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A system model for reliability assessment of smart structural systems

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Abstract. Smart structural systems are defined as ones that demonstrate the ability to modify their characteristics and/or properties in order to respond favorably to unexpected severe loading conditions. The performance of such a task requires a set of additional components to be integrated within such systems. These components belong to three major categories, sensors, processors and actuators. It is well-known that all structural systems entail some level of uncertainty, because of their extremely complex nature, lack of complete information, simplifications and modeling. Similarly, sensors, processors and actuators are expected to reflect a similar uncertain behavior. As it is imperative to be able to evaluate the impact of such components on the behavior of the system, it is as important to ensure, or at least evaluate, the reliability of such components. In this paper, a system model for reliability assessment of smart structural systems is outlined. The presented model is considered a necessary first step in the development of a reliability assessment algorithm for smart structural systems. The system model outlines the basic components of the system, in addition to, performance functions and inter-relations among individual components. A fault tree model is developed in order to aggregate the individual underlying component reliabilities into an overall system reliability measure. Identification of appropriate limit states for all underlying components are beyond the scope of this paper. However, it is the objective of this paper to set up the necessary framework for identifying such limit states. A sample model for a three-story single bay smart rigid frame, is developed in order to demonstrate the proposed framework.

Keywords: control; fuzzy; MR-dampers; neural; reliability; smart; system; uncertainty.

1. Introduction

Smart structural systems have emerged as a viable alternative to traditional design techniques, in response to highly uncertain loading conditions (Connor 2003, Soong 1990). A smart structural system is one that employs a unique set of adaptive components that allow the system to adjust its behavior, in response to unexpected loading conditions. For example, instead of designing a system capable of withstanding the most severe earthquake that has a return period of fifty years, it is a smarter approach to design a system that is capable of changing its properties/characteristics in order to behave in a more favorable manner. Guidelines for identifying such favorable response are, understandably, defined by applicable design codes. The need for such innovative approach is warranted by the ever-increasing size, complexity and flexibility of structural systems.

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Smart structural systems employ three basic components that allow the system to behave in the intended smart manner. These components are sensors, processors and actuators. These three components collectively expand the capabilities of the system in a way such that it can, independently, monitor and adjust its behavior. However, the reliability of such integrated components/devices pose a major concern that hinders practical application of smart systems (Alt *et al.* 2000, Ankireddi and Yang 1999, Gavin *et al.* 2003, Spencer *et al.* 1992, 1994, Wang *et al.* 2001, Yi and Dyke 2000). Time delay, accurate response evaluation, power requirements, interaction among individual components are practical problems that reflect on the reliability of the system and accordingly on its implementation. Such reliability is increasingly complicated to ascertain, as the degree of smartness of the proposed system increases. The smartness of any system is dependent on the capabilities and nature of the integrated components. Available structural reliability assessment models do not apply to the system under consideration, since the underlying components entail distinctive properties and failure modes. Therefore, it is imperative to formulate a suitable framework capable of handling all types of underlying components, i.e., sensors, processors, actuators and frame elements. Any potential reliability assessment model should follow the structure of the system in question (Ang and Tang 1975a,b, Nowak and Collins 2000). This leads to the first and most important step in a reliability assessment procedure, which is the identification of a system model.

In this paper, a system model for reliability assessment of smart structural systems is presented. As outlined in the following section, there are a multitude of smart systems that could be developed, simply by mixing and matching several types of sensors, processors and actuators. For purposes of this study, smart components are identified based on their practical applicability and auto-adaptive capabilities. A sample model for a three-story single bay smart rigid frame, is developed through the course of this paper, in order to demonstrate the proposed framework. System identification is considered the first stage of a multi stage research project that aims at the development of a reliability assessment procedure for integrated smart systems. The system model outlined in this paper is built in a hierarchical framework that reflects the structure of the modeled system. Component models are developed together with interrelations among individual components. The reliability of the modeled system is, eventually, evaluated knowing the reliability of underlying components. Aggregation techniques are employed in order to evaluate the system reliability measure. A fault tree model is developed for that purpose and is applied to the smart rigid frame being modeled through the course of this paper. The following section presents a brief outline of smart structural systems together with potential combinations of individual components.

2. Smart structural system

A smart structural system is defined as one that is capable of monitoring its performance, evaluating its current state in real time, suggesting corrective action to render an improved level of performance and, finally, to apply such action. In order for such systems to behave as outlined above, they need to extend their capabilities through the employment of three basic component categories, i.e., sensors, processors and actuators, (Spencer and Sain 1997, Spencer and Soong 1999). First, sensors are required in order to collect real-time data regarding the performance of the system in question. For the purposes of this study, acceleration and/or displacement transducers are considered as suitable devices for sensing any instantaneous state changes. Second, gathered real-time data are communicated to either a central processing unit or a set of decentralized processing units. The processing unit should be capable of identifying the current state of the system and, accordingly, suggesting corrective action if the response is beyond predefined and acceptable limits. Smart structural systems are perceived to mimic the mechanical behavior of a human body. Therefore, any potential processor needs to possess cognitive features that are similar to those of the human brain. Such features include an auto-adaptive nature, parallel processing capability and pattern recognition. Neural networks and/or fuzzy logic are capable of simulating such cognitive features. Neural networks possess an adaptive self-learning capability, while fuzzy logic is capable of modeling complex systems that incorporate the qualitative nature of the human brain (Casciati *et al.* 1994, Faravelli and Venini 1994, Faravelli and Yao 1996, Hassan and Ayyub 1997). For the purposes of this study, neural networks and/or fuzzy inference systems shall be employed as processors for the smart system under consideration.

Finally, the processing unit sends a proposed corrective action to a set of actuators that follow one of two potential approaches. The first is an external force application in order to balance the system. The second through the adjustment of the actuator's structural characteristics, thus, resulting in a more favorable response. External force application was one of the early forms of smart corrective actions (Connor 2003, Soong 1990). However, recent applications have shifted towards auto-adaptive actuators, which follow the second approach. Magneto-Rheological (MR) dampers are a good example to such actuators. MR dampers are proving to be very promising in civil and/or structural applications (Spencer *et al.* 1997, Carlson and Spencer 1996, Dyke and Spencer 1997, Dyke *et al.* 1996). MR dampers respond to a magnetic field with a change in viscosity, thus, changing their response characteristics. For purposes of this study, MR dampers are considered the actuator device of choice.

3. System model

The task of building an accurate model is a major and important task in the analysis of any system under consideration. Creation of this model of a building formulates an image of the real life system, the model often accentuates one or more attributes of interest (Ayyub and Hassan 1992, Hassan and Ayyub 1995, 1997, Klir 1985, Wilson 1984). Any model that is developed, for reliability assessment applications necessarily shall be able to trace all components of the system, together with their hierarchical structure. Interrelations among individual components as well as among the overall system and its underlying components need to be defined.

In the following sections a three-story single-bay smart rigid frame, is used to demonstrate the necessary stages for building a system model. Fig. 1 shows a schematic diagram for the assumed smart rigid frame. The system is comprised of a three-story steel rigid frame equipped with three sensors, one at each level, and a forth sensor to detect ground acceleration. A sensor collection unit, that is capable of integrating the information originating from the individual sensors into a single state evaluation of the system is employed. An example of such a unit is a trained neural network that is capable of recognizing the vibration pattern of the system in real-time. Initially, the system is equipped with three MR dampers located between the individual story levels. Such an arrangement is assumed in order to identify the model in the most general form. Naturally, the employed control strategy might suggest a specific actuator activation scheme that does not necessarily include all actuators at all times. An auto-adaptive processor is attached to the system in order to evaluate the

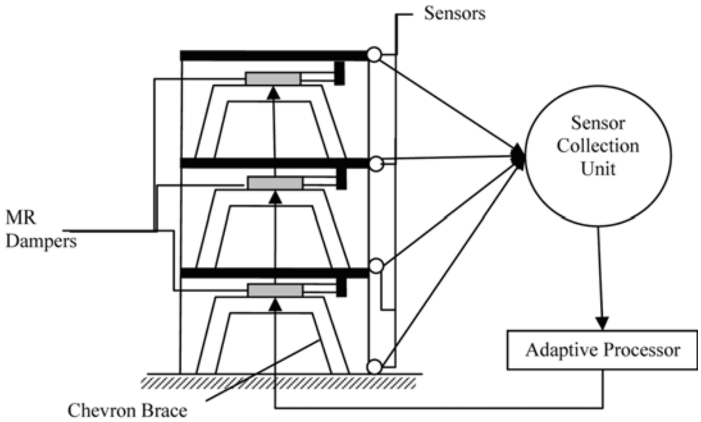

Fig. 1 Schematic diagram of a smart rigid frame

voltages necessary to drive the MR dampers. For the time being, the type of the employed processor is discussed in the most general terms. However, since the processor is adaptive, it is assumed that one of the following types applies; artificial neural network (ANN), fuzzy inference system (FIS) or neuro-fuzzy controller (NFC). The general system identification framework developed earlier (Hassan and Ayyub 1995, 1997) is adopted in the identification of a system model of the smart rigid frame. The referenced framework requires the breakdown of the system into a set of components and the identification of all performance functions as well as interrelations governing the behavior of such underlying components.

3.1 Component level

A comprehensive reliability assessment procedure should include all potential failure modes at the system as well as the component levels (Hassan and Ayyub 1995, 1997). Thus, the resulting reliability reflects the uncertainty inherent in the system as accurately as possible. Failure modes at the system level relate to failure of individual and/or a collection of specific components. However, the failure modes, at the component level, relates to the occurrence of an individual failure or a collection of limit states. Initially, the smart structural system is broken down into its basic components, i.e., sensors, actuators, processor and frame elements; that later, in turn, are classified as beam elements or column elements. Each component is then expressed further in terms of its potential failure modes, using the appropriate limit state equations. Fig. 2 summarizes a set of potential failure modes for each individual component in the system. The following discussion outlines the model of each individual component.

3.1.1 Sensors model

For demonstration purposes, only displacement transducers are considered herein. However, the same concepts and procedures could be extended to model any other sensor. In reference to Fig. 2, two potential failure modes are identified for any sensor device. The first occurs if the sensor *Crashes* while the second occurs if the sensor *Malfunctions*. A sensor is considered *Crashed* if it does not send any voltage to the processor. A *Malfunction*, however, is defined as inaccurate data being sent from the sensor to the processor. In the first failure mode the processor operates with a

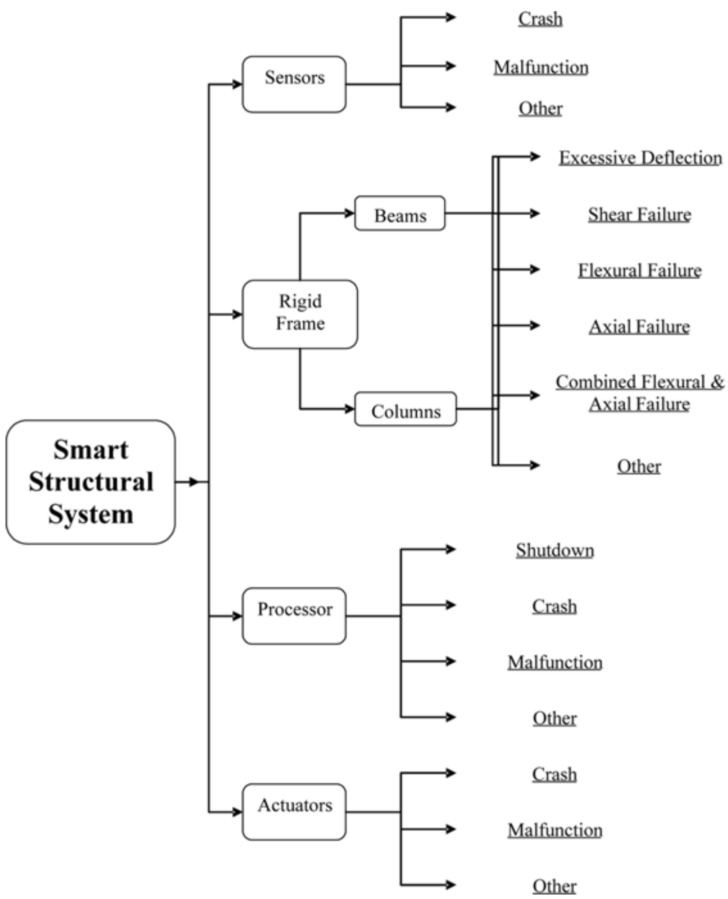

Fig. 2 Potential failure modes for smart rigid frame

reduced number of sensors which adversely affects its final recommended action. In the second failure mode, the processor operates with full sensor capability, yet, its recommended action would still be inaccurate. Such failure modes would understandably affect the reliability of the smart rigid frame as a whole. Identification of appropriate limit states for such failure conditions are beyond the scope of this paper. However, it is the objective of this paper to set up the necessary framework for identifying such limit states. In general, a mathematical model that represents the behavior of any given sensor, i.e., transducer, can be developed. For example, some displacement transducers are known to produce a voltage that is linearly proportional to the displacement of the sensor. Therefore, a model representing this behavior can be written as:

$$v = a + b\Delta \tag{1}$$

where, v = output voltage of sensor, Δ = displacement of sensor, and a and b = are sensor parameters. Based on the assumed failure modes, a limit state equation is written for each individual failure mode. Such limit state equation should define the boundaries between a safe and unsafe condition for the modeled sensor. The presumed limit state equation is expected to be a function of

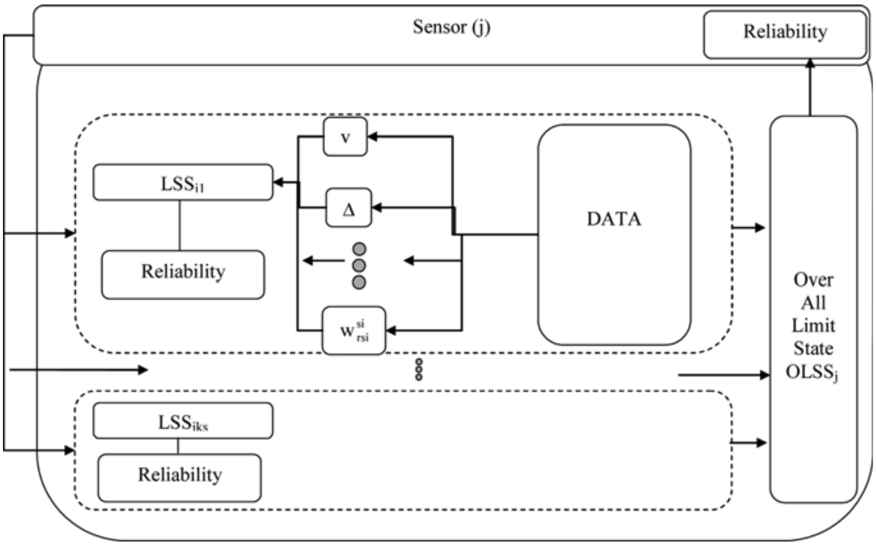

Fig. 3 Block diagram of sensor component

some or all of the variables and parameters modeling the behavior of the sensor. Fig. 3 shows the proposed model for the sensor component. The model is built using individual potential failure modes for the sensor. Each failure mode is expressed in the form of a sensor limit state. A sensor limit state equation is formally expressed as:

$$LSS_{ij} = gs_{ij}(v, \Delta, \ldots, w^{si}_{rsi}) \tag{2}$$

where, LSS_{ij} = jth limit state of ith sensor; $gs_{ij}(.)$ = jth performance function of ith sensor, v and Δ = are as defined above, w^{si}_{rsi} = generic variable affecting limit state of ith sensor, and rsi = total number of variables affecting limit state of ith sensor. When real-time data are presented to the model, reliability evaluations for each individual limit state equation can be developed. Finally, an overall reliability of the sensor is estimated using the following expression:

$$OLSS_i = OGS_i(LSS_{i1}, LSS_{i2}, \ldots, LSS_{iks}) \tag{3}$$

where, $OLSS_i$ = overall limit state of ith sensor, $OGS_i(.)$ = overall performance function of ith sensor, LSS_{i1}, LSS_{i2} and LSS_{iks} = potential limit states of ith sensor, and iks = total number of potential limit states of ith sensor. The overall performance function, defined above, is usually in the form of a union function. This, in fact, represents the type of connectivity among the individual limit states, i.e., any one of these failure modes is enough to result in a sensor failure. Fig. 3 shows a block diagram for the developed model where, the individual limit states and their underlying variables are identified. In addition, the overall limit state function is also shown.

3.1.2 Actuators model

MR dampers are employed, in this study, for their ability to adjust their characteristics and thus improving the response of the system. There are several mathematical models that express the

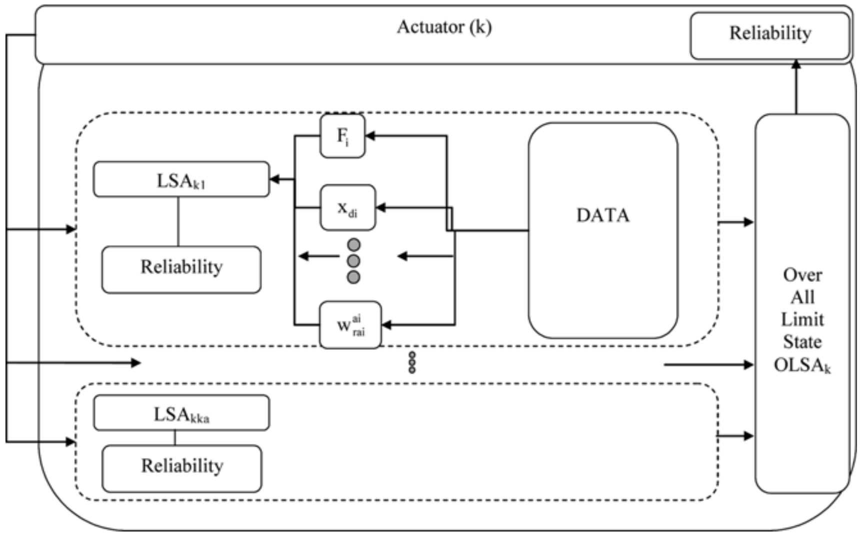

Fig. 4 Block diagram of actuator component

behavior of MR dampers. The phenomenological model developed by Spencer *et al.* (1997) has been proven to accurately reflect the behavior of such dampers. While this model is adopted for the purposes of this study, other models will be explored in future studies. Potential actuator failure conditions might include one or more of the following: *Crashing* of an actuator, which is defined as one or more of such dampers not responding to the voltage being sent by the processor or *Malfunction* of an actuator, which is defined as an inaccurate interpretation of the voltage signals sent by the processor. The phenomenological model that predicts the behavior of an MR damper has been previously defined by other researchers (Spencer *et al.* 1997):

$$F = c_1\dot{z} + k_1(x_d - x_o) \tag{4}$$

$$\dot{v} = -\gamma|\dot{x}_d - \dot{z}|v|v|^{n-1} - \beta(\dot{x}_d - \dot{z})|v|^n + Q(\dot{x}_d - \dot{z}) \tag{5}$$

$$\dot{z} = \frac{1}{c_o + c_1}\{\alpha v + c_o\dot{x}_d + k_o(x_d - z)\} \tag{6}$$

where, F = force applied by MR damper to the system. The model employs a set of fourteen parameters that are well documented in the literature. Fig. 4 defines a model for the actuator component. The model is built using the individual potential failure modes for the actuators. Each failure mode is expressed in the form of an actuator limit state. Similarly, the limit state expression is formally expressed as:

$$LSA_{ij} = ga_{ij}(F_i, x_{di}, k_{1i}, \ldots, w^{ai}_{rai}) \tag{7}$$

where, LSA_{ij} = jth limit state of ith actuator, $ga_{ij}(.)$ = jth performance function of ith actuator, F_i = force applied by ith actuator as defined in Eqs. (4-6), x_{di} and k_{1i} = ith damper parameters, w^{ai}_{rai} = generic variable affecting limit state of ith actuator, and rai = total number of variables affecting limit state of ith actuator. When data is fed through the model, reliability estimates for each individual limit state could be developed. The overall reliability of the component can be estimated using the following expression;

$$OLSA_i = OGA_i(LSA_{i1}, LSA_{i2}, \ldots, LSA_{ika}) \tag{8}$$

where, $OLSA_i$ = overall limit state of ith actuator, $OGA_i(.)$ = overall performance function of ith actuator, LSA_{i1}, LSA_{i2}, LSA_{ika} = potential limit states of ith actuator, and ika = total number of potential limit states of ith actuator.

3.1.3 Processor model

Artificial neural networks (ANN), fuzzy inference systems (FIS) and neuro-fuzzy controllers (NFC) are selected as the most appropriate processors for the current application. Several promising applications of such systems have been reported in the literature (Faravelli and Venini 1994, Faravelli and Yao 1996). As mentioned earlier, the reliability of the processor should be dependent on its potential failure modes. According to Fig. 2, any processor could suffer one or more of the following failure modes; *Shutdown*, *Crash* and/or *Malfunction*. *Shutdown* occurs as a result of a complete electrical power shutdown. *Crashing* is defined as the inability of the processor to come up with a control action, for a given set of input data. Finally, *Malfunction*, as explained above, relates to the inaccurate evaluation of the control command. Fig. 5 defines a model for the processor component. The model is built using the individual potential failure modes for the processor. Each failure mode is expressed in the form of a processor limit state. The limit state equation associated with each failure condition can be written in the following general format;

$$LSP_i = gp_i(E, T, \ldots, w_{rp}^p) \tag{9}$$

where, LSP_i = ith limit state of processor, $gpa_i(.)$ = ith performance function of processor, E = error vector of processor, T = output vector of processor, w_{rp}^p = generic variable affecting limit state of

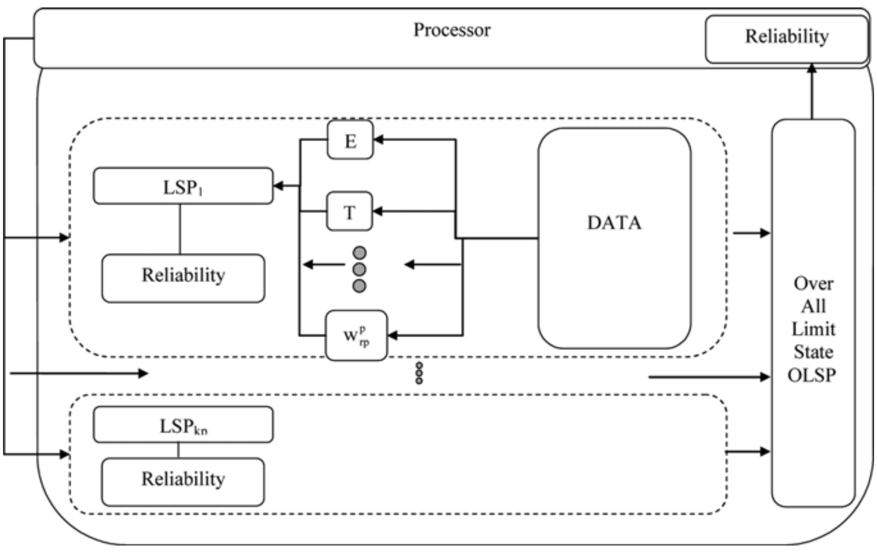

Fig. 5 Block diagram of processor component

ith processor, and rp = total number of variables affecting limit state ith processor. Although it is perceived that a set of decentralized processing units could be employed for highly complex systems, it is assumed in this study that only one processor is used. As explained in earlier component models, the overall reliability of the processor is expressed formally as follows:

$$OLSP = OGP(LSP_1, LSP_2, \ldots, LSP_{kp}) \tag{10}$$

where, $OLSP$ = overall limit state of processor, $OGP(.)$ = overall performance function of processor, LSP_1, LSP_2, LSP_{kp} = potential limit states; and kp = total number of potential limit states of processor.

3.1.4 Rigid frame model

Initially, the rigid frame is subdivided into its underlying elements, i.e., beam elements and column elements. Each element type experiences its own potential failure modes. Depending on code requirements, some or all of such limit states need to be considered, when designing suitable sections for the individual frame elements. As outlined in Fig. 2, both beam and column elements might encounter one or more of several failure modes: flexural failure, shear failure, axial failure, combined axial and flexure, combined shear and flexure, and excessive deflection. If a beam is behaving in pure bending, it would not encounter any axial failure modes, however, if such a beam is employed as a frame element, combined axial and flexural failure should be considered. It is clearly stated, by individual design codes, which failure modes shall be considered in the design of each individual element type. The limit state expression again is dependent on the type of design code adopted in the design. In general, the rigid frame limit state could be generally expressed as follows:

$$LSRF_{ij} = grf_{ij}(\sigma_y, A_w^i, S_x^i, \tau_y, \ldots, w_{rrfi}^{rfi}) \tag{11}$$

where, $LSRF_{ij}$ = jth limit state of ith rigid frame element, $grf_{ij}(.)$ = jth performance function of ith rigid frame element, σ_y = flexural yield strength of steel used, τ_y = shear yield strength of steel used, A_w^i = web area of section used for ith rigid frame element, S_x^i = elastic section modulus of section used for ith rigid frame element, w_{rrfi}^{rfi} = generic variable affecting performance function of ith rigid frame element; and $rrfi$ = total number of variables affecting limit state of ith rigid frame element. For example, if an allowable stress design (ASD) approach is utilized, a flexural failure limit state can be written as:

$$LSRF_{i1} = F_y S_x^i - M_{\max}^i \tag{12}$$

where, $LSRF_{i1}$ = first limit state of ith rigid frame element, F_y = yield strength of steel used, S_x^i = elastic section modulus of section used for ith rigid frame element, and $M_{\max}^i$ = maximum bending moment applied on ith rigid frame element. On the other hand, a shear failure limit state is written as:

$$LSRF_{i2} = \tau_y A_w^i - V_{\max}^i \tag{13}$$

where, $LSRF_{i2}$ = second limit state of ith rigid frame element, τ_y = shear yield strength of steel used, A_w^i = web area of ith rigid frame element section, and $V_{\max}^i$ = maximum shear force applied on ith

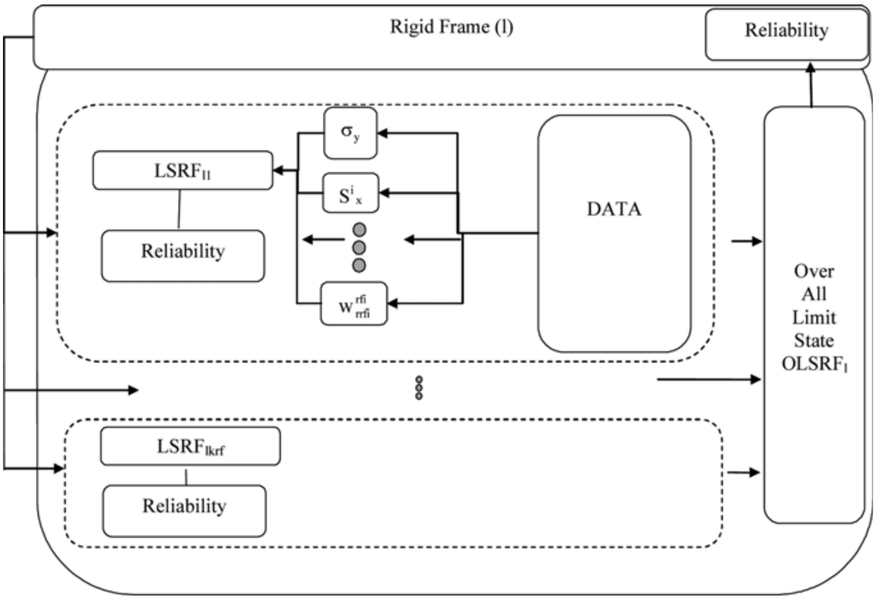

Fig. 6 Block diagram of rigid frame component

rigid frame element. Similar limit states could be established for each individual failure mode, outlined in the design code.

Fig. 6 defines a model for the rigid frame component. The model is built using the individual potential failure modes for appropriate element type, i.e., beam or column. Such models are employed in the evaluation of the reliability assessments of each individual element. The overall reliability of the rigid frame component can be expressed as;

$$OLSRF_i = OGRF_i(LSRF_{i1}, LSRF_{i2}, \ldots, LSRF_{ikrf}) \tag{14}$$

where, $OLSRF_i$ = overall limit state of ith rigid frame element, $OGRF_i(.)$ = overall performance function of ith rigid frame element, and $LSRF_1$, $LSRF_2$ and $LSRF_{ikrf}$ = potential limit states of ith rigid frame element, and $ikrf$ = total number of potential limit states of ith rigid frame element.

3.2 System level

Once the component level of any given system has been defined, the system level, which is a collection of undelying components, can be formulated. Since the objective of such model is the performance of a reliability assessment of the system, the identification process shall be defined in a limit state format. In other words, the system shall be defined as a collection of potential failure modes, each of which relates to some or all of the underlying components. For small and simple systems, it is quite straightforward to identify such potential failure modes. However, for complex and large systems a structured approach needs to be adopted in the identification of all potential failure modes. Fault tree analysis is one known approach to identify all potential causes of a top failure event (Ang and Tang 1975a,b, Haldar and Mahadevan 2000, Nowak and Collins 2000). Fig. 7 shows a fault tree model for the failure of the smart rigid frame. The model outlines the

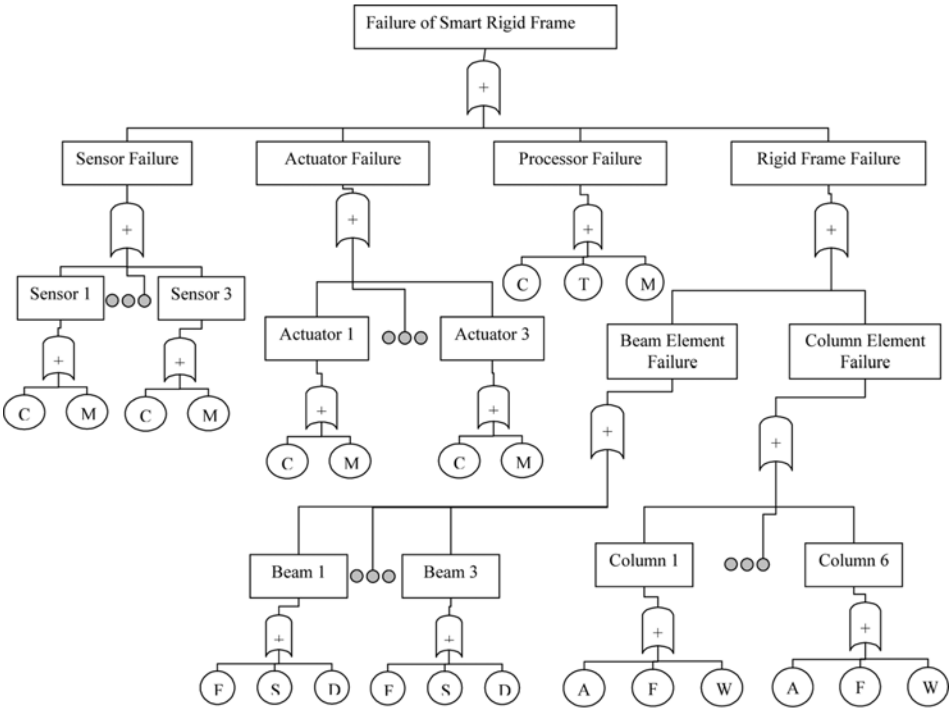

Fig. 7 Fault tree model of smart rigid frame

Table 1 Failure mode symbols

Symbol	Failure mode
C	Crash Failure
M	Malfunction Failure
T	Shut Down Failure
F	Flexural Failure
S	Shear Failure
D	Excessive Deflection Failure
W	Sway Failure
A	Axial Failure

interrelations among the individual failures of all underlying components. The plus sign symbol, shown in the model, reflects a union relationship, i.e., the failure of the upper level requires the occurrence of any of the lower level events. In reference to the model, the failure of the smart rigid frame would occur if any of the following failures occurred; sensor failure, actuator failure, processor failure or rigid frame failure. Similarly, each individual component failure is expressed, as indicated earlier, in terms of potential failure modes. In case of the rigid frame failure, it is further broken down into the failure of any of its underlying elements, i.e., beams or columns. Finally, the failure of each element is expressed as the occurrence of any of its potential failure modes. The letters identified in the circled symbols indicate the type of failure expected, which is defined in Table 1.

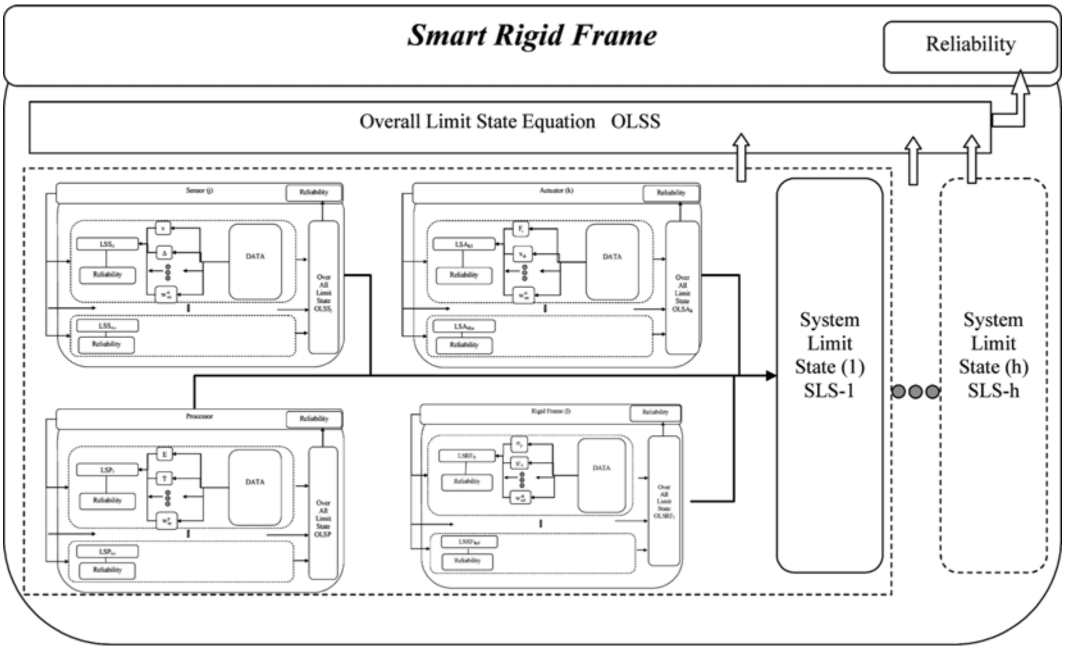

Fig. 8 Block diagram of smart rigid frame model

Fig. 8 shows a block diagram of the proposed system model, whereby the building blocks of such a model are the individual System Limit States (SLS-*i*). Each potential System Limit State defines a failure condition that involves some or all of the underlying components, as indicated by the fault tree model. A system limit state is formally expressed as:

$$SLS - i = SG_i(SF_j, AF_k, PF, RF_1) \tag{15}$$

where, *SLS-i* = system *i*th limit state, SG_i (.) = system *i*th performance function, SF_j = failure of *j*th sensor, AF_k = failure of *k*th actuator, *PF* = processor failure, and RF_l = failure of *l*th rigid frame element. For example, one potential limit state could be the failure of sensor (3), and the failure of actuator (2), or the failure of the beam (1). This limit state could be expressed in the format identified in Eq. (15) as follows;

$$SLS - 1 = SG_1((SF_3 \cap AF_2) \cup BF_1) \tag{16}$$

where, SF_3 = overall probability of failure of sensor (3) evaluated by employing the overall limit state expression identified in Eq. (3), AF_2 = overall probability of failure of actuator (2) evaluated by employing the overall limit state expression identified in Eq. (8), and BF_1 = overall probability of failure of beam (1) evaluated by employing the overall limit state expression identified in Eq. (14).

In order to evaluate the probability of failure of the system *i*th limit state, one has to be able to evaluate the probability of failure of all included components first. Fig. 8 outlines a sample system limit state, which is a function of all basic components, i.e., sensors, actuators, processor and the rigid frame elements. The probability of failure of each individual component, however, is evaluated based on all potential failure modes for that component, as outlined above. Each labeled block, in the system limit state, represents the component model in terms of its potential failure modes. Finally, if each individual system limit state is defined, an overall limit state expression could be developed in order to evaluate the overall reliability of the system. The overall limit state expression can be written as;

$$OSLS = OSG(SLS\text{-}1 \cup SLS\text{-}2 \cup \ldots \cup SLS\text{-}h) \tag{17}$$

where, $OSLS$ = overall system limit state, $OSG(.)$ = overall system performance function, $SLS\text{-}i$ = system ith limit state and $\cup$ = is a union operator. Eq. (17) simply states the fact that the failure of the overall system could occur due to any of the identified system limit states. This type of connectivity is indicated from the fault tree model that is shown in Fig. 7.

4. Conclusions

In this paper, a system model for reliability assessment of a smart rigid frame is outlined. A three-story, single bay, smart rigid frame, equipped with four sensors, three Magneto-Rheological dampers and an auto-adaptive processor unit are considered. The limit states of such a system are utilized as the building blocks of the proposed model. The selection of suitable building blocks is a crucial step in the system identification procedure. The system is broken down to its basic components, namely, sensors, actuators, processor, and beam/column elements. Each individual component was further expressed in terms of its potential failure modes. A limit state expression is employed to represent each potential failure mode. The system was then expressed in terms of potential failure combinations of individual components. A fault tree model was developed in order to identify all potential failure combinations of underlying components. An overall reliability assessment could be developed by exploring such potential combinations as indicated by the fault tree model. The development of the individual limit state equations for selected sensors, processors and actuators is currently underway. A general framework for the evaluation of the overall reliability of a smart structural system is also in progress.

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