# Fault Detection of a Linear Friction Welding Production System Using an Analytical Model

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***Abstract*—This paper presents a fault detection and isolation (FDI) model for an industrial Linear Friction Welding (LFW) production machine in Rolls-Royce. The LFW machine is a complex 11 actuator machine which has 6 degrees of freedom. The inplane axis is the most complex axis due to the high power and high dynamic response requirements, necessitating the use of two four-stage servo valves. We adapted a previously proposed model with fault diagnosis techniques to enable fault detection and isolation for the LFW inplane welding axis. This paper will demonstrate the models ability to detect and isolate faults during production, allowing immediate detection - enabling operators or maintenance to utilize the information to effectively get the LFW machine back into production.**

***Keywords-modelling; fault detection; fault isolation.***

## I. LFW INTRODUCTION

Linear Friction Welding (LFW) [1] has been a key technology in recent years for aircraft engine manufacture in both commercial and military market sectors. For joining Blades to Discs (Blisks) [1], LFW is the ideal process for the following reasons:

- LFW is a solid state process which gives reproducibility, and high quality bonds therefore improving performance
- More cost effective than machining Blisks from solid billets
- Blisks enable up to 30% weight saving over conventional rotors
- LFW enables hollow bladed Blisks
- Dissimilar materials can be joined for optimised blade and disc properties

The process can be divided into six phases: *contact* - initial advancement of actuators seating the blade onto the disc stub and applying a seating force, *ramp up* - blade oscillations start to occur, *conditioning* – maintaining the oscillations to enable frictional heat to build up, *burn-off* – material deforming plastically under compression, *ramp down* – blade decelerated to a static position, and *forging* – allowing the weld to complete under a constant pressure.

Fig. 1 outlines the process phases:

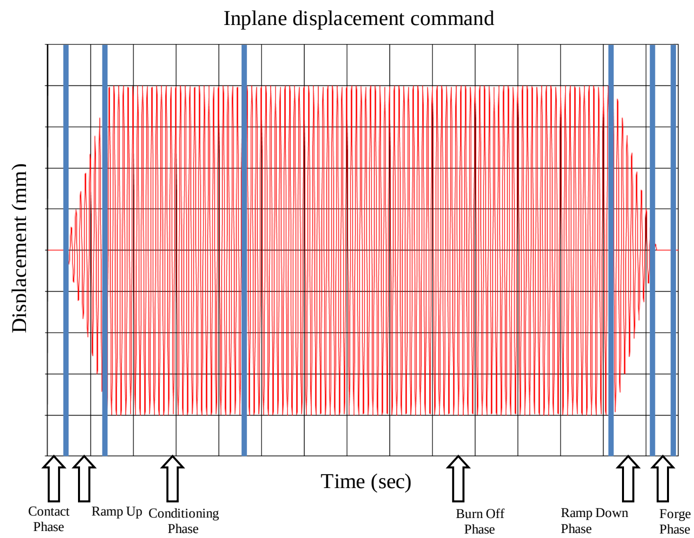


Figure 1 - LFW Process phases

Rolls-Royce's LF60 is a linear friction welding system that is designed to weld Blisks in a production environment. The system uses a combination of high performance, high accuracy servo-hydraulics to produce oscillatory motion between the components which creates frictional heating, and a forging force sufficient to produce a high strength and geometrically precise bond.

Faults occurring on the LF60 can lead to system downtime and the scrapping of components [2], both of which could lead to a monetary loss for the business. In order to reduce the likelihood of these issues a novel method of redundancy has been placed on the machine, with no additional sensors or hardware needing to be installed. Analytical redundancy in detecting faults has then been applied to the system.

Section 2 introduces the LFW machine and gives an overview of the modelled system. Section 3 reviews residual generation methods applicable to this work and section 4 outlines the chosen residual generation and evaluation methods for the FDI system. Section 5 evaluates the FDI model using two actual production fault cases. Section 6 concludes this paper.

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## II. FAULT DETECTION INTRODUCTION

Over the years different computer based diagnosis techniques have been tried and tested in a number of different domains. For the simpler and well understood systems, techniques such as decision trees, fault directories, and probability theory have been successfully applied [3, 4]. When applying these techniques with more complex systems, the accuracy of results reduces resulting in incomplete and inconsistent diagnosis. This is due to the fact that a high number of interactions could exist, therefore more complex techniques have been developed and used.
More complex techniques such as artificial intelligence have been used in the fault diagnosis area, but limitations such as incompleteness and inconsistencies in knowledge, knowledge extraction, and the dependency of the extracted knowledge exists [5]. To reduce these limitations fault diagnosis by the use of model-based techniques was approached, this involves capturing knowledge about the structure and behavior of the system, and the key system interactions. Simulating the knowledge alongside the system can then be used to predict the system behaviour, and identify when a fault could occur or diagnose it. This is done by the model generating the systems nominal behaviour, and any deviations identified.

Model-based fault detection and diagnosis/isolation (FDI) techniques have been researched widely in the literature, examples being [6-10]. This involves creating a residual signal by comparing the systems actual output signal and the estimated one from a nominal system model, once created this residual signal can be used as the indicator of abnormal system behavior. An example of residual indication can be seen in Fig. 2. As the error occurs in Fig. 2 the residual in a) appears out of its threshold, in b) there is a frequency change but the majority of the residual stays within the threshold. There is a threshold present due to system modeling uncertainties and noise. Fig. 2 identifies that faults can be detected but not simply by residuals appearing out of tolerance.

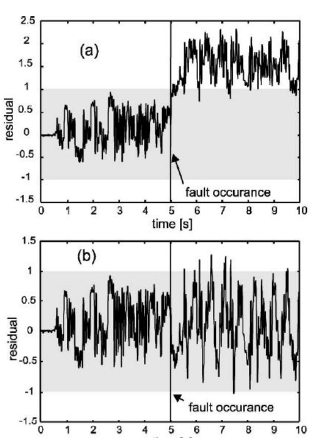


Figure 2 - (a) Detection of a sensor offset fault, (b) Detection of a sensor gain fault. [9]

FDI focuses on the use of fundamental knowledge to achieve efficient and effective diagnosis. Models of the correctly functioning system which can generate the expected system behavior are used to express the fundamental knowledge. Comparing the systems behavior with the models behavior can give the ability to derive possible faults, but the fault detection accuracy depends greatly on the existence of a good system model [11].
Other FDI techniques exist such as knowledge based methods [12] which don't involve an analytical model but are data-driven and knowledge based techniques able to estimate the system dynamics. Signal processing techniques in the time-frequency domain can also be applied to detect faults. Some examples of these are spectrogram and scalogram [13], and wavelet decomposition [14].

A fault can be defined as a departure from an acceptable range of an observed variable or a calculated parameter associated with a process [15]. The underlying cause of this abnormality is called the root cause. With increased systems complexity it is becoming difficult for human operators to continuously diagnose systems, manage system degradation, parameter drift, and component failures. This difficulty is compounded by production pressures, the amount of system variables, and incomplete or unreliable data. FDI deals with timely detection, and diagnosis of abnormal system behaviour. Once detected the human operator is able to take action accordingly.

A model of the LF60 Inplane actuation system has been developed in [16], fault detection methods have been placed onto the model to enable detection and isolation for faults which have previously occurred on the system.

## III. THE LF60 LINEAR FRICTION WELDING MACHINE

Each machine axis on the LF60 is independently controlled using a combination of PID and Amplitude and Phase control (APC). The six main degrees of freedom are referred to as inplane, forge, hade, roll, pitch and yaw. The inplane actuator, which is driven by two four stage valves, oscillates the blade tangentially to the disk. Forging pressure is obtained by a combination of four PID controlled hydrostatic actuators. The six hade actuators restrain the unwanted movement in the other degrees of freedom [17].

A CAD picture of the LF60 inner cage showing the actuator attachments can be seen in Fig. 3.

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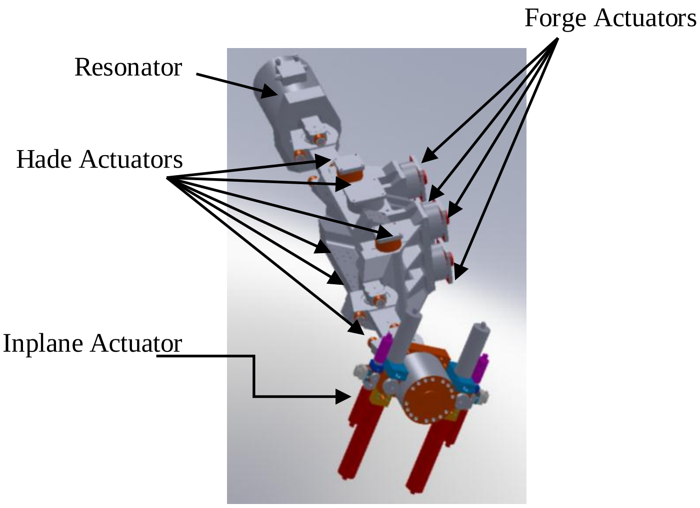


Figure 3 - Picture of the inner cage with actuators attached

The inplane actuation system provides the oscillating motion. This is the most complex system on the machine and therefore the one where the majority of faults occur [2]. It is driven by two 4 stage servo valves. Each one has a pilot two stagevalve rated at $6.31\text{x}10^{-5}\text{m}^3/\text{s}$; this drives the 3rd stage $2.52\text{x}10^{-3}$ $\text{m}^3/\text{s}$ spool which in turn drives the 4th stage $2.52\text{x}10^{-2}$ $\text{m}^3/\text{s}$ spool.

Fig. 4 shows a front view of the inplane servo valves.

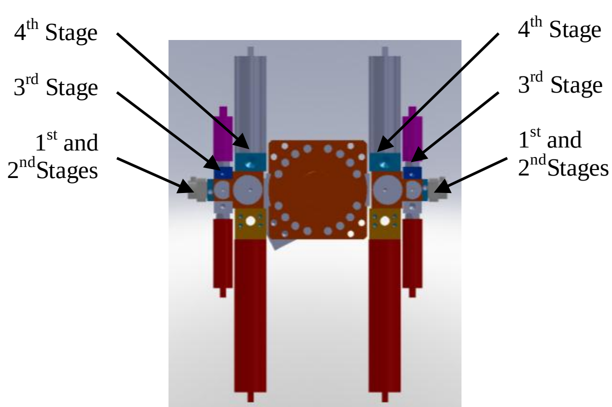


Figure 4 - LF60 4 stage inplane Valves arrangement: front view

The 4 stage servo valve works by the initial first stage torque motor controlling flow via a nozzle-flapper arrangement. The 2nd stage has a mechanically feedback spool linked to the first stage by the feedback spring. The 3rd stage spool, with electronic position feedback, acts as a flow amplifier to the 4th stage, which also has electronic closed-loop control of the spool position. The modelled system in [16] models important factors as outlined in [18] which include fluid compressibility, variable cylinder oil volumes, internal cylinder leakage, cylinder cross-port bleed, valve orifice pressure-flow characteristic, valve overlap, valve body pressure drop, manifold pressure drop and oil volume, valve spool dynamics, maximum valve opening, valve spool slew rate limit, friction, and geometric properties.

## IV. Residual Generation

A number of fault detection approaches exist in the literature. A classification of these different approaches can be seen in Fig. 5.

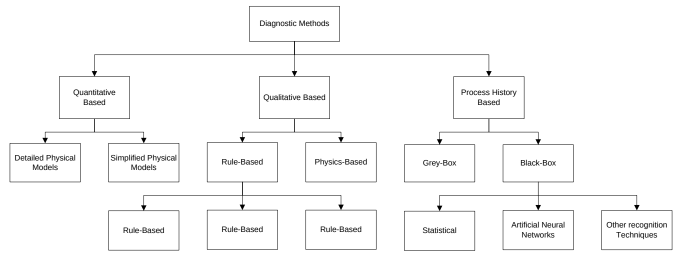


Figure 5 - Classification of the diagnostic system [19]

Quantitative based diagnosis methods involve creating analytical redundancy with the use of physical models to generate residuals that can be used for isolating process failures. These can be detailed or simplified physical models.

Qualitative based diagnosis methods can be rule based, or qualitative physics based. Rules based systems involve systems derived from expert knowledge, first principles, or limits checks.

Process history based diagnosis methods are used when a priori knowledge of the process is not known therefore input-output (black box) relationships are developed using statistical, neural network, or similar pattern recognition techniques. Grey box methods use process data to determine model parameters by using mathematical terms.

Given the availability of a system model (developed and validated in [16]) the diagnosis system used will be qualitative based, detailed physical modeling. A number of model-based fault diagnosis methods can be found in the literature [7, 8, 19]. The main two are parity equation methods and observer based approaches which are discussed in the following subsections.

### *A. Parity Equation Methods*

The Parity Equation Method involves providing a proper check of the parity (consistency) of the measurements for the monitored system first proposed by [20]. Mathematical models describing the relationships between system variables are used to describe the input-output or space-state characteristics of the system, the rearrangement of these gives the parity equations [19]. Output of the parity equation in theory should be zero mean, but in reality due to model inaccuracies, measurement and process noise the output will be nonzero. Parity methods are similar to observer methods but usually designed more intuitively. Fig. 6 shows two methods for parity generation, an output error method and the equation error method.

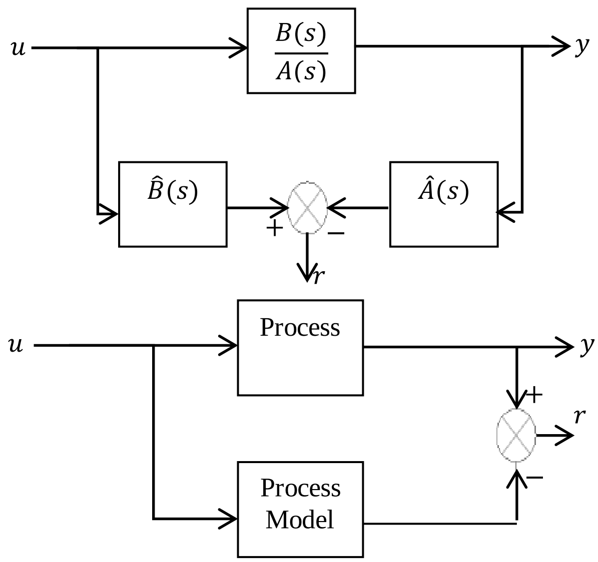


Figure 6 - Parity equations for fault detection: Equation error method (upper), Output error method (lower) [21]

*B. Observer approaches*

Reconstructing the outputs of a system from measurements using the estimation error with observers or Kalman filters is another commonly used approach for fault diagnosis [22]. With the observer approach the estimation error can be considered as the residual, in order to detect and isolate faults. For stochastic systems, the Kalman filtering technique can be used, which enables noise to be factored into the approach [23]. State estimation is improved with the use of Kalman filters due to the processing of all available measurements regardless of precision to estimate the current variable of interest.

For example, take the system state and measurement equations (1) and (2) respectively:

$$\dot{x} = Ax + Bu + Gw \tag{1}$$

$$y = Cx + Du + Hw + v \tag{2}$$

$u$ is the system input, the process noise is represented by $w$, and the measurement white noise is represented by $v$ with $E\ (ww^T) = Q$, and $E\ (vv^T) = R$. The state and estimation noise is uncorrelated i.e. $E\ (wv^T) = 0$. The Kalman filter equation can provide the optimal estimate of $y$ termed $\hat{y}$:

$$\dot{\hat{x}} = A\hat{x} + Bu + L(y - C\hat{x} - Du) \tag{3}$$

$$\hat{y} = C\hat{x} + Du \tag{4}$$

The weightings for $Q$ and $R$ are chosen by trading off fault sensitivity to the likelihood of false alarms using engineering experience. Fig. 7 shows the Kalman estimator, which uses the known inputs $u$ and the measurement $y$ to generate the output and state estimates $\hat{y}$ *and* $\hat{x}$. Riccati equations are solved to find the Kalman filter gain $L$.

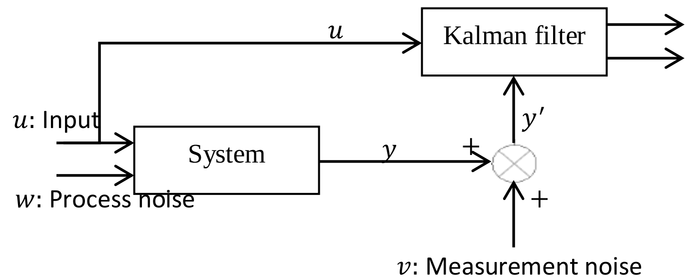


Figure 7–Kalman filter example

*C. Residual Generation Summary*

Each of the discussed approaches involves the creation of a residual (or series of residuals) which need to be analyzed further to provide indication and isolation of faults. Residual evaluation can be done using a constant threshold or an adaptive threshold, constant threshold residual evaluation has a number of disadvantages. Due to the inclusion of noise, or uncertainties in models false alarms can be triggered. Therefore, adaptive thresholds which take into account any modeled inaccuracies or noise can enable better fault detection, and the reduction of false alarms. Given the availability of a validated model, the preferred method of residual generation is the parity method, utilizing the model to compare outputs of the actual system to form residual signals.

## V. RESIDUAL EVALUATION

The fault diagnostic method used in this paper will be of the qualitative based type with detailed physical modelling of the system used to check the consistency of the actual system. The inplane system model developed in [16] will act as an intuitively designed observer providing analytical redundancy. Residual generation will be done by comparing the measured values of the system outputs $y_i$, with the corresponding analytically computed values $\check{y}_i$:

$$r_i = y_i - \check{y}_i \tag{5}$$

Fig. 8 outlines a flow diagram of the fault diagnosis system, indicating residual generation, evaluation in order to detect and isolate faults.

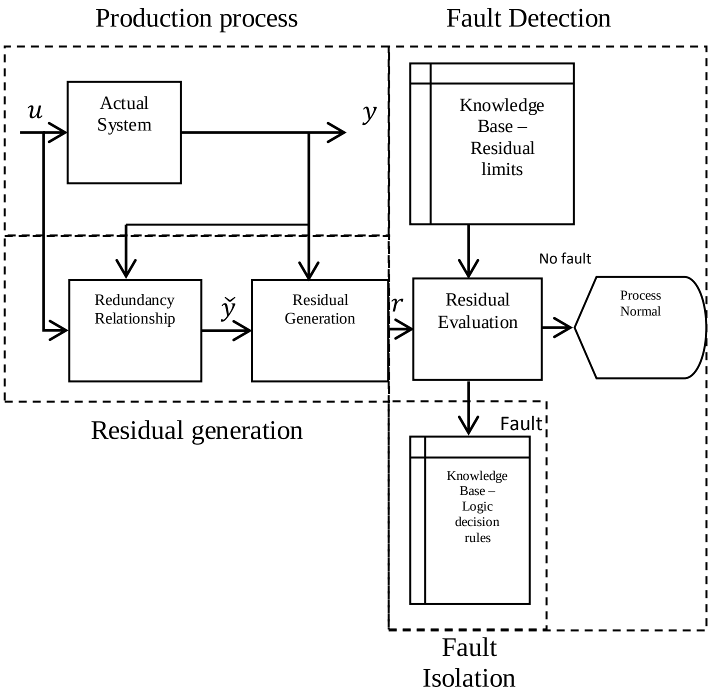


Figure 8–Fault diagnosis flow diagram

Once a residual has been generated, the residual would need to be evaluated to see if a fault is present or not. Various forms of residual evaluation exist in the literature, some of which include residual threshold setting based on the minimal detectable failure [24], posterior probabilities to process information in order to detect faulty circuits [25], the use of fuzzy logic enabling the incorporation of human operator knowledge to interoperate the residuals [26], and probabilistic methods based on likelihood ratios [27]. The residual limits in this research will be created by using previous fault free data executed through the model and used to capture the maximum residual limits for fault free conditions, therefore creating adaptive residual limits defined from previous fault free data, similar as in [28]. Due to the different components welded on the LF60 the residual limits will be component specific, therefore a number of knowledge based data files will be stored which hold residual limits for each residual and component. In the presence of a fault the residual signal will appear high i.e. $r_i = 1$ at that time signal.

The use of adaptive residual limits defined from previous fault free data will allow for any compared signals (model vs. new data) which deviate more than normal, outside of the modeling noise, disturbances, and inaccuracies to be picked up and therefore flagged by the model alerting to a fault, or a change in system performance. On the detection of a residual breach the system will decide on the type of fault, its cause, location, and possible solutions given a knowledge base of logical rules defined from previous fault occurrences. A flow diagram of the logical rules can be seen in Fig. 9. The logical rules would be triggered post residual evaluation of Fig. 8.

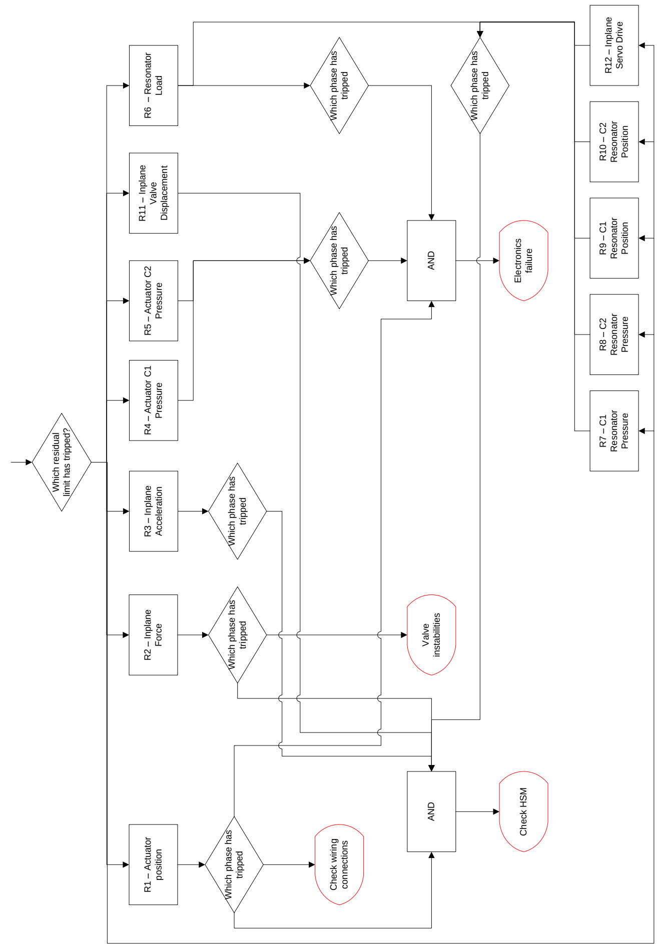


Figure 9– Flow diagram of the *Knowledge Base – Logic decision process*

The following section implements the fault detection scheme and tests it against a number of fault cases.

## VI. Fault Detection And Isolation Case Studies

This section evaluates the FDI with two actual production fault cases.

### A. *Fault case 1: Start-up instability*

The start-up instability shown in Fig. 10 was caused by a faulty relief valve [29], the machine alerted to this issue therefore production was immediately halted (due to Rolls-Royce confidentiality the current machine detection methods cannot be shown). The benefits of a fault detection model would not only be the ability to detect the fault, but also the isolation of the issue by the model informing the operators of its cause and possible solution.

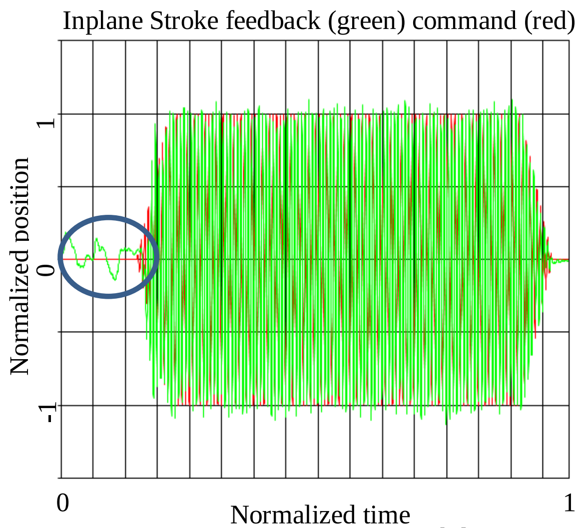


Figure 10 - Start-up instability

Simulating a non-faulty component of the same type through the FDI model yields the outputs shown in Fig. 11. The upper figure compares the actual (fault free) output with the models output, the 2nd figure shows the residual signal and adaptive limits. The 3rd figure indicates any trips of the adaptive residual limit by the residual, and the lower figure indicates detection of a fault on the signal. The fault detection signal only trips if the limit trip signal is triggered and remains triggered for a predefined persistence of 3ms, which is done to further reduce false fault detections.

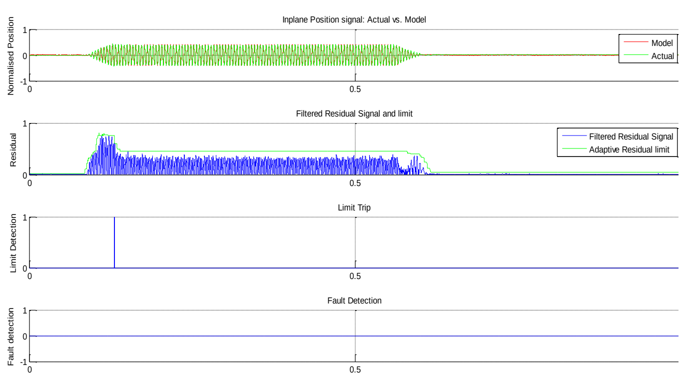


Figure 11 – Start-up Instability, Fault detection with the residual generation method (fault free)

Fig. 12 shows the FDI model simulated with the start-up instability fault. The limit trip signal is tripped immediately and a number of times throughout the simulation – therefore the fault detection signal trips also and stays high from the start of the simulation. This simulation shows an effective capture of the fault using the FDI model. Using the logic previously defined in Fig. 9, the model outputs an indication to the user to "Check HSM" after detecting the presence of the fault occurrence on the relevant signals.

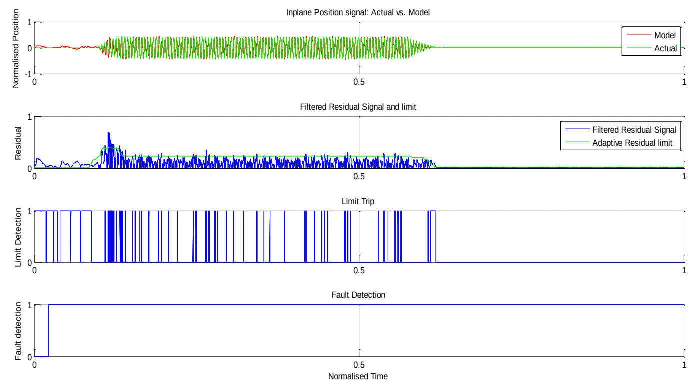


Figure 12 – Start-up instability, Fault detection with the residual generation method (fault)

## B. *Fault case 2: Force holding Instability*

The Inplane force holding instability of Fig. 13 was only captured during manual review of the data post Blisk completion. Therefore the immediate detection of this type of fault would be of great benefit to potentially saving the scrapping of the Blisk and rectify the issue immediately. On simulation of the fault through the FDI model, the model and residual limits are sensitive enough to capture the instability and therefore indicate the presence of a fault, as shown in Fig. 14.

Example of the instability:

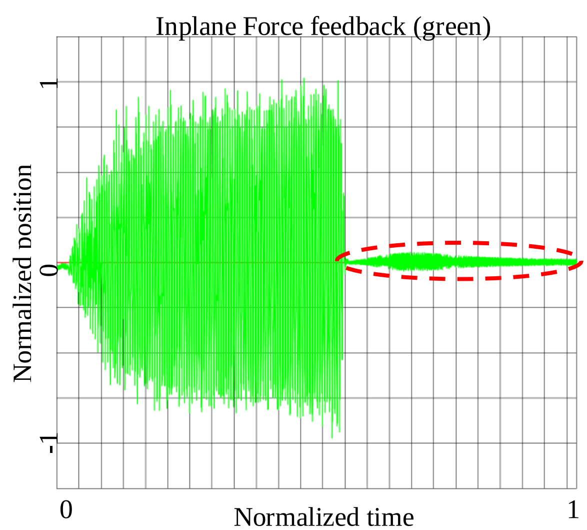


Figure 13 – Force hold Instability

FDI model output simulated with the fault in Fig. 14:

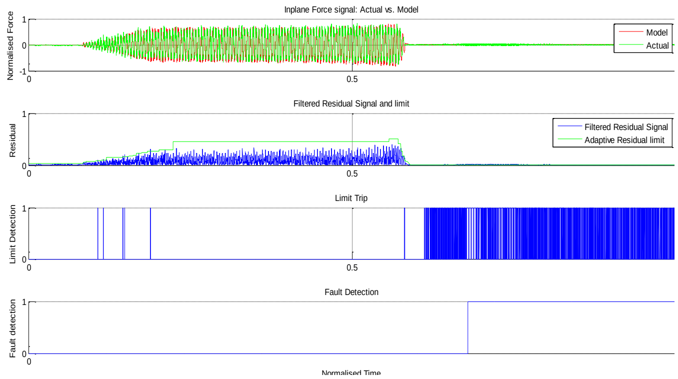


Figure 14 – Force hold instability, Fault detection with the residual generation method (fault)

FDI model simulated with fault free data:

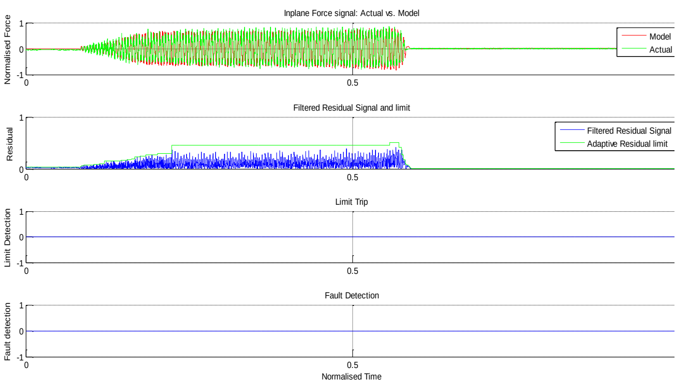


Figure 15 – Force hold Instability, Fault detection with the residual generation method (fault free)

Therefore this fault can be successfully detected and the operator/maintenance engineers notified immediately. A notification of “Valve instabilities” would be displayed post fault occurrence.

Therefore the model demonstrates effective capture of this fault at the first instance of its occurrence, enabling quick detection and isolation of the fault – reducing the potential for scrapping a component.

## VII. Conclusion

A fault detection system has been implemented on a model previously developed in [16]. Case studies of actual production faults have been examined with the FDI model proving the model’s ability in detecting abnormal system behaviour and using a series of logic steps to isolate the fault, its cause, and possible solutions.

The FDI system will be placed alongside the LFW system in order to detect faults upon the occurrence thus providing timely detection and identification, saving the business valuable time and money. Implementing the FDI system will involve careful understanding and integration with the LFW system and its users. This will be accomplished by utilizing the latest soft systems research knowledge.

## Acknowledgment

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## References

1. Linear Friction Welding of Blisks. [online] Available at: <http://www.twi.co.uk/aerospace/welding-of-aircraft-engines/linear-friction-welding-of-blisks/> [Accessed 10 September 2012].
2. G. Colin, "LFW Maintenance Issue Timeline". Rolls-Royce internal Report, 2012.
3. R.L. Flood, and R.C. Ewart, "Dealing with Complexity: An Introduction to the Theory and Application of Systems Science, Second Edition." New York: Plenum Press, 1993.
4. P.B. Checkland and L. Davies, "The use of the term "Weltanschauuug" in soft systems methodology." Jornal of Applied Systems Analysis, Vol. 13, No. 1, pp 109-115, 1986.
5. N.N. Mitev, "More then a failure? The computerized reservation systems at French railways." Information Technology & People, 9 (4), 8-19, 1996.
6. E.L. Russell, L.H. Chiang, and R.D. Braatz, "Fault Detection and Diagnosis in Industrial Systems." Springer, 2001.
7. C.H. Lo, Y.K. Wong, and A.B. Rad, "Model-based fault diagnosis in continuous dynamic systems." 2004, ISA Transactions 43 459-475.
8. R. Isermann, "Model-based fault detection and diagnosis - status and applications." 2005, Annual Reviews in Control 29 71-85.
9. M. Borner, H. Straky, T. Weispfenning, and R. Isermann, "Model based fault detection of vehicle suspension and hydraulic brake systems." 2002, Mechatronics 12 999-1010.
10. J.L. Aravena and F.N. Chowdhury, "Fault detection of flight critical systems." 2001, Proc. 20th Digital Avionics Systems Conference.
11. A. Mirijamdotter, A multi-modal systems extension to soft systems methodology. Doctoral thesis, Lulea Tekniska Universitet, 1998 (1998:06 ISSN: 1402-1544 ISRN: LTU-DT--98/06--SE).
12. S. Oblak, I. Skrjanc, and S. Blazic, "Fault detection for nonlinear systems with uncertain parameters based on the interval fuzzy model." 2007. Engineering Applications of Artificial Intelligence, Volume 20, Issue 4 pp. 503-510.
13. I. Yesilyurt, "The application of the conditional moments analysis to gearbox fault detection - a comparative study using the spectrogram and scalogram." 2003, NDT & E International Volume 37, Issue 4 pp. 309-320.
14. R. Zhou, W. Bao, N. Li, X. Huang, and D. Yu, "Mechanical equipment fault diagnosis based on redundant second generation wavelet packet transform."

 ISBN: 978-1-61208-246-2 

2009, Digital Signal Processing Volume 20 Issue 1 276-288.

15. D.M. Himmelblau, "Fault detection and diagnosis in chemical and petrochemical processes." 1978, Amsterdam: Elsevier press.
16. D.T. Williams, A.R. Plummer, and P. Wilson, "Dynamic Modelling of a Linear Friction Welding Machine Actuation System." Bath/ASME Symposium on Fluid Power and Motion Control, University of Bath 12-14th September 2012.
17. MTS, LF60 Operation Manual. Internal Rolls-Royce documentation. 2000.
18. A.R. Plummer, "A Detailed Dynamic Model of a Six-Axis Shaking Table," in Centre for Power Transmission and Motion Control. 2008, University of Bath: Bath. p. Journal of Earthquake Engineering, 12:4, 631 - 662.
19. V. Venkatasubramanian, R. Rengaswamy, K. Yin, and S.N. Kavuri, "A Review of process fault detection and diagnosis Part 1: Quantitative model-based methods." 2003a, Computers and Chemical Engineering 27 (2003) 293-311.
20. E.Y. Chow, and A.S. Willsky, "Analytical redundancy and the design of robust failure detection systems." IEEE Trans. on Automatic Control, 29(7),603-614., 1984.
21. R. Isermann, "Fault Diagnosis Applications." Springer-Verlag Berlin and Heidelberg GmbH & Co. K, 2011. 04 May 2011.
22. P.M. Frank, "Fault diagnosis in dynamic systems using analytical and knowledge-based redundancy - a survey and some new results." Automatica, 26(3), 459-474., 1990.
23. R.E. Kalman, "A new approach to linear filtering and prediction problems." Transactions of the ASME-Journal of Basic Engineering,, 1960. 82(Series D):35-45,1960.
24. A. Emami-Naeini, M.M. Akhter, and S.M. Rock, "Effect of model uncertainty on failure detection: The threshold selector." IEEE Transations on Automatic Control, 1988. volume 33 no.12.
25. D. Lave, T. Larrabee, and J. Colburn, "Automatic thresholds and probabilistic Isub DDQ diagnosis." In IEEE International test conference, pages 1065-1072, 1999.
26. J.M. Koscielny, M. Syfert, and M. Bartys, "Fuzzy-logic fault diagnosis of industrial process actuators." In Journal of applied mathematics and computer science, 1999. volume 9 no. 3, pages 637-653.
27. F. Hermans and M. Zarrop, "Model Based Statistical Change Detection for Automotive Applications." IEEE International Symposium on Computer-Aided Control System Design, 1996.
28. L. Guo, Y. Zhang, and H. Wang, "Fault diagnostic filtering using stochastic distributions in nonlinear generalized $H\infty$ setting." Fault Detection, Supervision and Safety of Technical Processes 2006, 2006. Volume 1, 2007, Pages 216-221.
29. H. Reader, Report detailing the LF60 breakdown resolution actions Rolls-Royce internal Report, 2012.