^{(j,k)} &= C^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} \\ \hat{F}_j^{(j,k)} &= \begin{bmatrix} \hat{f}_jI & O \\ O & O \end{bmatrix} \end{cases} \\ FE_k &:= \begin{cases} \dot{\hat{\boldsymbol{x}}}^{(j,k)} &= A^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} + B^{(j,k)}\boldsymbol{u}^{(j,k)} \\ & \quad + \hat{F}_k^{(j,k)}\boldsymbol{h}^{(j,k)}(\hat{\boldsymbol{x}}^{(j,k)}) + K_xe_y^{(j,k)} \\ y^{(j,k)} &= C^{(j,k)}\hat{\boldsymbol{x}}^{(j,k)} \\ \hat{F}_k^{(j,k)} &= \begin{bmatrix} O & O \\ O & \hat{f}_kI \end{bmatrix} \end{cases} \end{aligned} \tag{19}$$

with the following adaptation equations:

$$\dot{\hat{f}}_j = \dot{\hat{f}}_k = K_f^{(j,k)}\boldsymbol{h}^{(j,k)}(\hat{\boldsymbol{x}}^{(j,k)})e_y^{(j,k)} \tag{20}$$

Here, FE_j is a fault estimator based on the measurement at the end of any of the split elements to estimate the fault that happened before the split, and FE_k is a fault estimator based on the measurement at the end of the kth split elements to estimate the fault happened there.

In the same manner as before (see Eq (16)), with $\|F^{(j,k)}\| \in [0, 1)$, the same conclusion can be drawn for either FE_j or FE_k as long as the fault and k_E have small norm. Thus, a bank of linear observers described by Eq (17) along with the algorithm described by Eq (18) is used as fault detectors. Meanwhile, a bank of nonlinear observers described by Eq (19) along with its adaptation described by Eq (20) is used as fault estimators.

6. CASE STUDY

To verify and validate the proposed fault detection and estimation observer based method, a simulation model of a HEN connecting a heater to two consumers is used. In this case study, the energy output of a heater is distributed to the consumers via a hot pipe (H) which is then split into hot pipe 1 (H1) and hot pipe 2 (H2). The fluid from the consumers is fed back to the heater via cold pipe 1 (C1) and cold pipe 2 (C2) which are then joined into a cold pipe (C). It is assumed that the dynamics of each pipe can be represented as CL type connection with $n = 5$, $v = v_H = v_C = 2$, and $k_E = k_H = k_{H1} = k_{H2} = k_C = k_{C1} = k_{C2} = 1$. The splitting coefficients from H to H1 and H2 are $\beta_1 = \beta_2 = 0.5$. The diagram of this case study is shown in Fig 2. In this figure, the fault diagnostic blocks contain either a fault estimator (joining connection case) or both a fault detector and fault estimator (splitting connection case).

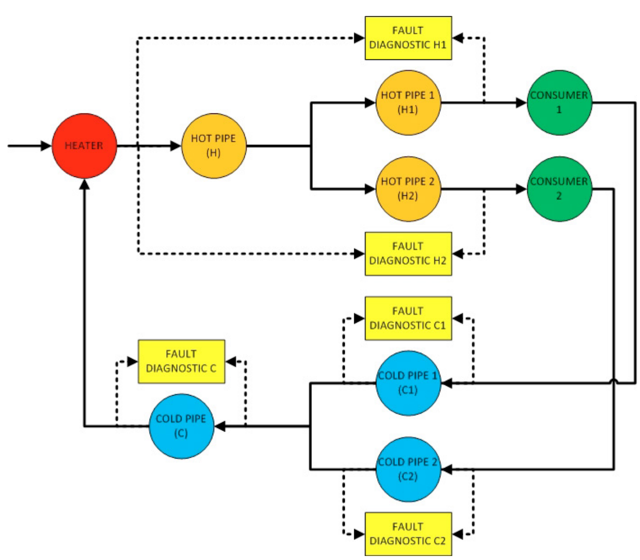


Fig. 2. Energy Network Case Study

To be able to detect and estimate the fault in each pipe, the sensors placement is done based on the previous structural observability analysis. For splitting connection in the hot pipe, it is enough to put the sensors at H for input measurement and the end of H1 and H2 for output measurements. Meanwhile, for joining connection in the cold pipe, we use the multiple sensors approach. Thus, the sensors are put at the beginning of C1, C2, and C for input measurements and the end of C1, C2, and C for output measurements. The fault estimator for each pipe is constructed using those measurements. For hot pipes, fault detectors are also constructed. The fault estimator for hot pipe H is a special case because it can be constructed based on either the sensor measurement at the end of H1 or H2. Eq (17) is used to construct the fault detectors for the splitting connection. As fault isolation logic, Eq (18) is applied ($k = 1, 2$). Meanwhile, because we used multiple sensors approach for the joining connection, only fault estimators are constructed to estimate specific faults for each cold pipe. To construct the fault estimators, we use Eq (19) for splitting connection and Eq (12) for joining connection.

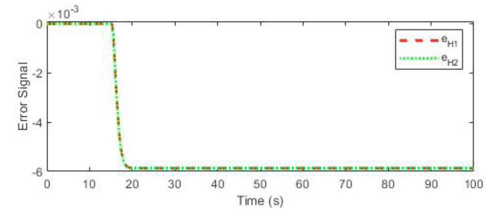
After the fault detectors and fault estimators are constructed, the related measurements are fed into each of those observers. Then, when a fault is happening in the splitting connection, the fault isolation logic will activate a specific fault estimator based on the error signals from the fault detectors. It should be remarked that this configuration works on assumption that *no simultaneous faults happen in the splitting connection*. To be able to detect and estimate simultaneous faults in the splitting connection, we must use the same multiple sensors approach as in the joining connection.

In this simulation, the fault detector gain K_x is chosen using the pole placement method while the fault estimator gain K_f is chosen so that the settling time is small enough without oscillation. First, a fault at the 15th second with an amplitude of 0.5 is introduced into the system. Fig 3a shows the error signals from the fault detector H1 and H2 when this fault is happening in the hot pipe H before the split. It can be seen that both the error signals e_{H1} and e_{H2} have the same non-zero value indicating that a fault has occurred at the hot pipe H. The estimated fault from the fault estimator for this hot pipe H is shown in Fig 3b which displays that the fault is successfully estimated. Furthermore, this fault estimator can also estimate the unmeasurable states which are shown in Fig 3c.

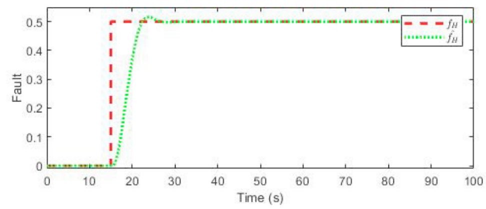
In the second simulation, the fault is simulated to be happening at the hot pipe H2 after the split. Fig 4a shows the error signals from the fault detector H1 and H2. It is seen that only the error signal e_{H2} has a non-zero value indicating that a fault is happening in the hot pipe H2. The estimated fault from the fault estimator for hot pipe H2 is shown in Fig 4b which reveals that it also successfully estimated the fault. Meanwhile, the state estimation from this fault estimator is shown in Fig 4c.

7. CONCLUSIONS

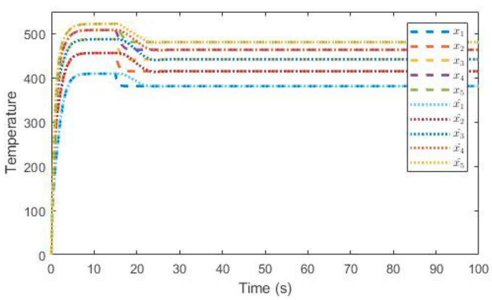
In this paper, contributions are presented to handle the parameter fault identification problem in HENs with distributed time delay. The change in the heat transfer coefficient k_E, that is a parameter of the state space model is considered as fault. The network contains realistic connections in the form of joining and splitting elements. Thus, an investigation of the sensors placement problem was done to identify every possible fault around the branching elements. An analysis of observability conditions using SDG is done to handle this. In the case of splitting connection, it is enough to put the sensors only at the end of the elements after the split to detect and estimate the fault that occurred either before or after the split. However, in the case of joining connection, a sensor at the end of the joining elements before the connection is necessary.



(a) Error signals of fault detectors, fault at H

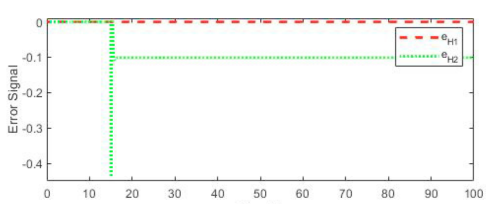


(b) Fault estimation, fault at H

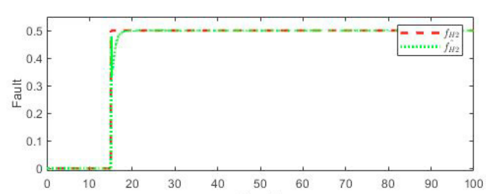


(c) States estimation of fault estimator, fault at H

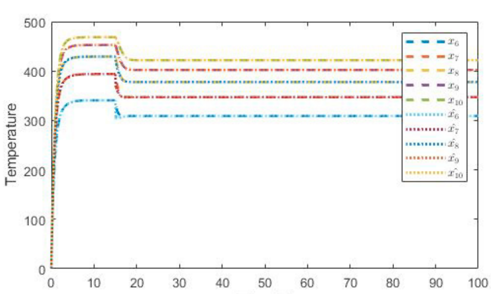
Fig. 3. Fault diagnostic signals with fault at H



(a) Error signals of fault detectors, fault at H2



(b) Fault estimation, fault at H2



(c) States estimation of fault estimator, fault at H2

Fig. 4. Fault diagnostic signals with fault at H2

With the the change of heat transfer coefficient being the model parameter, the presence of faults in HEN yields bilinear fault-input terms into the model. To handle it, a fault diagnosis method was developed that is based on a nonlinear observer.

In the case study, a HEN simulation model was developed that includes both splitting and joining connections. Faults either before or after the split are simulated to test the performance of the fault detector and fault estimator observers. The simulation results show that the observers successfully detect and estimate the faults. Moreover, the fault estimators can also correctly estimate the unmeasurable states of the system affected by the fault.

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