Prognosis and Health Management using Energy Activity

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Abstract: Accurate detection of faults in a dynamic system is very beneficial as this information can be used in wide variety of ways by the machine operators or designers. This advantage becomes many folds when regarding the future condition i.e. time to failure, named remaining useful life, is available in addition to that of the present condition. Thus, prognosis is one of the most useful tools to improve the working of a machine as many critical decisions can be made. Prognosis can be critical for applications which risk loss of life and property. In this paper, a hybrid method, utilizing bond graph and artificial intelligence, is proposed for achieving fault diagnosis and prognosis. The Bond Graph model is used to calculate Energy Activity, which is used as a common metric for both diagnosis and prognosis. While diagnosis is achieved by using Energy Activity with neural network and short time fourier transformation, prognosis is achieved using mathematical form of Energy Activity. The proposed method is checked by simulation on a spring mass damper system undergoing a fault.

Keywords: Bond Graph, Prognosis and Health Management, Energy Activity, Maintenance

1. INTRODUCTION

Maintenance is one of the most important and one of the most under appreciated aspect for the proper operation of any system. In most of the industries, the maintenance strategy falls under one of the two approaches i.e. Preventive maintenance and Corrective maintenance. Under the preventive maintenance approach, maintenance action is implemented after some fixed intervals of time. The objective in such approach is to perform maintenance action before the occurrence of the failure itself. On the other hand, in corrective maintenance approach, the maintenance action is performed once the system has failed. Both the above mentioned approaches have certain disadvantages. While there is a high monetary cost associated with the preventive maintenance due to frequent maintenance actions, high cost is also associated to corrective maintenance approach on account of the loss in working time of machine under failure. Therefore, a new Condition Based Maintenance approach is gaining popularity. Under this approach, the operating conditions of the system are continuously monitored. Whenever fault (not failure) is detected, i.e. system is in a degraded state but still in a functioning condition, further action is suggested by the monitoring system. Condition based maintenance is achieved using Prognostics and Health Management (PHM). The sequence of steps involved in PHM are shown in figure 1 and are in detail as follows Atamuradov et al. (2017):

- *Data processing*: System is characterised by a set of physical values that have to follow predefined trajectories expressed by system input-output relations. Data processing extracts from the sensor signals the relevant information used for further analysis and system control.
- *System health estimation*:System health estimation groups the FDI procedures allowing to estimate the health state of the system (faulty or non faulty). These procedures consist in three steps.
  - · *Fault Detection*: Fault detection investigates the consistency between the actual values of the system outputs provided by the sensors and the predicted values of these outputs obtained from the reference system model.

    A fault is detected as soon as this consistency, expressed on the form of mathematical expressions called residuals, is not respected. Equation 1 gives the general form of a residual where $Y_{measured}$ is the actual value of the system output Y and $Y_{estimated}$ is its estimated value predicted by the model or other reference tables.

$$Residual = Y_{measured} - Y_{estimated} \qquad (1)$$

  - · *Fault Isolation*: Fault isolation consists in finding the faulty component using sensor information and, for examples, logic procedures, signal processing or reference tables.
  - · *Diagnosis*: Diagnosis gives an interpretation of the nature and the cause of the fault.
- *Prognosis*: Prognosis is a dynamic estimate of the degradation of the system. This deals with calculation of the End of Life of a system, a point in time at which the fault increases to its maximum limit resulting in system failure. Remaining Useful Life (RUL) of the system is expressed by equation 2 where $t_{failure}$ is the predicted time where the system cannot continue

to operate due to complete failure and $t_{current}$ is the time at which the RUL is calculated.

$$RUL = t_{failure} - t_{current} \tag{2}$$

This RUL is represented on figure 2

- *Decision making*: Detecting the occurring fault and estimating the RUL of the system can help in both protecting the system components, the system environment and/or ensuring the continuity of service when possible.

  Decision making can range from immediate human intervention to implementation of fault tolerant control by putting in priority users safety measures, system protection and continuity of service.

Prognosis is the most important step of PHM and has attracted the attention from researchers all over the world. The quick and accurate prediction of RUL is important because the subsequent action after the appearance of fault depends on the RUL. The various approaches introduced for prognosis fall under one of the following:

(1) *Data-based approach*
(2) *Model-based approach*
(3) *Hybrid approach*

For data driven approach Sutharssan et al. (2015), the failure history from previous failed operation condition is utilised for calculation of the RUL. Various mathematical and statistical techniquesSi et al. (2011) can be used achieve prognosis. Neural Networks Byington et al. (2004), Fuzzy Logics, Principal Component Analysis Zhang et al. (2006), Hidden Markov model Peng and Dong (2011) etc or their combination Jahromi et al. (2016) can also used to improve results. However, for certain applications, especially for critical systems like space shuttles, nuclear plants etc., it is not easy to have a large database of failure information as every system failure can be accompanied by huge loss in life and property. In such systems, it is always preferred to use model-based approach. In model-based approach the system behavior is known with accurate mathematical equations. The mathematical model can be used with various mathematical tools of ways like dissociation Chelidze and Cusumano (2004), particle filterJha et al. (2016), similarity Roychoudhury and Daigle (2011), neural network Singh et al. (2018). The availability of mathematical equations can allow faster diagnosis and prognosis without the need of a failure database. The accurate model parameters are seldom known for physical systems, hence hybrid approaches are commonly employed for prognosis. Hybrid Neerukatti et al. (2014) approaches are a combination of data-based and model-based approaches. The voids observed in the model-based techniques are filled using data, and hence a combination model is used for prognosis.

Modern physical systems contain subsystems of different domains like electrical, rotational, hydraulic etc. The management of interaction between such subsystems is a tedious task. Energy being the common currency of exchange between sub-systems, makes it an ideal parameter for study and analyses of complex systems. Energy has been studied in various forms like Analytical Redundancy Relations Bouamama et al. (2003), Energy Activity IndexSingh et al. (2018), Junction Activity Jha et al. (2014), Energy Efficiency Hoang et al. (2017) for various stages of Prognosis and Health Management. However, an energy based framework for both diagnosis and prognosis can be of great interest. In this paper, such a framework is developed using Energy Activity. Energy Activity is chosen because the increasing nature of energy activity has potential to capture minute faults over time. The occurrence of the mathematical singularities due to inherent nature of Energy Activity are avoided by using Neural Networks instead of mathematical evaluation. Energy activity is well developed for application using bond graph. Therefore, the current framework is developed using bond graph model. Also, bond graph has been used previously for integrated diagnosis and prognosis frameworks Jha (2015) Yu et al. (2010). Hence, bond graph is a proven tool for such framework.

This paper is organised as follows. Section 1 gives a basic introduction to Prognosis and Health Management and it's various processes. In Section 2 the concept of Pseudo Energy Activity is introduced and developed in the context of bond graph modelling. Section 3 gives the detailed methodology of the using pseudo energy activity for for prognosis and health management. In Section 4, the proposed method is simulated using a spring mass damper system and the simulation results are presented. The paper is concluded in Section 5.

2. PSEUDO ENERGY ACTIVITY FOR PROGNOSIS

2.1 Bond Graph

Bond Graph Mukherjee et al. (2006) is a technique used to model the behavior of dynamic systems. Bond Graph is a component based technique therefore the individual components and subsystems can be easily visualised while modelling the dynamics. This also gives a better understanding of the results. The bond graph technique is based on the law of conservation of energy and therefore used power, i.e. time derivative of energy, to capture the dynamics of the system. As energy is the common currency of exchange among the different domains, therefore bond graph technique is suited for modelling of multi-physics system with a combination of different domains of energy like mechanical, electrical, thermal etc.

In bond graph technique power in every component is measured as a product of an agent bringing about the change, called generalised effort e, and the rate of observed change, called generalised flow f. The components in the system can be either energy storing elements or energy dissipators. Components storing generalised kinetic energy are represented as I elements, components storing generalised potential energy are represented as C elements and the energy dissipators are represented as R elements. The system can also have energy conversion elements i.e. Transformers TF and Gyrators GY. The different components can interact with each other and the system in general, through either a 1 or 0 junction. Components sharing a common 1 junction have same generalised flow whereas those sharing common 0 junction have a common generalised effort. External input to the system can be either an effort source SE or a flow source SF.

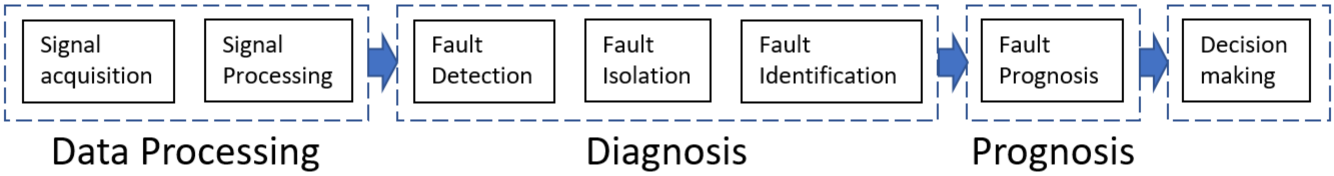

Fig. 1. Prognosis and Health Management process.

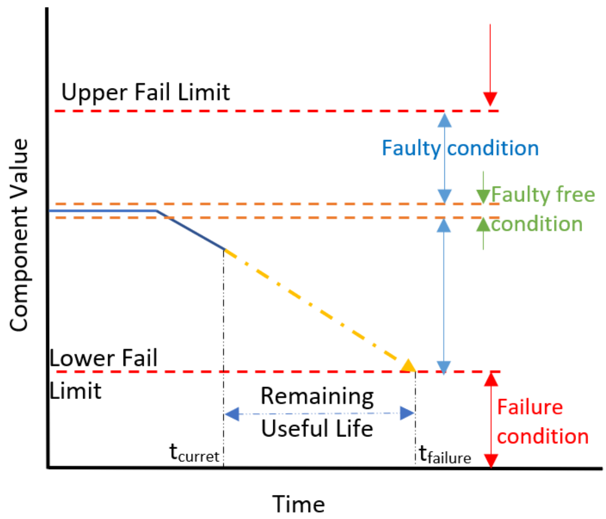

Fig. 2. Extrapolation of Component parameter for Remaining Useful Life

As discussed above, it is very easy to manage individual components when using bond graphs, therefore use of bond graphs is beneficial for the fault diagnosis. Also, the 0 and 1 junctions impose a structural condition on the behavior of on the various components of the system. This condition always represents a physical phenomenon like kirchhoff's law or physical condition like physical junction etc. Hence, the structural nature of bond graph modelling has been successfully used for fault diagnosis Bouamama et al. (2003).

2.2 Energy Activity

All dynamic components, in any dynamic system, irrespective of the domain interact with energy. The components can either absorb energy during certain phase and release the absorbed energy during the other. Some components just dissipate energy. The amount of energy that they interact with depends on the component values of the system. When a system is under fault, the component value, and hence the energy interaction for that of the system component changes. As energy can not be created or destroyed, the whole system experiences a redistribution of energy as a consequence of the fault. Also, for a system to work properly, every component should play it's role in energy interaction within certain limits. Monitoring this energy interaction in the various components of the system can help in PHM. Bond graph being a component based approach is suited for study of such interaction.

This section deals with the introduction to the known concept of Energy Activity and Energy Activity Index. Furthermore the modified pseudo-Energy Activity and pseudo-Energy Activity Index are introduced for utilization in prognosis and health management.

Energy Activity and Energy Activity Index Energy Activity was introduced in Louca et al. (2010) as a tool for physical model reduction. EA is the total energy interaction that a component has with the system over a time period. The major difference between energy and energy activity is that while the energy associated with a component can increase or decrease, the energy activity of the component always increases with time. This makes energy activity a more suited component for prognosis than energy. The equations for energy and energy activity is given by equation 3 and eqution 4 respectively.

$$Energy = \int_a^{a+\Delta t} (Power) dt \tag{3}$$

$$EA = \int_a^{a+\Delta t} |Power| \, dt \tag{4}$$

Energy Activity Index of a component during a time interval is the ratio of the energy activity of that component to the total energy activity of the system during this time. Therefore, energy activity index analysis provides the relative picture of the activity of different components on the system. The expression for calculation of energy activity index of component i in a system with n components is given by equation 5.

$$EAI_i = \frac{EA_i}{\sum_{i=1}^{n} EA_i} \tag{5}$$

Pseudo Energy Activity and Pseudo Energy Activity Index In the context of bond graph, EA is given by equation 6 and 7. Here e and f are the generalized effort and flow respectively.

$$EA = \int_a^{a+\Delta t} |e.f| \, dt \tag{6}$$

$$EA = \int_a^{a+\Delta t} |S.\phi g(S)| \, dt \tag{7}$$

S is the signal input from the system to the component. According to the causality (derivative or integral) associated with the component, S represents the flow or effort input signal. Function g in equation 7 expresses the relation between the component input and output. It corresponds to the physical law applied by the component. It uses the component parameter value ϕ. For the bond graph element R, g is algebraic

$$e = \phi_R f \text{ or } f = \phi_R^{-1} e \tag{8}$$

Consequently, equation 6 and equation 7 can be written as

$$EA = \int_a^{a+\Delta t} |f.\phi_R f| \, dt = \phi_R \int_a^{a+\Delta t} S^2 dt \tag{9}$$

For bond graph element C and I, g is an integral or differential relation since:

$$\begin{aligned} e(t) &= \phi_C \int_0^t f(t)dt \\ f(t) &= \frac{\mathrm{d}}{\mathrm{d}t}(\phi_C^{-1} e(t)) \\ f(t) &= \phi_I \int_0^t e(t)dt \\ e(t) &= \frac{\mathrm{d}}{\mathrm{d}t}(\phi_I^{-1} f(t)) \end{aligned} \tag{10}$$

When a component in a system undergoes a fault, physical law imposed by the component is modified since the parameter value is modified (as example, more energy than expected is dissipated by R element or less energy than expected is stored by C element). Parameter modifications due to component faults are not known in advance. This is the aims of the PHM i.e. to detect, locate and quantify them. In this case, the actual Energy Activity of the component is different of its predicted one. To compare the predicted EA to the actual one, the concept of pseudo-Energy Activity (pEA) is introduced. For calculation of pseudo-Energy Activity, the ideal parameter value θ is used instead of the actual parameter value ϕ. The equation defining pseudo-Energy activity is given by equation 11.

$$pEA = \int_a^{a+\Delta t} |S.\theta g(S)| \, dt \tag{11}$$

Similarly the Energy Activity Index calculated using pseudo-Energy Activity is called pseudo-Energy Activity Index. The expression for calculation of pseudo energy activity index of i^{th} component in a system with n components is given by equation 12.

$$pEAI_i = \frac{pEA_i}{\sum_{i=1}^{n} pEA_i} \tag{12}$$

Hereafter, in this paper, unless otherwise stated Energy Activity and Energy Activity Index refer to pseudo-Energy Activity and pseudo-Energy Activity Index.

Residuals generated from Energy Activity Indexes have inherent characteristics which make them ideal for fault detection or isolation in time domain Singh et al. (2018). However, the mathematical evaluation of the discussed characteristics is not possible due to singularities in the solution. Hence, a neural network approach is suggested.

3. PHM PROCESS USING ENERGY ACTIVITY

A general overview of PHM process using Energy Activity is shown in figure 3. A virtual system in fault-free conditions is simulated in parallel with the actual system. Similar outputs from both the systems are used for the remainder of the process. The outputs from the virtual system are used to calculate the reference Energy Activities. However, for calculation of the Energy Activities associated with real components, the output signals must be de-noised. The energy activity indexes of various components corresponding to the actual and virtual system are calculated and subsequently residuals are generated. The process of filtering can modify signal phase & magnitude. This introduces error in the residuals. These errors can be easily removed by analysing the residuals in frequency domain. As frequency of residual signal changes when system moves from a fault-free state to faulty state, residuals are analysed using Short Time Fourier Transformation technique. The results from Short Time Fourier transformation are compared with a pre-trained Neural Network to achieve fault isolation. Once fault isolation is performed, fault prognosis can be performed using mathematical equations. The equations are discussed in detail in the following sections.

3.1 Neural Network

Neural network is trained to use the residuals from Energy Activity Indexes to classify the fault location. The neural network must be trained before the actual application, using the residuals generated from simulation as training data. The process of generation of Neural Network training data is shown in figure 4.

A fault is simulated by changing the value of a component parameter. Therefore to have an exhaustive database, a range of fault for every component is decided. A fault-free system is simulated in parallel with the faulty system. The generated residual is the difference of energy activity indexes from faulty and fault-free system. Fourier transformation is performed on the residuals to have a frequency picture of the residual. The location of the peaks is recorded in the frequency domain. The noisy peaks i.e. peaks at high frequency and low amplitude are removed. The remaining peaks are added to the neural network training data.

The neural network is trained under the following conditions

- At a time only one component can have fault.
- Fault is introduced at the start of the simulation.
- For every iteration the fault magnitude remains the same.

3.2 Fault Isolation

As discussed earlier, for fault isolation, Fourier transformation is performed on the residuals. However, in a real system, fault can occurs after some period of fault-free operation. Hence, the residuals change from zero to non-zero after some time. In such a case, a direct fourier transformation does not properly capture the change in behavior of residuals. Therefore, short time fourier transformation is used. In short time fourier transformation Liu et al. (2016), the residual signal is divided into small windows of equal duration, and subsequently fourier transformation is applied on it. Using the short time fourier transformation,

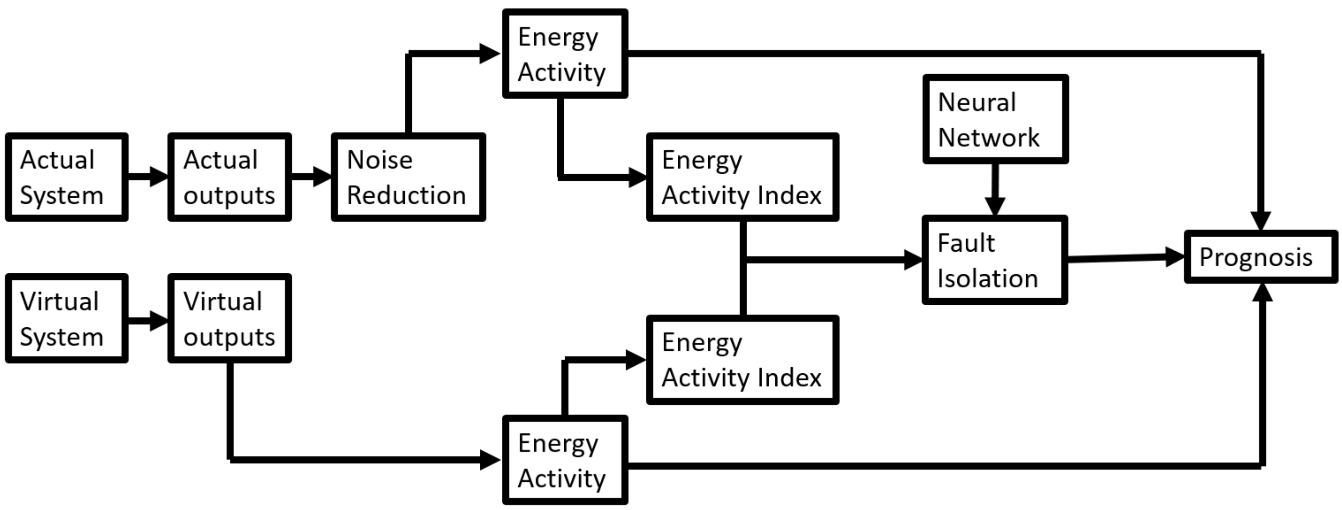

Fig. 3. Generalised procedure.

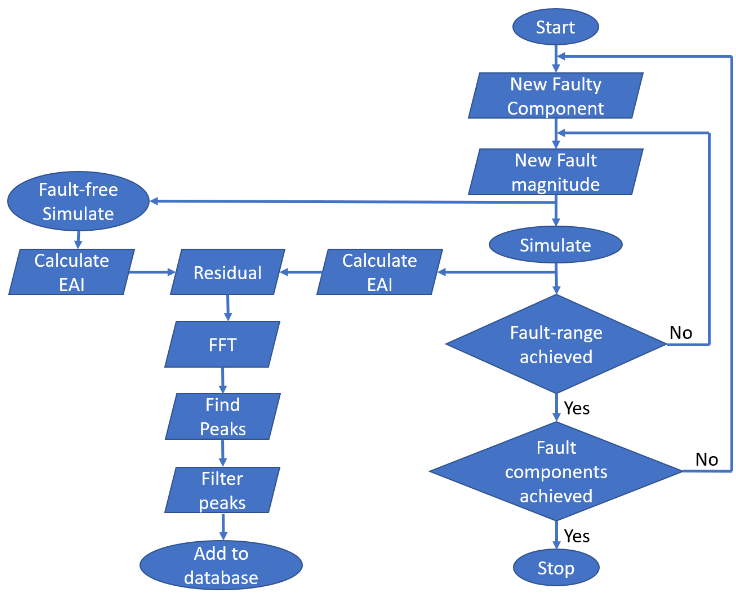

Fig. 4. Neural Network training.

a time frequency map is obtained for the residual signals. The signal processing used for training the neural network is also applied to the results in the time-frequency map.

The window for short time fourier transformation should be equal to the simulation time used for training the neural network. This assures that the neural network is able to recognise the pattern properly. The window of short time fourier transformation should also be more than the time Δt used in equation 11 to calculate the energy activity.

3.3 Fault Prognosis

Once fault isolation is achieved, the mathematical form of Energy Activity can be used to calculate the real variation in the fault parameter, and furthermore the remaining useful life, assuming that the allowable limits of a parameter are known for failure.

In order to estimate the dynamics of the degradation (i.e. the time variation in the value of parameter), the time derivative of the EA is required.

As the fault (degradation) is due to a modification of the value of the component parameters in time, the Energy Activity for a faulty component can be expressed as a function of the component input signals, which itself is a function of the all the component parameters ϕ (considered as time varying) and time t. (See equation 13)

$$EA = f(S(\phi), t) \tag{13}$$

From equation 13 the following can be calculated

$$\mathrm{d}EA = \frac{\partial EA}{\partial S}\frac{\partial S}{\partial \phi}\mathrm{d}\phi + \frac{\partial EA}{\partial t}\mathrm{dt} \tag{14}$$

$$\frac{\mathrm{d}EA}{\mathrm{d}t} = \frac{\partial EA}{\partial S}\frac{\partial S}{\partial \phi}\frac{\mathrm{d}\phi}{\mathrm{d}t} + \frac{\partial EA}{\partial t} \tag{15}$$

$$\frac{\partial \phi}{\partial t} = \frac{\frac{\mathrm{d}EA}{\mathrm{d}t} - \frac{\partial EA}{\partial t}}{2\theta \int_a^b S dt \cdot \frac{\partial EA}{\partial S}} \tag{16}$$

- $\frac{\mathrm{d}EA}{\mathrm{d}t}$ is the time derivative of the Energy Activity calculated from the real system.
- $\frac{\partial EA}{\partial t}$ represents the variation of the Energy Activity only in time, i.e. due to no change in ϕ. This term can be calculated as the time derivative of the Energy Activity of the fault free system.
- $\frac{\partial S}{\partial \phi}$ represents the variation of the input signal of the component due to the modification of component parameter value. As the dynamic model of the component is known as a pre-requisite this value can be calculated easily.
- $\frac{\partial EA}{\partial S}$ depends on the nature of relation g in the equation 7.

For an R-element, g is algebraic and from equation 9

$$EA = \theta_R \int_a^b S^2 dt \tag{17}$$

Therefore,

$$\frac{\partial EA}{\partial S} = \theta_R \int_a^b \frac{\partial S^2}{\partial S} dt = 2\theta \int_a^b S dt \tag{18}$$

For C and I elements, the calculation of $\frac{\partial EA}{\partial S}$ is more difficult due to the forms of expressions in equation 10.

Equation 16 can now be integrated as shown in equation 19 to have an estimation of fault parameter from sensor data.

$$\phi = \int \frac{\mathrm{d}\phi}{\mathrm{d}t}\mathrm{d}t + \phi_{ideal} \tag{19}$$

The continuous calculation can then be extrapolated according to a know degradation trend. If a degradation trend is unknown, then a polynomial equation can be used to extrapolate the component value. The Remaining Useful Life can be easily calculated if the safe limits of the component values are known beforehand (figure 2). The trend of component degradation is extrapolated to find the point in time when the component value reaches the allowable limit. This point is called the End of Life. The time difference between present and end of life is the Remaining Useful Life.

4. APPLICATION

4.1 System

In order to check the proposed methodology, a simulation is performed using a simple spring-mass-damper system. The system is shown in figure 5. The pre-requisites i.e. the dynamic model using bond graph, and the ideal & and safe working limits of components are given by figure 6, and table 1 respectively.

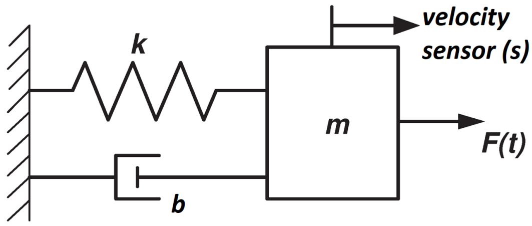

Fig. 5. Spring Mass Damper System.

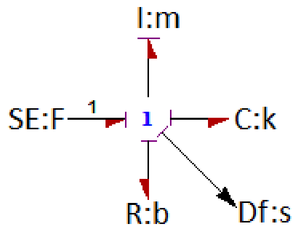

Fig. 6. Bond Graph of Spring Mass Damper System.

4.2 Neural Network Training

The first step is to pre-train a neural network. The procedure explained in figure 4 is used to train the neural network. The fault range for training the neural network are those given in table 1. For creating the training dataset, the fault range for every component is divided into 20 equal intervals. The residual defined in equation 1 is calculated at the I element i.e. mass. The frequency-amplitude graph used for training of neural network is shown in figure ??. The x-axis represents the frequency in Hz and the y-axis represents the amplitude. The cross marks of different colors represent the peaks observed at different magnitudes of faults. From the figures it is evident that peaks locations can provide a unique fault signature to the components and can be easily used to train a neural network. A default pattern recognition/classification algorithm provided in MATLAB is used with 5 hidden layers. 70% of the available database is used for training while 15% of database is used for validation and testing each.

4.3 Fault Isolation

During the simulation, a fault condition is indicated by deviation in the component value from ideal. For the purpose of the simulation, the fault magnitude is modelled as change in component value. Fault is introduced in the spring. The variation in spring stiffness is shown in figure 9. A fault is introduced at 5 seconds which continues to decrease the spring stiffness. At 50s from the start of simulation, a corrective action is simulated and spring stiffness starts to increase to recover its initial value at 100s. The Time-Frequency map obtained from the Short Time Fourier Transformation is applied on the obtained

Table 1. Ideal value of system components

Element	Value in SI	Lower limit	Upper limit
Force	10		
Spring stiffness	100	85	105
Mass	10	9	11
Damping coefficient	0.5	0.4	0.6

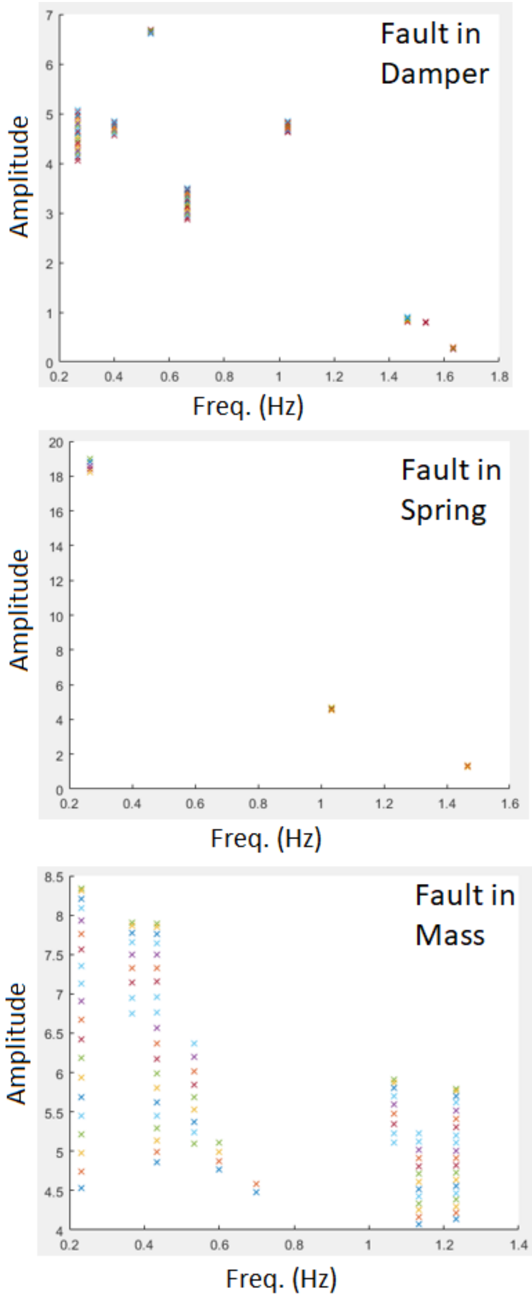

Fig. 7. Neural Network Dataset.

residual. The Time-Frequency map is shown in figure 8. The data entries corresponding to the each time interval are given as input to the neural network trained in the previous step. The neural network is able to correctly predict the fault location as spring.

4.4 Fault Prognosis

The equation 16 is used for evaluating the spring stiffness change rate. The change in spring stiffness ϕ introduces a change in the damper input S, which affects the Energy Activity. The calculated stiffness change rate is passed through a median filter in order to remove sharp peaks due to numerical anomalies. The stiffness change rate after filtering is shown in figure 10. This change rate can be integrated to find the actual spring stiffness. The calculated variation of spring stiffness is shown in figure

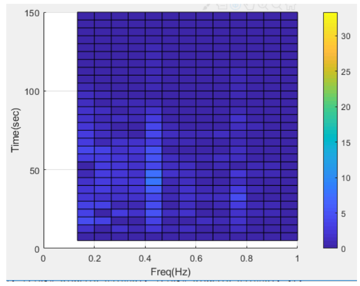

Fig. 8. Time-Frequency map of Short Time Fourier Transformation.

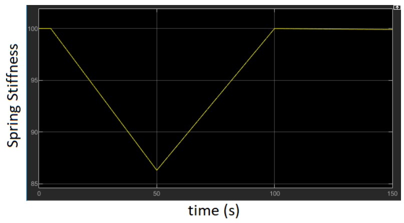

Fig. 9. Fault as a variation in spring stiffness.

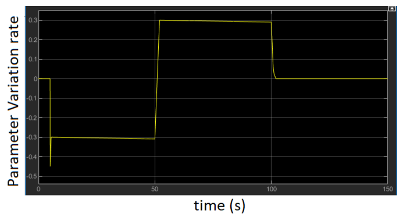

Fig. 10. Calculated Parameter variation Rate.

11. The error in the calculated spring stiffness is shown in figure 12. From the figure it is evident that the spring stiffness is calculated with good accuracy.

At any time when the fault is observed the trend of the parameter variation can be extrapolated using a polynomial equation. For the current example a first order polynomial is used. The point of failure a.k.a. End of Life is reached when the extrapolation trend reaches the allowed limit of the component value. The Remaining Useful Life is continuously monitored. Once the corrective action is applied the calculation of Remaining Useful Life is continued. This represents the amount of time for which the corrective action can be applied before the component value overshoots the allowable limits. Calculation of End of Life is shown in figure 11.

Table 2. Calculated End of Life

Cause of variation	End of Life Time
Fault	55s
Corrective action	113s

5. CONCLUSION

In this paper a model based method for Prognosis and Health Management is proposed using Energy Activity. Both the diagnosis and prognosis processes are completed using variants of Energy Activity as a metric. Diagnosis

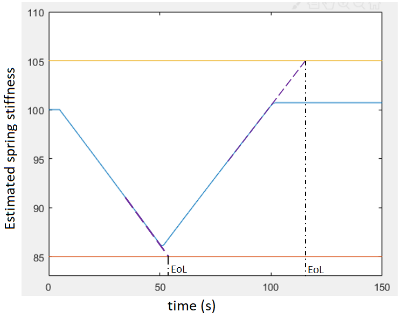

Fig. 11. Calculation of End of Life.

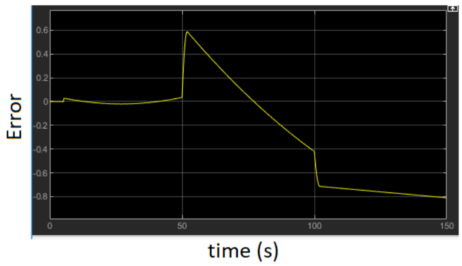

Fig. 12. Error in calculated spring stiffness.

is achieved by using a combination of Neural Network and Short Time Fourier Transformation. Given that the dynamic model of the system is known, the neural network is trained using fault simulations and does not require failure data. The prognosis process is completed using the mathematical nature of Energy Activity for energy dissipators. This can also be a limitation for the proposed process as the prognosis process can not utilize the energy storing elements. The proposed method is simulated for finding the end of life of a spring mass damper system undergoing a fault. The method is able to predict the fault location correctly and recreate the parameter values of the component under fault with good accuracy.

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