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Bond Graph Reduced Order Observers for Active Fault Tolerant Control

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Abstract

Objectives: In order to compensate the sensor fault effect, the diagnosis and the reconfigurable control laws are proposed. **Methods/Statistical Analysis:** We propose the use of the Bond Graph (BG) tool. The suggested law is based on reduced observer set for fault diagnosis, and weighting functions for blending the estimated states vector obtained from the different observers. To ensure the control closed loop strategy, and to eliminate in the steady state the tracking error, the reconfigurable feedback and feedforward controllers are presented using Lyapunov technique. **Findings**: The findings achieved are simulation tests, which applied on the stringing machine, provide better results. **Application**: The stringing machine elements modeling is a step indispensable before estimation, diagnosis, control and simulation tasks.

Keywords: Bond Graph (BG) Tool, Diagnosis, Reconfigurable Control, Reduced Observer Set

1. Introduction

For modeling dynamical systems, the BG approach is a powerful tool to be used.[1] It's based on power transfer between the different parts of the systems. Due to its structural and causal properties, the BG tool can be used to model, to study the inversion of system, to detect the fault, to diagnose, to estimate the fault and to control tasks.[2-7]

For the general case of systems modeled by BG tool, and referring to structural properties of, the graphical Luenberger observer's based-fault diagnosis achieved by the presented article.[8] Following's work, and referring to, the authors in built a robust BG observer in proportional integral form.[9-11] The work done by the article investigate a BG observer for unknown inputs.[12] For fault and state estimation, and diagnosis tasks, the authors in references used the BG adaptive and Luenberger (reduced and proportional) observers , respectively.[13-15]

Using the information cited above, it seems clear that the reduced order observers are not exploited yet to date, for the fault detection and isolation tasks. So, in this paper we will particularly extend these observers to fault diagnosis.

To improve systems running or performance, different control laws which are sufficient and which guarantee better performance in presence of disturbances, are generally used. We talk about the Fault Tolerant Control (FTC) which synthesized after generation of the diagnosis algorithm.[16,17] As to FTC, passive (PFTC) and active (AFTC) techniques are known.

As graphical active approaches, so that the fault should be compensate, the inversal BG model introduced using the Analytical Redundancy Relations (ARR) technique.[18] In most of the cases, before fault compensation we need for failure isolation and estimation blocks. We can use the residues provided by the classical Luenberger observer, which becomes then an input to the inversal BG model, in order to avoid the fault estimation block.[19]

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The aim of this work is to treat the reduced Luenberger obsever using graphical approach as BG tool for modeling, diagnosis and fault tolerant control tasks.

This manuscript is organized such as: section 2 proposes the diagnosis by reduced observer using BG tool. Section 3 introduces the integrated design scheme for the AFTC by providing some essential definitions related to basic formalisms, used later in the case study. An application on the stringing machine and simulation results are done in order to validate the proposed method in section 4. Last, section 5 draws some remarks as a conclusion.

2. Reduced Observer Model Based Fault Diagnosis

2.1 Analytical Model

The principle of diagnosis consists on estimating all state vector components or the process output using the estimation error as residual.[8] However, the estimation of the non-accessible variables which noted $\hat{x}_b(t)$ using the reduced observer is possible. The reduced observer diagnosis block diagram is given by Figure 1.

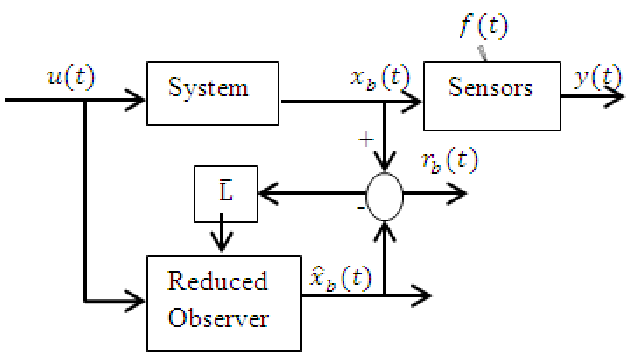


Figure 1. Diagnosis by reduced observer.

The system state space representation along with sensor faults is as follows:

$$\begin{cases} x(t) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Ef(t) \end{cases} \qquad (1)$$

$x(t)\varepsilon\mathbb{R}^n$ denote the state space vector. $y(t)\varepsilon\mathbb{R}^p$ and $u(t)\varepsilon\mathbb{R}^m$ are the measurement output and input vectors respectively. $f(t)\varepsilon\mathbb{R}^p$ indicates the set of the faults (faults related to sensor in this case).*A*, *B*, *C* and *E* are known as constant matrices with appropriate dimensions.

The residual equation is defined according to the non-accessible state

$$r_b(t) = x_b(t) + \hat{x}_b(t) \qquad (2)$$

2.2 BG Model

To build the reduced observer, we have to verify the following two conditions:[8]

Condition 1: When we put the system BG model with preferred integral causality, there are at least causal paths between the actuators (respectively sensors) and each dynamic element or in the integral causality.

Condition 2: When we put the BG model in derivative causality, and when we dualize the actuators (respectively sensors), all *I* or *C* elements have derivative causality.

The BG reducer observer model for items *I* and *C* is given by Figure 2.

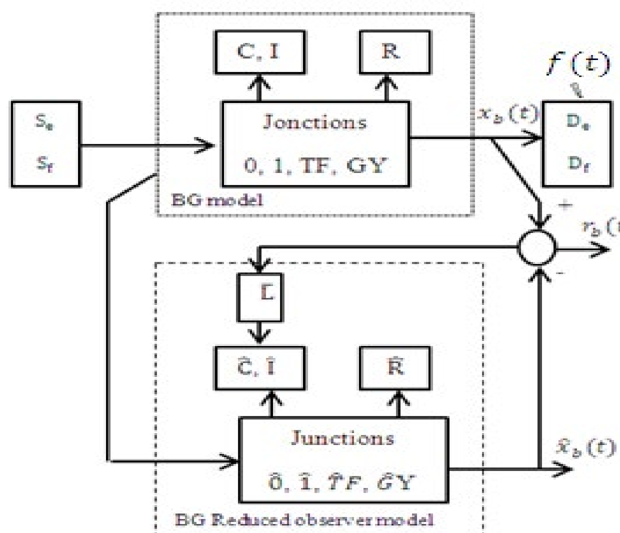


Figure 2. Reduced order observer based on BG modeling.

The structure of the reduced observer in space state representation is given by Figure 3. The state equation is as bellow:

$$\begin{cases} \hat{z}(t) = \bar{M}\hat{z}(t) + \bar{N}u(t) + Py(t) \\ \hat{x}\begin{pmatrix} \hat{p}_I \\ \hat{q}_C \end{pmatrix} = \hat{z}(t)Ly(t) + E\hat{f}(t) \end{cases} \qquad (3)$$

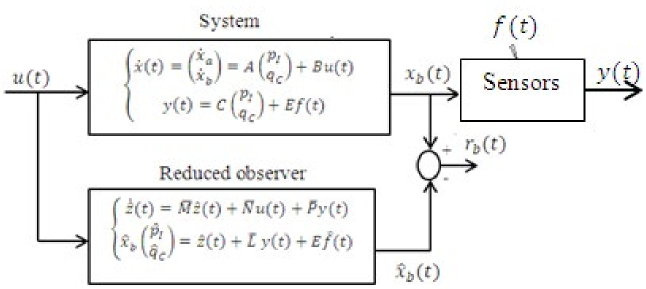


Figure 3. Reduced observer structure.

With z is auxiliary variable which avoid the time derivation of the output, when we calculate the estimated state,

$$\bar{M} = \bar{A}_{bb} - \bar{L}\bar{A}_{ab} \tag{4}$$

$$\bar{N} = \bar{B}_b - \bar{L}\bar{B}_a \tag{5}$$

$$\bar{P} = \bar{A}_{ba} + \bar{A}_{bb}\bar{L} - \bar{L}\bar{A}_{aa} - \bar{L}\bar{A}_{ab}\bar{L} \tag{6}$$

$x_b(t)\varepsilon\mathbb{R}^{(n-p)}$ denotes the estimated state vector, $\bar{L}$ is the observer gain matrix, $\hat{f}(t)\varepsilon\mathbb{R}^{p}$ is the estimation of sensor fault, $\bar{A}_{aa} = (C_a A_{aa} + C_b A_{ba})C_a^{-1}$, $\bar{A}_{ab} = (C_a A_{ab} + C_b A_{bb} - \bar{A}_{aa}C_b$ $\bar{A}_{ab} = (C_a A_{ab} + C_b A_{bb} - \bar{A}_{aa}C_b)$, $\bar{A}_{ba} = A_{ba}C_a^{-1}$, $A_{bb} = A_{bb} - A_{ba}C_a^{-1}C_b$, $\bar{B}_a = C_a B_a + C_b B_b$, and $\bar{B}_b = B_b$ are the submatrices.

Note that the adjustment of $(\bar{A}_{bb} - \bar{L}\bar{A}_{ab})$ matrix eigenvalues, can lead to the fast dynamics than the dynamics of the real system.

By resolving the following inequality, the reduced observer gain matrix can be computed:[20]

$$\begin{cases} P > 0 \\ (\bar{A}_{bb}\alpha I)^T P + P(\bar{A}_{bb} + \alpha I) - (\bar{A}_{ab})^T Z^T(\bar{A}_{ab}) < 0 \end{cases} \tag{7}$$

P is a symmetric, positive and defined matrix and α is the quadratic decay rate. For every P and Z satisfying the LMI inequality, it corresponds stabilizing observers. Solving the LMI inequality (7) permit to find the observer gain which is given by

$$\bar{L} = P^{-1}Z \tag{8}$$

2.3 Fault Isolation Strategies

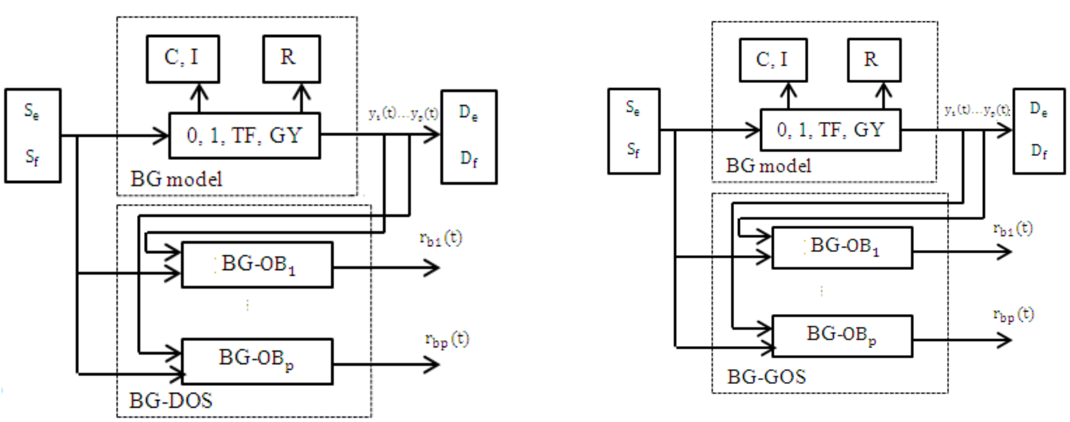
The multiple observer set, based on analytical models proposed in the literature for FDI are: Dedicated observer scheme (DOS): the i^th^ observer is driven by the i^th^ output and all inputs. Other outputs are considered unknown.[21]

Generalized observer scheme (GOS): the i^th^ observer is driven by all outputs and all inputs except the i^th^ output.[22]

We have extended this scheme to the FDI purpose of dynamic systems modeled by BG approach. A bank of BG_DOS and BG_GOS structures for FDI sensor are depicted in Figure 4.

The residuals deduced from the observer banc are grouped in the FDI table. Its rows and columns correspond to faults and residuals. The table is filled with binary values (fault signature). When we found zero (0), we deduce that the residual is robust to the fault, while when we found one (1), we prove that the residual is sensitive.

Once, the diagnosis is carried out, the occurred faults are detected and identified. So we try to limit their effects on the system by applying a control law. We are interested in the Fault Tolerant Control (FTC).[16]



(a) (b)

Figure 4. BG banc observer structures : (a) BG-DOS Structure, (b) BG-GOS Structure.

3. Fault Tolerant Control Strategy

Various techniques have been developed in the literature to recover the system performances in the fault occurrence, such as the switching strategy which based on the residual vector signals, delivered by the residual generator, or using the estimated states provided by the different observers through weighting functions.[23,24]

The proposed AFTC approach design for linear system affected by disturbance $d(t)\varepsilon\mathbb{R}^{n_d}$ and sensor faults $f(t)\varepsilon\mathbb{R}^{p}$ is depicted in Figure 5. Indeed, The AFTC strategy composed of four blocks:

- A reduced observer based residual generator block. The residual generator aims at detecting and isolating each sensor fault based on a dedicated residual signal which generated by the BG-LFT form in order to be estimated.
- The banc of reduced observer to estimate the non-accessible state vector.
- The new estimated state $\hat{x}_b^i(t)$ is computed from the residual by blending the different estimates, through the weighting functions in such a way to satisfy the convex sum property which is described by the following expression and the continuity to avoid the switching phenomenon. If a given sensor fault is isolated, the weight of the corresponding estimated state is lowered.

$$\Sigma_{i=1}^{p}\mu_i(\varepsilon(t)) = 1, 0 \le \mu_i(\varepsilon(t)) \le 1, \forall i = 1,\ldots,p \tag{9}$$

With $\varepsilon(t)$ is the decision variable which can be measurable like $u(t)$ or $y(t)$, or not measurable like $x(t)$.

- The feedback block to acheive the system stability and to generate the obtained blended estimated state.

With $y_1(t)\ldots y_p(t)$: measured system outputs.

$f(t)$: Sensor fault.

$\hat{x}_b^1(t)\ldots\hat{x}_b^p(t)$: Estimated states vector obtained from the different observers.

$r_d(t)$: dedicated residual signal generated by BG-LFT model.

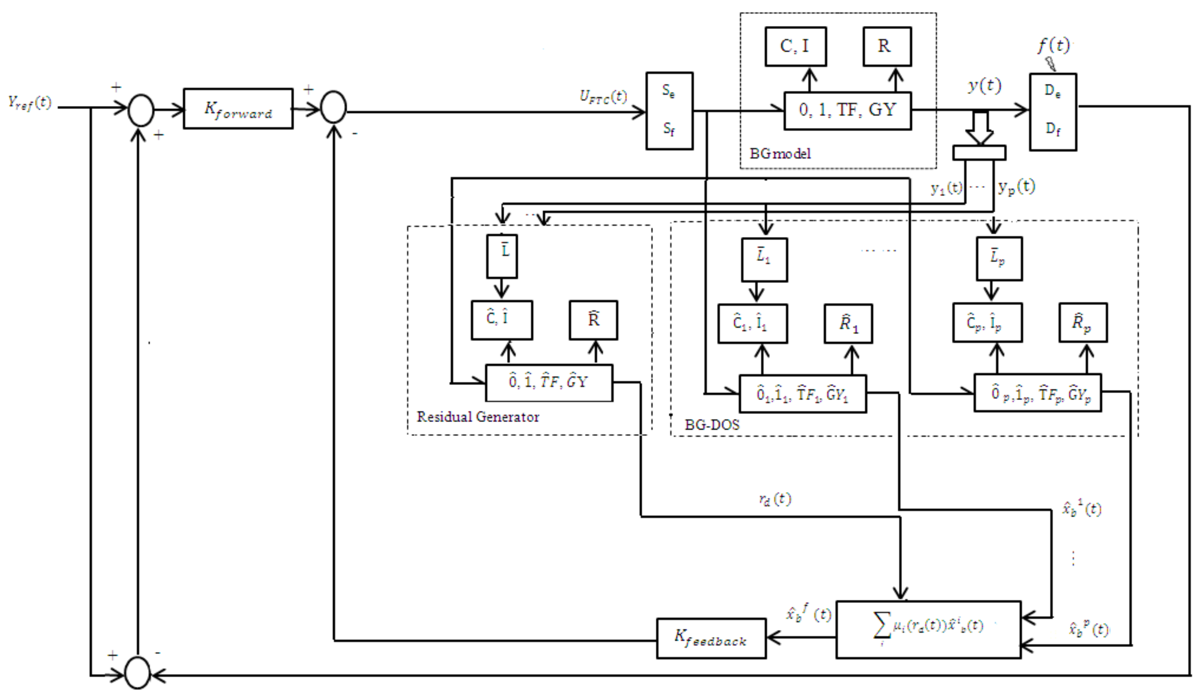


Figure 5. AFTC strategy based on BG approach.

$\hat{x}_b^{\,f}(t)$: Blended state estimation vector.

$U_{\mathrm{FTC}}(t)$: control input.

$Y_{\mathrm{ref}}(t)$: Desired output.

After generating the residual vector by BG-LFT form, the fault tolerant controller approach is described.[25] First, the reduced observer banc is designed. As illustrated in Figure 5, the k^{th} observer is supplied with the control input vector and the k^{th} output of system $y^{k}(t)$

Based on this information, the k^{th} observer donates the different estimated state vector $\hat{x}_b^k(t)$ for $k = 1, \ldots p$ which are then blended to build a representative state estimation vector $\hat{x}_b^{\,f}(t)$ according to:[26]

$$\hat{x}_b^f(t) = \Sigma_{k=1}^{p} \mu_k(r_d(t))\hat{x}_b^{\,k}(t) \tag{10}$$

Depending on the residual $r_{\mathrm{d}}(t)$, the blending is ensured by the weighting functions $\mu_k(r_d(t))$. This function must be close to zero in order to minimize the influence of , which is affected by the k^{th} sensor faultIn order to satisfy this property, it is proposed to define the functions μ_k, for $k$from to p as follows

$$\omega_k(r_{dk}(t))) = exp^{-r_{dk}{}^2/_k)} \tag{11a}$$

$$\mu_k(r_d(t)) = \frac{\omega_k(r_{dk}(t))}{\Sigma_{j=1}^{p}\omega_j(r_{dj}(t))} \tag{11b}$$

Where σ_k parameters are used to take into account the spreading of r_{dk} around zero. The Gaussian function (11a) causes an exponentially decreasing weight around zero. Equation (11b) ensures the standardization of the different functions in order to satisfy the convex sum property.

In this sequel, the proposed AFTC law will be developed. Indeed, the author's in the articel, have proposed a tolerant control law as presented in equation (12)[27]

$$U_{FTC}(t) = K_{forward}Y_{ref}(t) - K_{feedback}x \tag{12}$$

Y_{ref} is the reference input.

The last expression has ameliorated as equation (13), in order to improve the fault tolerance:[28]

$$U_{FTC}(t) = K_{forward}Y_{ref}(t) + K_{feedback}(x - x^{*}) \tag{13}$$

With $x*$ considered in the equation above as a reference. The proposed control law suggested by the article presented is similar to a classical Parallel Distributed Controller (PDC) which is based on $\hat{x}_b^k(t)$ blended state estimate computation:[24]

$$U_{FTC}(t) = -\Sigma_{k=1}^{p}\mu_k(r_i(t))K_i\hat{x}_b^{\,i}(t) \tag{14}$$

With K_i is the gain of the parallel distributed controller.

Taking into account these previous expressions, we have to propose the tolerant control law as written in equation (15):

$$\begin{aligned} U_{FTC}(t) &= K_{forward}Y_{ref}(t) + K_{forward}(Y_{ref}(t) - y(t)) \\ &\quad - K_{feedback}\Sigma_{i=1}^{p}\mu_i(r_d(t))\hat{x}_b^i(t) \end{aligned} \tag{15}$$

K_{forward} and K_{feedback} are the gains of feedforward and feedback controllers respectively to be computed, is our input reference, $\mu_i(r_d(t))$ is our weighting functions and $\hat{x}_b^i(t)$ is our blended state estimation.

- ***K**_feedback* **Computing**

The gain K_{feedback} computed using the LMI resolution. Indeed, the decay rate is strictly upper to α, if there exists a Lyapunov function $V(x)$, for all $x \neq 0$, $V(x) > 0$ and $V(x) = -2\alpha V(x)$. We choose $V(x) = x^T Px$, with P is a symmetric matrix will be determined.[20]

$$\begin{cases} V(x) > 0 \\ V(x) < -2\alpha V(x) \end{cases} \Leftrightarrow \begin{cases} p > 0 \\ A^T P + PA + 2\alpha P < 0 \end{cases} \Leftrightarrow \begin{cases} p > 0 \\ (A + \alpha I)^T P + P(A + \alpha I) < 0 \end{cases} \tag{16}$$

The linear time invariant system in closed-loop is quadratically stable, if the following LMI are feasible:

$$\begin{cases} P > 0 \\ (A - BK_{feedback})^{\mathrm{T}} P + P(A - BK_{feedback}) + 2\alpha P < 0 \end{cases} \tag{17}$$

P is a symmetric, positive and defined matrix, and is the decay rate. In summary, the controller design is the result of the following LMI problem, where Q is a symmetric, positive and defined matrix

$$\begin{cases} Q > 0 \\ (A + \alpha I)Q + Q(A + \alpha I)^{\mathrm{T}} + BY + Y^T B^T < 0 \end{cases} \tag{18}$$

The resulting controller feedback gain is given by:

$$K_{feedback} = -YP \tag{19}$$

Y and P are the solutions, such that LMI problem given by (17) is feasible.

- $K_{forward}$ **Computing**

The gain $K_{forward}$ computed such as $Y_{ref}(t)$ equal to the reference input. To ensure that $\lim_{t\to 0} y(t) = Y_{ref}(t)$, so

$$K_{forward} = \frac{1}{C(-A+BK_{feedback})^{-1}B} \tag{20}$$

4. Case Study

The considered process is a stringing machine. It's composed of a DC motor which is used to associate the physical phenomenon or components considered by the induced current I_m, and of the mechanic part which depends on the rotation speed of its axe. Whether, U_m is the induced tension, R_m is the resistance, L_m is the inductance, R_1 is the resistive viscous friction, and J_m is the moment of the rotor inertia and the shaft of inertial type. The gyrator element has as $r_1$constant, and transforms the electromotive force into rotation speed of the reducer tree. The tree compressibility is presented by C_1 element. The third block transforms the rotation movement into translation movement, via winding up the rope which is presented as the transformer element which has as r_2 constant. The chain mass is given by m and the frictions at the gable are negligible. We consider that the tree is of elastic type (whether $C_2 = \frac{Kr}{1+K_r/K_c}$) ($K_r$ is the spring stiffness and K_c is the rope stiffness), the loss resistance donates by R_2). The trolley mass is negligible.

We can deduce the state space representation of the string machine as written as (21), from its BG model (Figure 6):

$$\left\{\begin{aligned}
\begin{bmatrix} \dot p_{Lm} \\ \dot p_{Jm} \\ \dot p_{C1} \\ \dot p_m \\ \dot q_{C2} \end{bmatrix} &= \begin{bmatrix} -R_m/L_m & -r_1/J_m & 0 & 0 & 0 \\ r_1/L_m & -R_1/J_m & -1/C_1 & 0 & 0 \\ 0 & 1/J_m & 0 & -1/m.r_2 & 0 \\ 0 & 0 & -1/C_1.r_2 & 0 & -1/C_2 \\ 0 & 0 & 0 & 1/m & 0 \end{bmatrix} \begin{bmatrix} p_{Lm} \\ p_{Jm} \\ p_{C1} \\ p_m \\ q_{C2} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} Um \\
\begin{bmatrix} Df_1 \\ Df_2 \\ De_3 \\ Df_4 \end{bmatrix} &= \begin{bmatrix} 1/L_m & 0 & 0 & 0 & 0 \\ 0 & 1/L_m & 0 & 0 & 0 \\ 0 & 0 & 1/L_m & 0 & 0 \\ 0 & 0 & 0 & 1/L_m & 0 \end{bmatrix} \begin{bmatrix} p_{Lm} \\ p_{Jm} \\ p_{C1} \\ p_m \\ q_{C2} \end{bmatrix}
\end{aligned}\right. \tag{21}$$

The sensor fault is applied to the motor's current of our process. So, the state space representation in faulty case as written as (22):

$$\left\{\begin{aligned}
\begin{bmatrix} \dot p_{Lm} \\ \dot p_{Jm} \\ \dot p_{C1} \\ \dot p_m \\ \dot q_{C2} \end{bmatrix} &= \begin{bmatrix} -R_m/L_m & -r_1/J_m & 0 & 0 & 0 \\ r_1/L_m & -R_1/J_m & -1/C_1 & 0 & 0 \\ 0 & 1/J_m & 0 & -1/m.r_2 & 0 \\ 0 & 0 & -1/C_1.r_2 & 0 & -1/C_2 \\ 0 & 0 & 0 & 1/m & 0 \end{bmatrix} \begin{bmatrix} p_{Lm} \\ p_{Jm} \\ p_{C1} \\ p_m \\ q_{C2} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} Um \\
\begin{bmatrix} Df_1 \\ Df_2 \\ De_3 \\ Df_4 \end{bmatrix} &= \begin{bmatrix} 1/L_m & 0 & 0 & 0 & 0 \\ 0 & 1/L_m & 0 & 0 & 0 \\ 0 & 0 & 1/L_m & 0 & 0 \\ 0 & 0 & 0 & 1/L_m & 0 \end{bmatrix} \begin{bmatrix} p_{Lm} \\ p_{Jm} \\ p_{C1} \\ p_m \\ q_{C2} \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} f(t)
\end{aligned}\right. \tag{22}$$

The parameters values of the stringing machine are presented in Table 1. The control input is a step signal of 100 $m^{3/s}$ amplitude, the additive sensor fault introduced is a step signal with amplitude of -20 $m^{3/s}$ for t≥4s. The gauss-

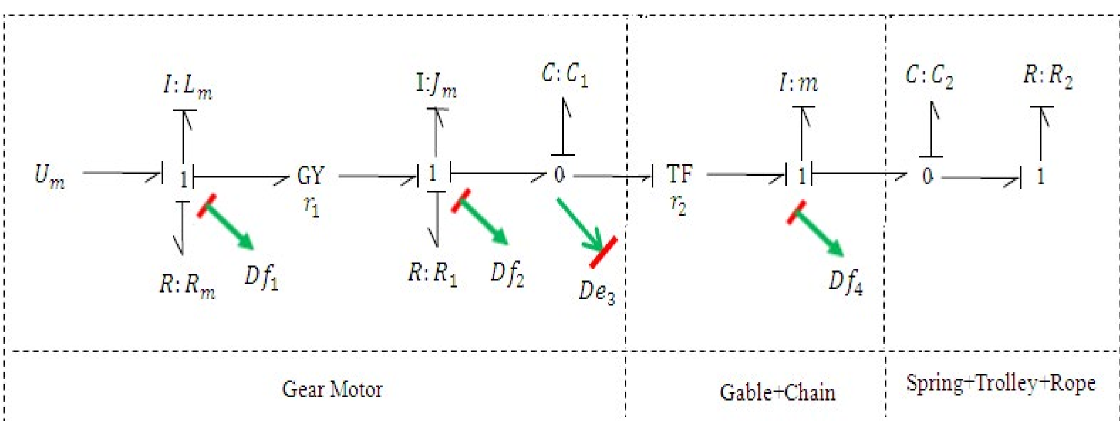


Figure 6. Stringing machine BG model.

Table 1. Stringing machine Parameters

Symbol	Designation	Nominal Values
R_m	Rotor resistance	1.1 Ω
L_m	Rotor inductance	1 mH
J_m	Moment of geared motor	0.05 $Kg.m^2$
R_1	Viscous coefficient	0.28 $N.m/rad/S$
r_1	Torque coefficient	0.0386 $N.m/A$
r_2	Ratio of reduction	0.01 $N.m/A$
m	Mass of chain	0.3 Kg
K_r	Stiffness of spring	4 N/mm
K_C	Stiffness of rope	32.7 N/mm
C_1	Compressibility coefficient	$10^{(-4)}$
C_2	Compressibility coefficient	0.00028
R_2	Loss resistance	1000 $N.m/rad/S$

ian noise amplitude is equal to 0.25, and the initial conditions are null.

The reduced observer is graphically designed as illustrated in Figure 7, in order to detect and estimate the sensor fault. The value of the reduced observer gain matrix is

$$\bar{L} = 10^5[0\ \ 0\ \ 0\ \ -2.6624], with\ \alpha = 10.$$

With σ_1=1, the blended estimated state is computed.

The state feedback and the feedforward controllers gain matrices are respectively

$K_{feedback} = 10^5\ [8.988\ \ 0.039\ \ -0.0001\ \ 0.0015\ \ 0]$, with $\alpha = 10^4$

And $K_{forward} = 10^5[8.988\ \ 0\ \ 0\ \ 0]$.

The evolutions of system output in nominal and faulty cases are illustrated in Figures 8 and 9 respectively. It can be seen on the Figure 10, that the residual signal response is diffrent from zero, when the fault appeared. The control law response is depicted in Figure 11.

The obtained residual signal shown in Figure 10 is an estimation of the fault achieving both its detection and isolation. We can confirm that the reduced observer is a good estimator. To achieve the active tolerance task, a reduced controller bank, an additive and feedforward control laws are implemented. We can see from the Figure 10, that the proposed control law compensates fault effect. It's seems clear that the effect of the fault on the control law response with proposed approach have been attenuated, as shown in Figure 11.

From this graphs, we conclude that the obtained control law ensures the stability of the system due to the proposed reduced controller.

5. Conclusion

In this manuscript, a novel approach to design a sensor fault tolerant controller modeled by BG tool is developed. In order to compensate the sensor fault, the failure was

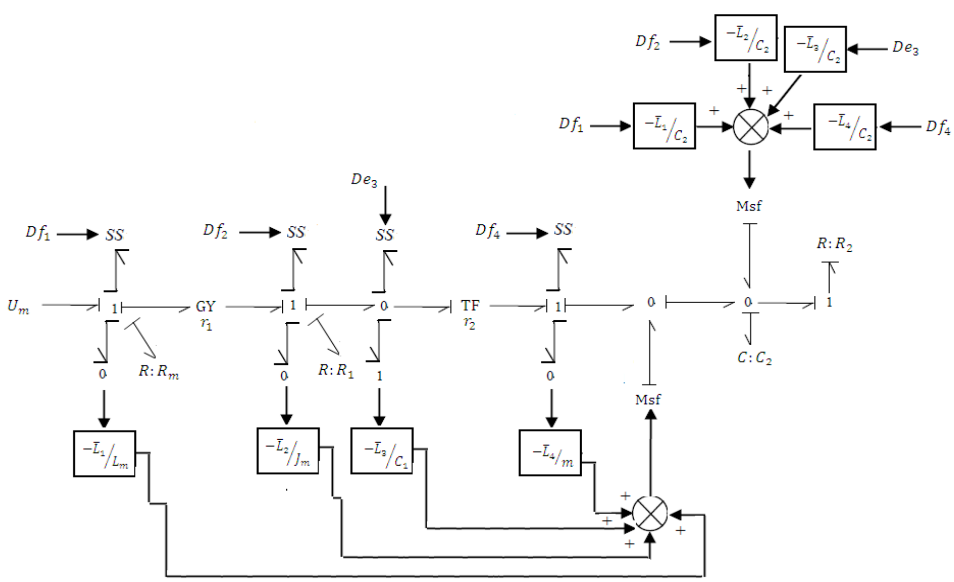


Figure 7. BG reduced observer model.

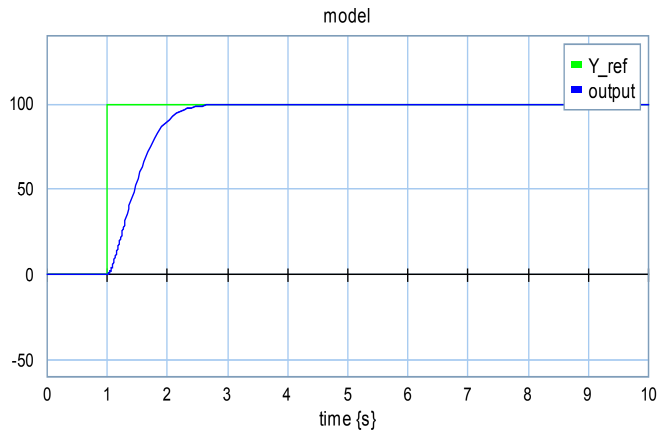


Figure 8. Output signal in fault-free case.

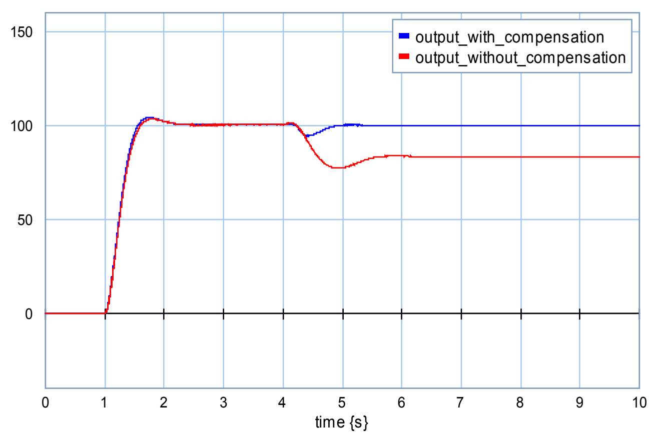


Figure 9. Output signal.

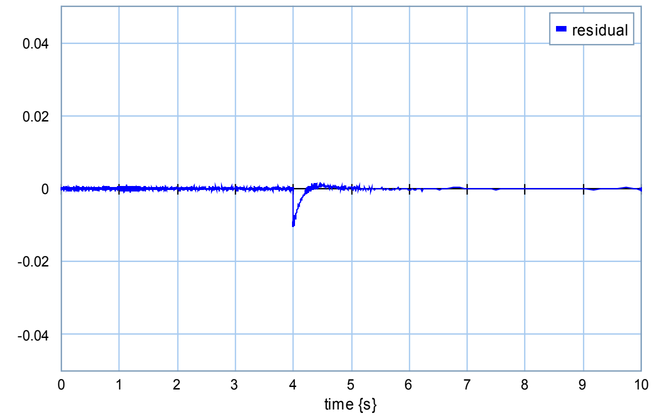


Figure 10. Residual generator.

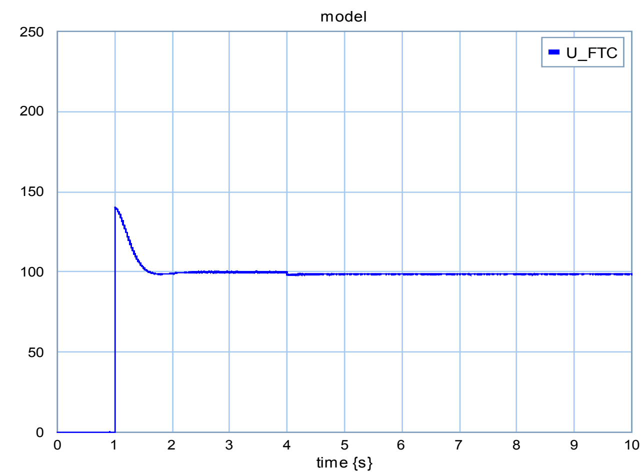


Figure 11. Control law response with proposed approach.

detected and identified through a residual generator. The proposed control law has been based on the blending estimated states provided by the reduced observer banc. To improve the reconfiguration block, a state feedback and forward controllers are incorporated. The fault diagnosis task with single sensor fault is investigated. At the last particular attention will be paid to study multiple faults.

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