Model based supervision and monitoring of a hoisting mechanism: A simulation study

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Nomenclature (excluding standard bond graph elements)

M	mass	ω	circular frequency of voltage source	***Subscript***	
J	rotary moment of inertia	A	amplitude of voltage source	t	truck
K	stiffness	g	acceleration due to gravity (9.81m/s^2)	f	front wheel
R	resistance (electrical or damping),	a	distance of front wheel centre from C.G	r	rear wheel
m_h	mass of hoist load	b	distance of rear wheel centre from C.G.	h	hoist
r	radius of pulley	c	distance between pulley centre and rear wheel centre	m	measured variable
μ	gyrator modulus corr. to motor	De	detector of effort	p	pulley
τ	torque	Df	detector of flow	a	armature of motor
i	current	R_d	residual		
f	flow				
e	effort				

Abstract

A simulation model for a hoisting mechanism mounted on a vehicle with planer oscillation with two degrees of freedom is presented in this paper and that model is virtually instrumented for the purpose of fault diagnosis and condition monitoring. The developed model is of multi energy complexity and intended to isolate the components responsible for abnormal behavior of the system using structural analysis of some constraint relations, called Analytical Redundancy Relations (ARR), the numerical evaluation of which are residuals. Bond graph modelling, which is a unified tool for multi-energy domain system representation, is used to model the system. Moreover, the fault indicators are derived from the bond graph model and fault signatures are obtained by direct exploitation of causal path information from the bond graph model. Thereafter, the model simulation with fault is carried out in MATLAB-Simulink environment and results are presented.

Keywords: Bond graphs, Fault diagnosis, Analytical redundancy, Residual, Signature matrix, Block diagram, Simulation.

1 Introduction

In supervision platform of safety-critical systems different approaches for condition monitoring and Fault Detection and Isolation (FDI) procedures have been developed: quantitative model-based, qualitative model-based and process history based approaches [1]. The present study is focused on a particular branch, i.e the quantitative model-based approach using Analytical Redundancy Relation (ARR) for FDI, which consequently enables better fault accommodation through an appropriate decision support system. Generally, model-based methods provide superior diagnostic performance while requiring the development of mathematical model to describe the behavior of the physical system for various operating conditions.

Therefore, modeling is an important and difficult step because of the complexities of the modern industrial systems and their control equipment. Bond graph modeling [2-3], which is a unified multi-energy domain modeling method, is especially suitable for developing analytical models of most engineering systems. Bond graph modeling has also been used in the past for different Fault Detection and Isolation approaches [4]. Moreover, the structural control properties (controllability, observability, etc.), which can be deduced by analyzing the causalities (cause and effect relationships) on a bond graph model [5], have been already used to optimize sensor placements [6] and to determine hardware redundancies.

FDI procedures are generally comprised of four stages: alarm or fault detection, isolation of fault, estimation of faulty parameter, and operational change [1]. In the alarm stage, the system behavior is continuously monitored for the occurrence of process faults. Once a failure is declared, the isolation phase attempts to identify the failed system component. The estimation stage determines the extent of failure to enable the implementation of operational changes needed for fault accommodation. In this work, we focus only on the first two stages of FDI paradigm.

Isolation of the faulty component can be done based on the structural properties of the ARR [7]. It is better to write the ARRs in differential form to solve the initial condition decoupling problem, i.e., avoiding any integration [4]. Off course, there are pitfalls in this due to sensor noises, whose derivatives cause diagnosis problems and need specific filters.

In the present study, the methodology given in [4] is followed for deriving ARRs of the plant and also for monitorability and isolability analysis of the possible faults. The system behavior of a vehicle mounted hoisting mechanism, virtually instrumented with seven sensors, is investigated through simulation of bond graph model and simulation results of FDI analysis are presented. Three assumptions made for the analysis are: 1. at a time, a single independent parameter of the system may be faulty (single-fault-hypothesis), 2. sensors are considered non-faulty, 3. measurement and process noise and parameter uncertainties are not taken into account.

2 Generation of Fault Indicators

An ARR is a relationship between a set of known process variables. In a bond graph based approach, the known variables are the sources (*Se* and *Sf*), the modulated sources (*MSe* and *MSf*), the measurements from sensors (*De* and *Df*), the model parameters (θ), and the controller outputs (u). A fault indicator or residual, r, which represents the error in the constraint, is formed from each ARR and can be written as $r = f(De, Df, Se, Sf, MSe, MSf, u, \theta) = f(K) = 0$, where f is the constraining function. For a system with n structurally independent residuals; $r_i = f_i(K_i)$, where $i=1...n$ and K_i is the set of known variables in the argument of function f_i; the following property is satisfied : $K_i \neq K_j \ \forall i \neq j$, where $i, j = 1...n$. Although the residuals are theoretically equal to zero, they are never so in an online application involving measurements from real sensors due to the sensor noises and the uncertainties associated with the parameters.

The evaluation of the ARR using the actual sensor data and the process parameters is used to detect the faults in the process. This leads to the formulation of a binary coherence vector $C=[c_1, c_2, ..., c_n]$, whose elements, c_i ($i=1...n$), are determined from a decision procedure, Θ, which generates the alarm conditions. Robust decision procedures minimize misdetection and false alarms by treating the residual noises.

In this paper, we use a decision procedure, $C = \Theta(R_{d1}, R_{d2}, .. R_{dn})$, whereby each residual, R_{di}, is tested against a threshold, $\pm\delta_i$, to generate the coherence vector, C. The elements of C, c_i ($i=1...n$), are determined from

$$c_i = \begin{cases} 0, \text{if } r_i \text{ is bounded by } \delta_i; \\ 1, \text{otherwise.} \end{cases} \tag{1}$$

All residuals are normalized to account for process uncertainties as follows:

$$\bar{r}_i\Big|_{t=t_k} = \frac{r_i\big|_{t=t_k} - \psi_i(t_k)\eta_i(u_k)}{z\phi_i(t_k)\sigma_i(u_k)}, \tag{2}$$

where, subscript k stands for k^{th} sample, $\psi(t_k)$ and $\phi(t_k)$ are time varying coefficients modifying the mean and the variance, respectively; u_k is the input, t_k is the time, and z is a coefficient related to the confidence level.

The coherence vector is calculated at every sampling interval. A fault is detected, when $C \neq [0,0,\dots,0]$, i.e. at least one element of the coherence vector is nonzero (alternatively, at least one residual exceeded its threshold). The isolation of the faulty component is done using the binary Fault Signature Matrix (FSM), S. The fault signature matrix describes the participation of various components (physical devices, sensors, actuators and controllers) in each residual. Thus, matrix S forms a structure that links the discrepancies in components to changes in the residuals. The elements of matrix S are determined from the following analysis:

$$S_{ji} = \begin{cases} 1, \text{if } i^{th} \text{ ARR is sensitive to faults in } j^{th} \text{ component;} \\ 0, \text{otherwise.} \end{cases} \tag{3}$$

It is important to note that the component's faults need not be explicitly modeled in the residuals. Faults in any physical component can be mapped to the undesirable changes in the values of the parameters of the component. A residual is sensitive to faults in a component, when the parameters or the measurements belonging to that component appear in the symbolic residual, or are causally linked in the numerical form of the residual. The elements of the fault signature matrix can as well be constructed through experimentation by introducing various faults, one at a time.

3 Case Study: A Hoisting Mechanism

3.1 System modeling

A schematic of simplified hoisting mechanism mounted on a truck having planer oscillation with pitch and bounce motion is shown in Fig. (1) and the bond graph model for the system is given in Fig. (2). Junction $1_{\dot{\theta}}$ and $1_{\dot{y}}$ represent the pitch and bounce velocity, to which are attached the inertia terms, J_t

and M_t, respectively. The current-torque relation for the motor is idealized as: $\tau = \mu . i_a$

Seven number of sensors have been with the system: Df($f_{\theta m}$), Df(f_{ym}), Df(f_{pm}), Df(f_{hm}), De(e_{fm}), De(e_{rm}), and De(e_{hm}). The model in Fig. (2) is simulated with the parameter values given in Table 1 having no initial fault in the system and thereafter at time 10 s motor fault is introduced by changing μ from the nominal value 1 to 0.8 N.m/Amp, i.e 20% deviation is realized. The variation of all sensor data with time are plotted in Fig. (3), (4) and (5), from which one can conclude that something has happened at time 10 s but the particular faulty component cannot be isolated by online inspection although the information is contained in those signals.

Table-1: Nominal values of model parameters of hoisting mechanism

Symbol	Value	Symbol	Value
M_t	10,000 kg	R_a	1 Ω
J_t	500 kg.m^2	μ	1N.m.Amp^{-1}
J_p	1 kg.m^2	ω	10 rad.s^{-1}
m_h	100 kg	A	1 V
K_f, K_r	1×10^5 Nm^{-1}	a	1 m
R_f, R_r	0.3 N.s.m^{-1}	b	1.7 m
K_h	1×10^3 Nm^{-1}	c	0.3 m
R_h	0.1 N.s.m^{-1}	r	0.2 m

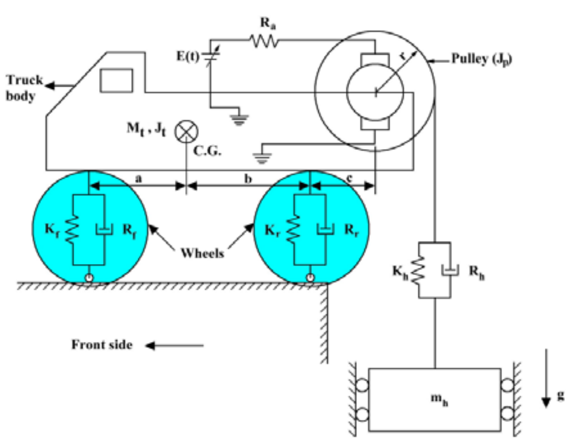

Fig.1: Schematics of a vehicle mounted hoisting system

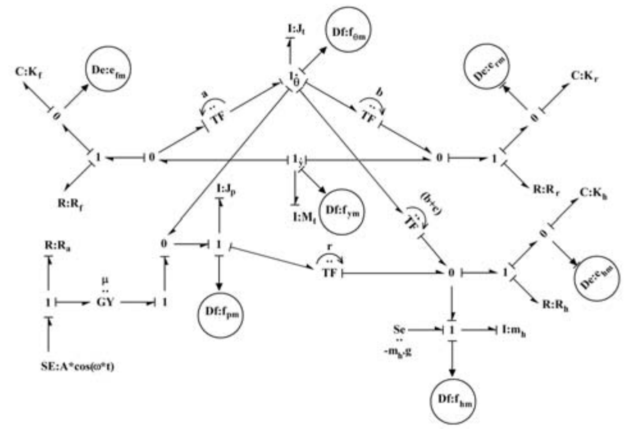

Fig.2: Bond graph model of the system in Fig.(1) in integrated causality

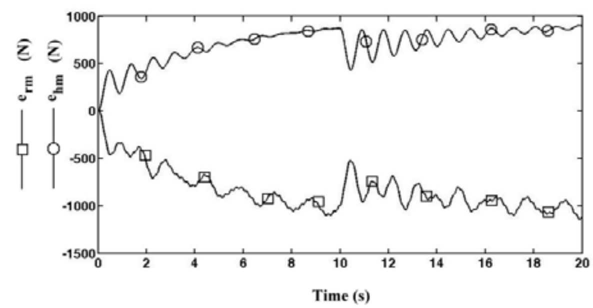

Fig. 3: Force variation with time in rear wheel (e_{rm}) and hoisting rope (e_{hm})

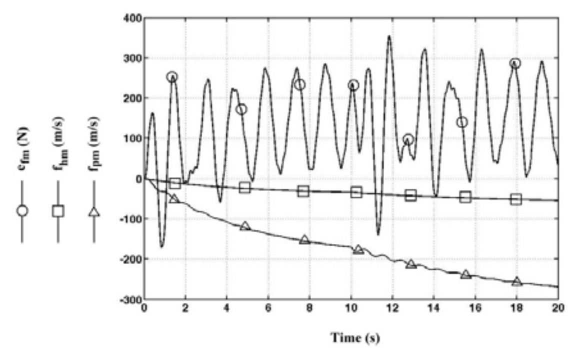

Fig. 4: Time response of e_{fm}, f_{hm} and f_{pm}

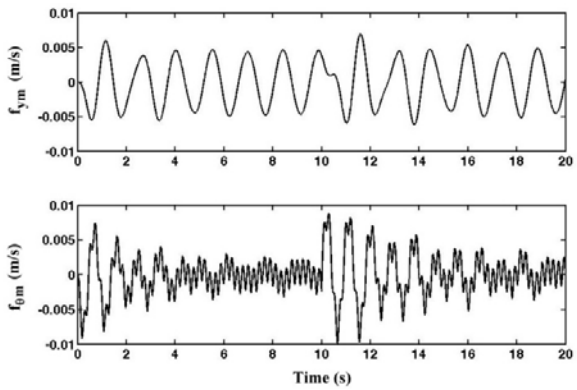

Fig. 5: Time response of f_{ym} and $f_{\theta m}$

3.2 Fault detection and isolation (FDI)

For FDI analysis inverse dynamics is to be studied, i.e one has to go to the past based on the present data exploitation unlike that of model simulation, where the present state is evolved on the basis of past history of a system. Hence the derivative causality is assigned to the bond graph model (Fig. (6)). The ARR (in differential form) from a bond graph model can be derived using a well established algorithm given by Ould Bouamama and his co-workers [4]. In that algorithm, to derive the ARR all the storage elements are to be brought under preferred differential causality and negative of measured quantities from detectors are imposed on the system (i.e. on 1 or 0 junction of the bond graph) as pseudo source and reactive factor in the bond corresponding to the pseudo source is ARR when expressed in symbolic form. The number of ARRs thus derived is equal to the number of sensors installed in the plant. Seven numbers of ARRs, given in Eq. (4), are obtained as the same numbers of sensors are installed in the system. The structural observability condition is satisfied from causal path analysis of the bond graph model [5]. The FSM obtained from the above ARRs is given in Table 2. Note that the ARRs and FSM can be derived by model builder software using bond graph tools [8]. All the component faults listed in the matrix are isolable except the motor fault. Motor fault may result if the armature resistance (R_a) or the gyrator modulus μ changes, resulting identical signature C = [0 0 0 0 1 0 1]. We can define a fault subspace S_p in FSM (Table 2) corresponding to this signature where higher level fault isolation technique need to apply. In this work, this aspect is not addressed; however one can generally recognize a motor fault when this signature would result.

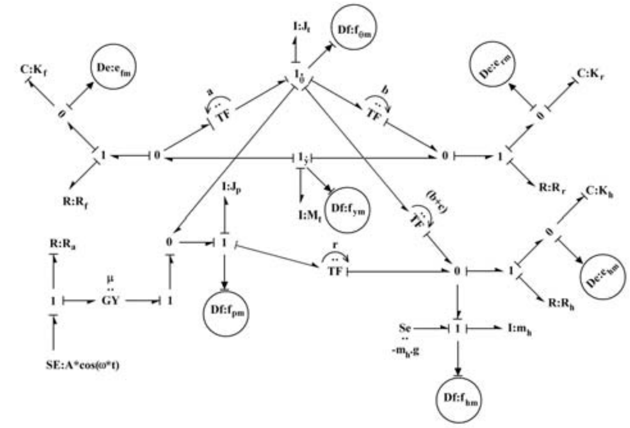

Fig. 6: Bond graph model of the system in Fig.(1) in derivative causality

$$
\begin{aligned}
&ARR_1 : -m_h.g - m_h.\frac{d}{dt}\left(f_{hm}\right) \\
&\qquad + \left(e_{hm} + R_h\left(r.f_{pm} + f_{ym} + (b+c).f_{\theta m} - f_{hm}\right)\right) = 0 \\
&ARR_2 : (b+c).f_{\theta m} + f_{ym} + r.f_{pm} - f_{hm} - \frac{1}{K_h}\frac{d}{dt}\left(e_{hm}\right) = 0 \\
&ARR_3 : f_{ym} + b.f_{\theta m} - \frac{1}{K_r}.\frac{d}{dt}\left(e_{rm}\right) = 0 \\
&ARR_4 : f_{ym} - a.f_{\theta m} - \frac{1}{K_f}.\frac{d}{dt}\left(e_{fm}\right) = 0 \\
&ARR_5 : -J\frac{d}{dt}\left(f_{\theta m}\right) + a\left(e_{fm} + R_f\left(f_{ym} - a.f_{\theta m}\right)\right) \\
&\qquad - \mu\frac{\left(A\cos(\omega.t) - \mu\left(f_{pm} - f_{\theta m}\right)\right)}{R_a} \\
&\qquad - (b+c)\left(e_{hm} + R_h\left(f_{ym} + r.f_{pm} + (b+c)f_{\theta m} - f_{hm}\right)\right) \\
&\qquad - \left(e_{rm} + R_r\left(f_{ym} + b.f_{\theta m}\right)\right) = 0 \\
&ARR_6 : -\left(e_{fm} + R_f\left(f_{ym} - a.f_{\theta m}\right)\right) \\
&\qquad - \left(e_{rm} + R_r\left(b.f_{\theta m} + f_{ym}\right)\right) - M\frac{d}{dt}\left(f_{ym}\right) \\
&\qquad - \left(e_{hm} + R_h\left(rf_{pm} + f_{ym} + (b+c)f_{\theta m} - f_{hm}\right)\right) = 0 \\
&ARR_7 : \mu\frac{A\cos(\omega.t) - \mu\left(f_{pm} - f_{\theta m}\right)}{R_a} - J_p\frac{d}{dt}\left(f_{pm}\right) \\
&\qquad - r\left(e_{hm} + R_h\left(r.f_{pm} + f_{ym} + (b+c)f_{\theta m} - f_{hm}\right)\right) = 0
\end{aligned}
\tag{4}
$$

Table 2: Fault signature matrix (FSM)

	R_{d1}	R_{d2}	R_{d3}	R_{d4}	R_{d5}	R_{d6}	R_{d7}	I_b
K_f	0	0	0	1	0	0	0	1
R_f	0	0	0	0	1	1	0	1
K_r	0	0	1	0	0	0	0	1
R_r	0	0	0	0	1	1	0	1
K_h	0	1	0	0	0	0	0	1
R_h	1	0	0	0	1	1	1	1
m_h	1	0	0	0	0	0	0	1
J_p	0	0	0	0	0	0	1	1
R_a	0	0	0	0	1	0	1	0
μ	0	0	0	0	1	0	1	0

S_p

3.3 Validation through simulation

To study the inverse dynamics we have converted both the integrally (see Fig. (2)) and differentially causalled (see Fig. (6)) bond graph model to block diagram in MATLAB Simulink to study the process behaviour and residual responses with the implementation of FDI schemes, as the bond graphs do not support simulation of differentially causalled model directly.

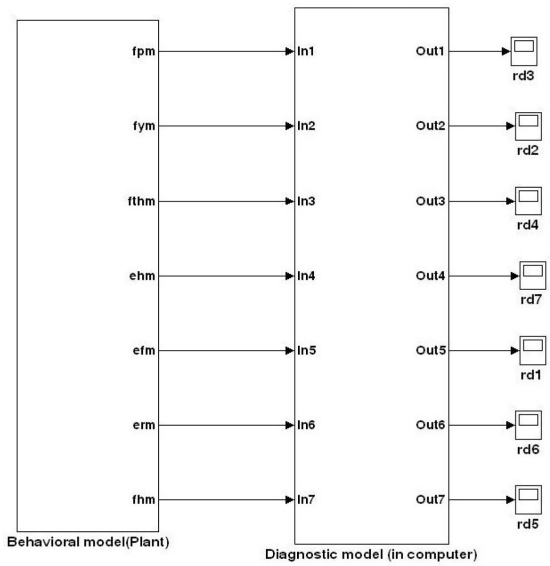

Fig. 7: Coupling of behavioral and diagnostic model to derive fault indicators (residuals)

The former block model may be called as behavioural model or plant and the later may be called as diagnostic model is simulated with the nominal parameter values given in Table 1. The sensor outputs from the behavioural model are becoming the inputs for the diagnostic model and the outputs from the diagnostic model are residuals. Both the models (behavioural and diagnostic) are squeezed to subsystems and coupled together as shown in Fig. (7). Motor fault is introduced once reducing μ by 20% and then increasing R_a by 20% both at time 10 s in separate simulation and the residuals response are shown in Fig. (8) and Fig. (9), respectively.

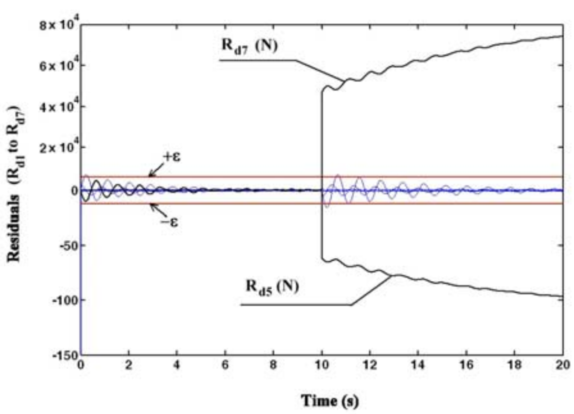

Fig. 8: Time response of residuals with motor fault introduced by changing μ at 10 s.

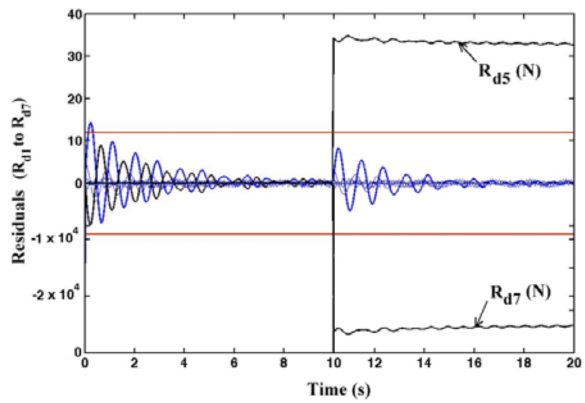

Fig. 9: Time response of residuals with motor fault introduced by changing R_a at 10 s.

A bilateral constant threshold, $\varepsilon = \pm 12$ is chosen to envelop all the normalized nominal residuals. The residuals R_{d5} and R_{d7} are being abnormal at 10 s (see Fig. (8) and Fig. (9)) resulting the coherence vector C = [0 0 0 0 1 0 1], which is matching the signature of the component parameters R_a and μ , thus validating the fault occurrence and isolating the subspace S_p. Further analysis such as pattern matching of the residuals responses are required to isolate the particular faulty component within the subspace, not addresses in this work. Fig. (10) shows the residuals (normalized) responses for a simulated hoist rope fault (K_h is reduced by 20% of nominal value) at a time of 10 s. The residual R_{d2} is crossing the threshold after the fault which matches the signature of K_h in Table 2, which agrees with the fault hypothesis.

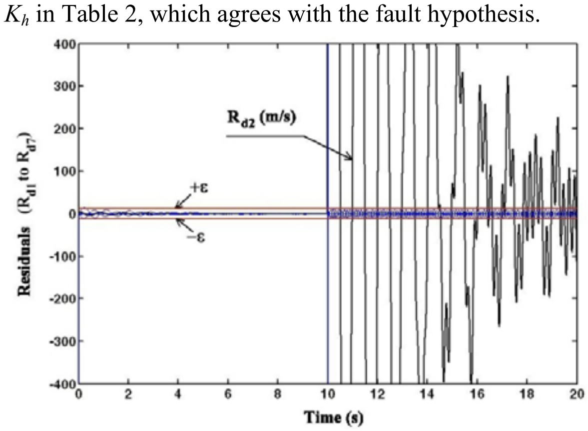

Fig. 10: Time response of residuals with hoisting rope fault introduced by changing K_h at 10 s.

5 Conclusions

Model based FDI of hoisting mechanism are discussed in this article. The information gathered in this problem is that ARRs and FSM for a system containing in different energy domains can be algorithmically derived from a bond graph model and those can be effectively used for condition monitoring and fault isolation.

Although residuals are normalized to account for the uncertainty of parameters, but there is a scope of enhancing robustness of FDI by appropriate design of adaptive threshold instead of constant bilateral threshold as applied in this work. Work can also be extended toward multi fault analysis, where more than one fault may be faulty at a time (may or may not be simultaneous) and different types of fault (abrupt, progressive or incipient) may be associated with different components. The parameter can be estimated quantitatively in nominal and faulty state and those quantitative analyses are required for fault accommodation either through system reconfiguration or through fault tolerant control.

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