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Robust fault detection and accommodation of the boiler unit using state space neural networks

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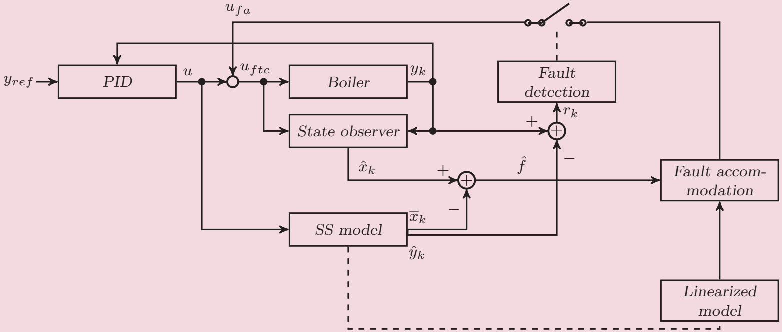
Introduction

- Recently, it has been observed an increasing development of the Fault Diagnosis (FD) methods for the Fault Tolerant Control (FTC) system design purposes.
- This presentation focuses on the design of the fault detection and accommodation system.
- The State Space Neural Network (SSNN) is applied, to construct the model of the system as well as for the fault diagnosis of the system.
- To accommodate the possible fault the so called instantenous linearization technique is used.
- Different methods of fault detection are considered.
- The proposed methodology is tested on the example of a boiler unit.

Fault tolerant control

- Objective of a Fault Tolerant Control (FTC) system – to maintain the current performance of the system as close as possible to the desirable one, and preserve stability conditions in the presence of faults
- Main two approaches to FTC realization:
  - **passive** methods work with a presumed failure modes and its performance tends to be conservative, especially in the case of unanticipated faults
  - **active** methods reacts to the occurrence of system faults on-line and attempt to maintain the overall system stability and performance even in the case of unanticipated faults.
- Objective of the work: to design active FTC system using neural networks based on the existing control with PID controller

FTC scheme



Fault Tolerant Control Scheme.

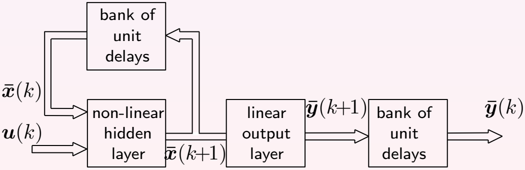
State Space Neural model

The state space representation of the neural model is described by the equations

$$\begin{aligned} \bar{\mathbf{x}}(k+1) &= \bar{g}(\bar{\mathbf{x}}(k), \mathbf{u}(k)), \\ \bar{\mathbf{y}}(k) &= \mathbf{C}\bar{\mathbf{x}}(k) \end{aligned} \tag{1}$$

where $\bar{g}$ is a nonlinear function characterizing the hidden layer, and $\boldsymbol{C}$ represents synaptic weights between hidden and output neurons..
Introducing matrices of synaptics weights $\boldsymbol{W}^x$ i $\boldsymbol{W}^u$ (1) can be represented as:

$$\begin{aligned} \bar{\mathbf{x}}(k+1) &= h(\mathbf{W}^x\bar{\mathbf{x}}(k) + \mathbf{W}^u\mathbf{u}(k)), \\ \bar{\mathbf{y}}(k) &= \mathbf{C}\bar{\mathbf{x}}(k) \end{aligned} \tag{2}$$



State Space Neural model (SSNN)

Most important properties of the state space neural network:

- Ability to approximate a wide class of non-linear dynamic systems;
- Possibility to approximate the states even in situation when the characteristic of the system is unknown;
- Possibility to design nonlinear state observer,
- SSNN seems to be more promising than fully or partially reccurent neural networks.

SSIF model

The State Space Innovation Form (SSIF) can be used to build nonlinear state observer. This neural network is represented as follows:

$$\begin{cases} \hat{\boldsymbol{x}}(k+1) = \hat{g}(\hat{\boldsymbol{x}}(k), \boldsymbol{u}(k), \boldsymbol{e}(k)) \\ \hat{\boldsymbol{y}}(k) = \mathbf{C}\hat{\boldsymbol{x}}(k) \end{cases} \tag{3}$$

where $\boldsymbol{e}(k)$ is the error between the model output $\hat{\boldsymbol{y}}(k)$, and measured system output $y(k)$. Introducing weight matrices representation (3) can be rewritten:

$$\begin{cases} \hat{\boldsymbol{x}}(k+1) = h(\mathbf{W}^x\hat{\boldsymbol{x}}(k) + \mathbf{W}^u\boldsymbol{u}(k) + \mathbf{W}^e\boldsymbol{e}(k)) \\ \hat{\boldsymbol{y}}(k) = \mathbf{C}\hat{\boldsymbol{x}}(k) \end{cases} \tag{4}$$

This form can be treated as extended Kalman filter (Nørgaard et. al., 2000).

Fault Approximation

Nonlinear dynamic system considered:

$$\boldsymbol{x}(k+1) = g(\boldsymbol{x}(k), \boldsymbol{u}(k)). \tag{5}$$

where g is a process working at the normal operating conditions, $\boldsymbol{x}(k)$ is the state vector and $\boldsymbol{u}(k)$ is the control input vector.
State space model of the system:

$$\bar{\boldsymbol{x}}(k+1) = \bar{g}(\bar{\boldsymbol{x}}(k), \boldsymbol{u}(k)), \tag{6}$$

where $\bar{\boldsymbol{x}}$ is the output state of the model and a $\bar{g}$ is estimation of function g in (5).

With a unknown fault f occurrence, equation (5) takes the form:

$$\boldsymbol{x}(k+1) = g(\boldsymbol{x}(k), \boldsymbol{u}(k)) + f(\boldsymbol{x}(k), \boldsymbol{u}(k)). \tag{7}$$

To model the faulty system the SSIF model can be used in the form of state equation:

$$\hat{\boldsymbol{x}}(k+1) = \hat{g}(\hat{\boldsymbol{x}}(k), \boldsymbol{u}(k), \boldsymbol{e}(k)) \tag{8}$$

Fault approximation – cont.

With the system model and the system observer there is a possibility to approximate the fault function f:

$$\begin{aligned} \hat{f} &= \hat{\boldsymbol{x}}(k) - \bar{\boldsymbol{x}}(k) \\ &= \hat{g}(\hat{\boldsymbol{x}}(k), \boldsymbol{u}(k), \boldsymbol{e}(k)) - \bar{g}(\bar{\boldsymbol{x}}(k), \boldsymbol{u}(k)). \end{aligned} \tag{9}$$

The fault effect can be eliminated/compensated by a proper definition of the augmented control u^{ftc}:

$$\boldsymbol{u}^{ftc}(k) = \boldsymbol{u}(k) + \boldsymbol{u}^{fa}(k), \tag{10}$$

where $\boldsymbol{u}^{fa}$ is the fault compensation term.

Instantaneous linearization

The $\boldsymbol{u}^{ftc}$ can be determined via the instantaneous linearisation of the state-space model. Linearisation can be carried out by expanding function describing system into Taylor series about the point $(\boldsymbol{x}, \boldsymbol{u}) = (\boldsymbol{x}(\tau), \boldsymbol{u}(\tau))$ and giving up nonlinear parts of equation. Linearised state-space model can be presented in the form:

$$\begin{cases} \bar{\boldsymbol{x}}(k+1) = \boldsymbol{A}\bar{\boldsymbol{x}}(k) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{D} \\ \bar{\boldsymbol{y}} = \boldsymbol{C}\bar{\boldsymbol{x}}(k) \end{cases} \tag{11}$$

where $\boldsymbol{A} = h'\boldsymbol{W}^x$, $\boldsymbol{B} = h'\boldsymbol{W}^u$, $\boldsymbol{D} = \boldsymbol{x}(\tau) - \boldsymbol{A}\bar{x}(\tau-1) - \boldsymbol{B}u(\tau-1)$.

In case of activation function in form of hyperbolic tangent, h', can be easily calculated as:

$$h' = 1 - tanh^2 \tag{12}$$

Augmented control law

With linearised state-space model, previously shown equation can be represented as:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}(\boldsymbol{u}(k) + \boldsymbol{u}^{fa}(k)) + f(\boldsymbol{x}(k), \boldsymbol{u}(k)). \tag{13}$$

also:

$$\boldsymbol{B}\boldsymbol{u}^{fa}(k) + f(\boldsymbol{x}(k), \boldsymbol{u}(k)) = 0 \tag{14}$$

then:

$$\boldsymbol{u}^{fa}(k) = -\boldsymbol{B}^{-} f(\boldsymbol{x}(k), \boldsymbol{u}(k)). \tag{15}$$

And with adding $\boldsymbol{u}^{fa}$ to control signal compensation effect can be achieved.

Fault detection

- For the fault detection purpose methods of simple and adaptive thresholding as model error modelling are applied.
- In methods with threshold, fault is detected when residuum signal is out of thresholds bounds.

$$\boldsymbol{r} = \boldsymbol{y} - \hat{\boldsymbol{y}} \tag{16}$$

where y is system output, a $\hat{y}$ is model output

- Threshold selection is a compromise between precision and efficiency of fault detection.

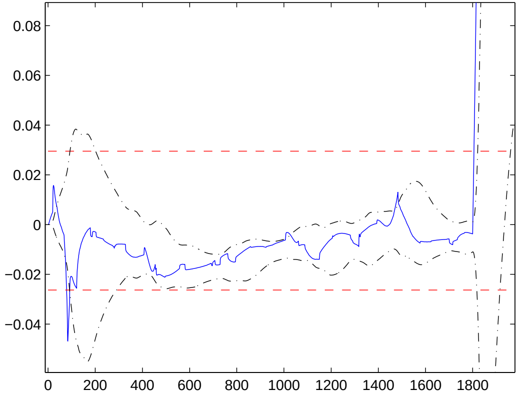
Simple Thresholding:

$$T = m \pm 3\sigma \tag{17}$$

	threshold range
$m \pm 3\sigma$	-0.0263 ÷ 0.0295

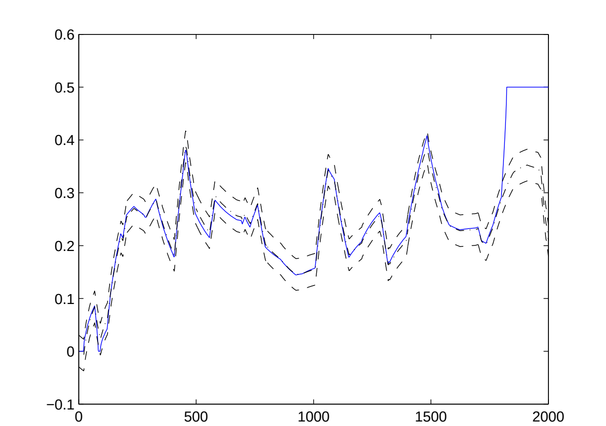
In case of adaptive thresholding bounds are calculated on-line on certain sample window.

Fault detection – cont.

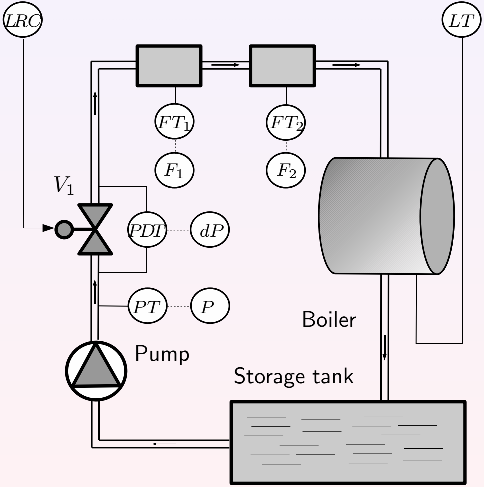


Model error modelling

- Creation of model which represents error of the system model.
- Use of autoregressive models (ARX, NLARX, NNARX).
- Using such model to build uncertainty regions.
- Leaving uncertainty region by output signal results on true fault decision.



The Boiler unit



CV – control value
dP – pressure difference on the valve V_1
P – pressure before the valve V_1
$F1$ – flow (electromagnetic flowmeter)
$F2$ – flow (Vortex flowmeter)
L – water level in the boiler

Faults scenarios

- the model of the boiler unit makes it possible to generate a number of faulty situations
- all faults were introduced to the system on the 500th time instant

Specification of faults considered

fault	desc.	type
f_1	fluid choking	partly closed (0.5)
f_2	level transducer failure	additive (-0.05)
f_3	positioner failure	multiplicative (0.7)
f_4	valve head or servo-motor fault	multiplicative (0.8)

Neural network model

- The sampling period was set to 5s.
- The neural network state space innovation form was trained for 100 epochs using Levenberg-Marquardt algorithm.
- The model was selected using Sum of Squared Errors (SSE) index and Final Prediction Error (FPE).
- The best results were achieved for the second order neural model consisting of seven hidden neurons with the hyperbolic tangent activation function.

Fault detection

σ	Decision making method: simple thresholding		adaptive thresholding		error modeling	
	t_{dt}	r_{fd}	t_{dt}	r_{fd}	t_{dt}	r_{fd}
1	20	0.5189	5	0.7600	10	0.1339
2	25	0.1333	10	0.4217	20	0.0117
3	35	0.0072	10	0.0494	25	0.0039

t_{dt} - fault detection time

r_{fd} - false alarm ratio

Fault detection – cont.

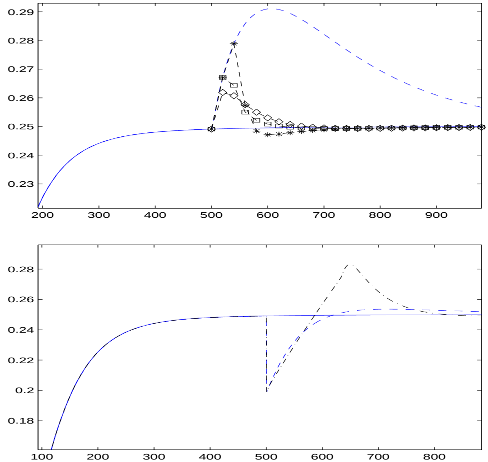
Detection method	simple thre.	adaptive thre.	mem
	t_{dt}	t_{dt}	t_{dt}
$f1$	40	10	30
$f2$	5	5	5
$f3$	55	6	8
$f4$	80	8	10

t_{dt} - detection time

Faults considered 1

(*A*)

(*B*)

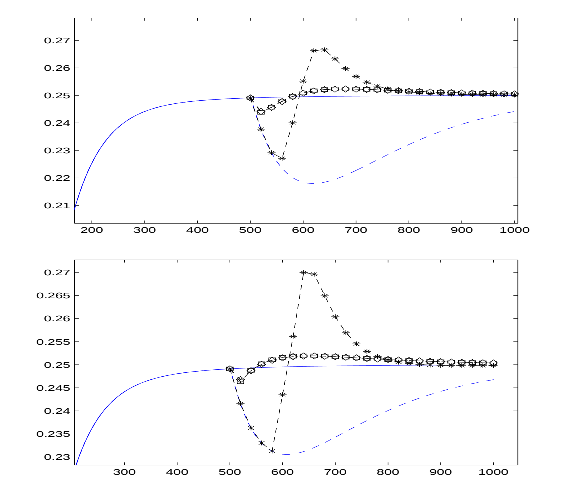


Faults considered f_1 (A) i f_2 (B) (simple -stars, adaptive-diamonds, mem-squares).

Faults considered 2

(A)

(B)



Faults considered f_3 (A) i f_4 (B) (simple -stars, adaptive-diamonds, mem-squares).

Method performance indexes

Experiments results as sum of squared error and percentage index.

Detection method - simple thresholding.

	$f1$	$f2$	$f3$	$f4$
SSE without FTC	0.3448	0.0626	0.2188	0.0756
SSE with FTC	0.0234	0.1302	0.0424	0.0425
improvement(%)	93.2232	-107.7533	80.6367	43.7514

Detection method - adaptive thresholding.

	$f1$	$f2$	$f3$	$f4$
SSE without FTC	0.3448	0.0626	0.2188	0.0756
SSE with FTC	0.0083	0.1302	0.0022	0.0012
improvement (%)	97.5959	-107.7533	99.0034	98.4780

Detection method - model error modelling.

	$f1$	$f2$	$f3$	$f4$
SSE without FTC	0.3448	0.0626	0.2188	0.0756
SSE with FTC	0.0134	0.1302	0.0023	0.0012
improvement (%)	96.1010	-107.7533	98.9563	98.3546

Conclusion

- As was shown through the experiments, the neural network state space model (NNSS) and nonlinear neural network state observer (NNSSIF) can be effectively and easily used to find the value of additional control to achieve fault compensation.
- In all faulty scenarios investigated, model behaves pretty well and it is possible to use it effectively to fault accommodation.
- Future researches will focus on real life application and stability analysis of proposed approach.

Thank You very much for Yours attention!!!