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Y Pang, L Giovanini*, **M Monari,** and **M Grimble**
Industrial Control Centre, University of Strathclyde, Glasgow, UK

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Abstract: A critical component of an advanced gas-cooled reactor station is the graphite core. As a station ages, the graphite bricks that comprise the core can distort and may eventually crack. Since the core cannot be replaced, the core integrity ultimately determines the station life. Monitoring these distortions is usually restricted to the routine outages, which occur every few years, as this is the only time that the reactor core can be accessed by external sensing equipment. This paper presents a monitoring module based on model-based techniques using measurements obtained during the refuelling process. A fault detection and isolation filter based on unknown input observer techniques is developed. The role of this filter is to estimate the friction force produced by the interaction between the wall of the fuel channel and the fuel assembly supporting brushes. This allows an estimate to be made of the shape of the graphite bricks that comprise the core and, therefore, to monitor any distortion on them.

Keywords: fission reactor monitoring, fault detection and isolation, unknown input observer, directional residual generation

1 INTRODUCTION

Within the United Kingdom, the *advanced gas-cooled reactor* nuclear power stations are approaching the end of their predicted operational lives. The major factor that dictates the life of a station is the condition of the graphite reactor cores, which distort over time with prolonged exposure to heat and radiation. Currently, it is proposed that the operational lifetime of the plants could be extended if the distortions of the reactor cores are not as severe as initially predicted and that it can be demonstrated that the reactors are still safe to operate. The reactor core is composed of a large number of interlocked hollow graphite bricks that form channels into which the uranium fuel and the control rods are inserted. Over time, heat and radiation cause stresses to build up within these bricks causing them to shrink and distort, and they may eventually crack. To date, these distortions have been within the expected and predicted limits. The continued operation of the plants have been supported through rigorous monitoring and inspection processes, including core channel diameter measurements, ovality measurements, and chemical analysis of trepanned core samples, which take place during planned outages approximately every three years. However, as the core becomes older and the distortions become more severe, the need for increased information relating to the core condition becomes greater.

One source of information is the *fuel grab load trace* data, which are routinely gathered during reactor refuelling. Although not originally intended for core condition monitoring purposes, the fuel grab load trace data contain a contribution from a frictional interface between the fuel channel wall and the fuel assembly. Changes in the fuel channel shape are reflected in the fuel grab load trace data and if this relationship can be understood then it may be possible to derive information relating to the condition of the core from these data. Also, refuelling is undertaken on a weekly basis and the fuel grab

* *Corresponding author: Industrial Control Centre, University of Strathclyde, Graham Hill Building, 50 George Street, Glasgow G1 1QE, UK. email: l.giovanini@eee.strath.ac.uk*

load trace data are kept as part of station records, a requirement of the nuclear generating licence, providing a more frequent, albeit less comprehensive, source of information relating to the core condition than that obtained during outages. In addition, the records stored at the station would allow historic analysis of these data to be performed.

To date, little research has been undertaken in the field of using fuel grab load trace measurements to determine the advanced gas-cooled reactor core condition. An earlier project in a related area resulted in the development of a system that examines the final part of a load trace [**1**], in an attempt to determine automatically whether fuel has been set down correctly in the reactor. The system employs a combination of *k*-means clustering, Kohonen network, and rule induction techniques to assess elements of the load trace. These tools are combined with a rule-based system to provide an assessment of fuel set-down. In the application of intelligent system techniques to nuclear power plants, there are many reported examples in the areas of plant operation, emergency response, maintenance, and some in design activities [**2**]. One application that deals with examining a time-series set of data for condition monitoring of motor-operated valves in a nuclear power plant is reported in reference [**3**]. This system deals with extracting known features from a set of response data from motorized valves. However, in this application, various faulty conditions are simulated to obtain expected responses.

Recently, West *et al.* [**4**] developed a data-mining technique for supporting the condition monitoring of the core. This paper describes a data-mining approach adopted to meet this need of understanding the new domain of fuel grab load trace data analysis for core-condition monitoring. The proposed technique includes the process of analysing and visualizing data in order to discover previously unknown, or confirm previously suspected, patterns and knowledge. The data-mining approach employed for examining the data in this work is based on the work of Fayyad *et al.* [**5**]. This allowed the raw data to be explored for patterns, without necessarily having an understanding of how the load data directly related to the core condition. Subsequent discussions with plant experts allowed a deeper understanding of the nature of certain channel features and distortions, and how they relate to the fuel grab load data, to be developed.

Analytical redundancy [**6**] is a fault-detection method that allows the explicit derivation of the maximum possible number of linearly independent system model-based consistency tests for a system. Using the model of the system of interest, analytical redundancy exploits the null-space of the state-space observability matrix to allow the creation of a set of test residuals. These residuals use sensor data histories and known control inputs to detect any deviation from the static or dynamic behaviours of the model in real time. Such an approach to fault detection and diagnosis, which is clearly intensive (and expensive) in process and fault modelling efforts, provides redundant information and failure cross-checking, which are highly desirable in safety critical areas. The resulting solutions are high-fidelity detection and diagnosis schemes that are tightly coupled to the individual application. More recent work (see references [**7**] and [**8**] for example) has also dealt with a range of so-called *robust fault detection* problems in which it is possible to distinguish explicitly between faults and modelling errors in the detection scheme.

For enhancing the isolability and accuracy of a disturbance estimation, the generation of residuals that have directional properties in response to a particular fault is an attractive idea in order to accomplish fault detection and isolation. The detection filter, a special dynamic observer which generates directional residuals, was first developed by Beard [**9**] and Jones [**10**]. The problem was later revisited by Massoumnia [**11**] in the geometric framework and by White and Speyer [**12**] in the context of eigenstructure assignment. Further improvements were suggested by Liu and Si [**13**] and Keller [**14**].

This paper presents a monitoring module based on analytical redundancy and directional residual generation using measurements obtained during the refuelling process. The role of this filter is to estimate the friction force produced by the interaction between the wall of the fuel channel and the fuel assembly supporting brushes. This allows an estimate to be made of the shape of the graphite bricks that comprise the core and, therefore, to monitor any distortion on them.

Another aim of this research is to prove that the analysis of fuel grab load trace data can provide useful and meaningful results in terms of identifying and estimating deformation and distortion within the core of advanced gas-cooled reactors. It is currently the belief of the experts that when deformations occur, they are more likely to occur on an individual brick basis, rather than affecting the whole channel. With the knowledge that over a period of 5 years every channel in the reactor would be refuelled at least once, it was hypothesized that the load trace data could give an indication of the condition of the core. Characterizing this relationship would allow analysis of the load trace data to provide information relating to the condition of the core on a more frequent basis.

The paper is organized as follows. In section 2, an overview of advanced gas-cooled reactor core design is provided. The key components of the reactor for the development of a model for the core monitoring are described. Section 3 is devoted to the development of a simplified mathematical model of the refuelling process for fault detection and isolation filter development. In section 4, the unknown estimation problem is formulated and solved using an unknown input observer. Finally, in section 5 the results obtained are presented and discussed. Conclusions and future work in this topic are discussed in section 6.

2 BACKGROUND OF NUCLEAR REFUELLING

The advanced gas-cooled reactor is a pressurized carbon dioxide cooled, graphite moderated nuclear reactor which uses enriched uranium as fuel (Fig. 1). The reactor core is located inside a large pressure vessel and a concrete biological shield. On-load refuelling was an economically essential part of the design, to maximize power station availability by eliminating refuelling downtime. This was particularly important for the original design (Magnox nuclear reactor) as the unenriched fuel had a low burn-up, requiring more frequent changes of fuel than most enriched uranium reactors.

Nuclear fission is used to generate heat in order to produce steam to generate electricity from a turbine. In order to sustain a constant power output, the uranium dioxide fuel needs to be periodically replaced. This process, termed *reactor refuelling*, is carried out in batches of around 10 fuel assemblies on a monthly basis. Exact times between refuelling operations and numbers of channels refuelled in a batch are station-dependent. A fuel assembly consists of two main elements: the fuel stringer which houses the uranium dioxide fuel, which is free-standing when in-core, has lateral supports above the top fuel element and the fuel plug unit which provides shielding from heat and radiation and is also used to lock the fuel assembly in the channel during operation (Fig. 2). Each fuel assembly is replaced every 5 to 7 years. During this refuelling process measurements of the load, and sometimes height, of the fuel assembly being extracted or inserted into the core are taken for control and protection purposes.

The core of an advanced gas reactor is constructed from thousands of interlocking cylindrical graphite bricks (Fig. 3). These bricks are arranged in layers of about 300 fuel moderator bricks, which form the fuel channels into which the uranium fuel is inserted, combined with interstitial bricks that provide channels into which boron control rods can be inserted to control the rate of fission, or used to shut down the reactor. Typically the core comprises of 11 or 12 layers, resulting in fuel channels of around 10 m deep. On top of the core are guide tubes and stand

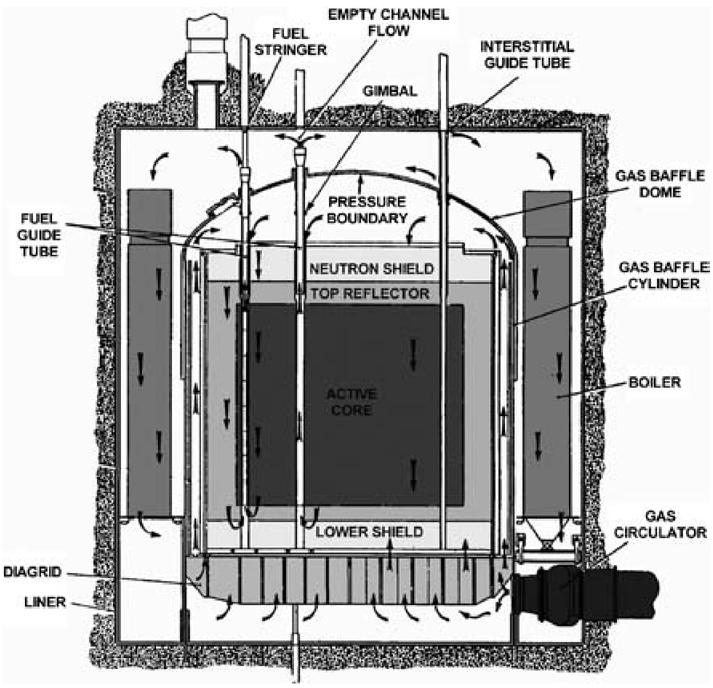

Fig. 1 Schematic diagram of an advanced gas-cooled reactor

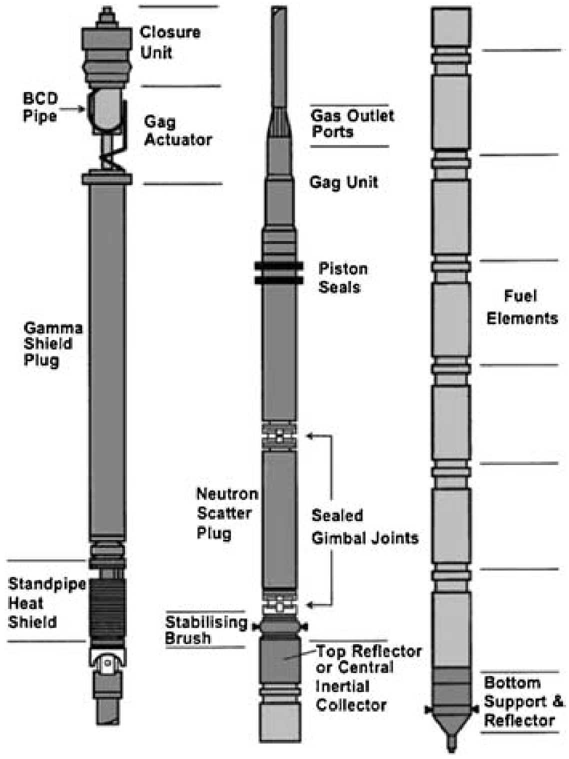

Fig. 2 Fuel assembly

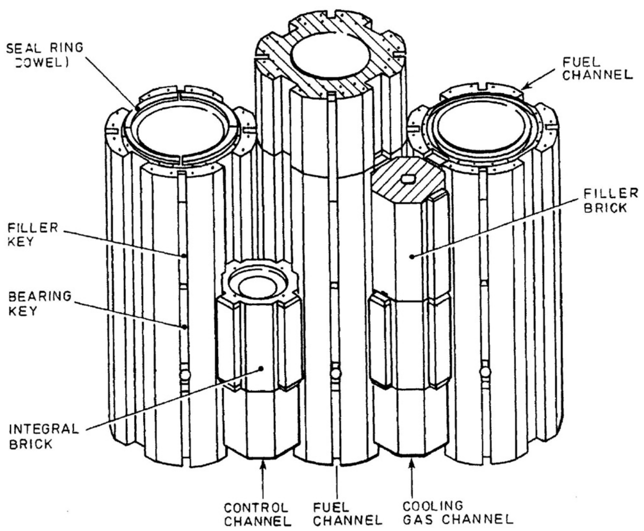

Fig. 3 Core keying system

pipes for each channel, resulting in a channel of approximately 30 m through which the fuel assembly must travel during refuelling (Fig. 4).

3 MODEL DESCRIPTION

Load cells on the refuelling machine directly measure the apparent load of the fuel assembly, as it is being lowered into, and raised out of, the reactor core. A

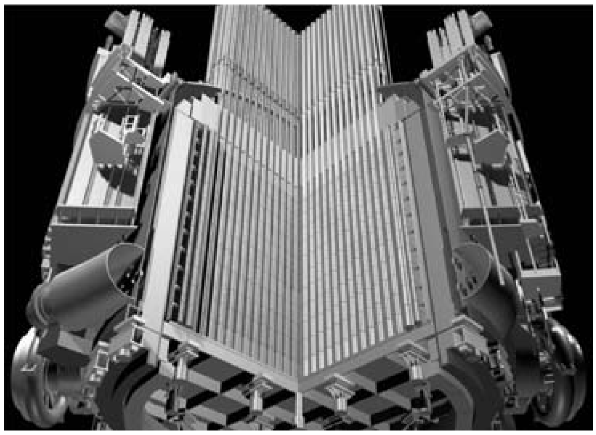

Fig. 4 Three-dimensional cutaway view of an advance gas reactor

number of factors contribute to the value of the net load, the most significant ones being:

(a) the weight of the fuel assembly;
(b) frictional forces caused by the interaction between stabilizing brushes on the fuel assembly and the channel wall;
(c) up-thrust effects of the gas circulating through the core supporting some of the weight of the fuel assembly.

The *weight* of the fuel assembly depends on its mass, which changes during the reactor's operation. During the extraction process it is unknown, but can be determined once the fuel assembly is out of the reactor from the grab load trace data.

The *frictional forces* are caused by the interaction between the stabilizing brushes on the fuel assembly and the channel wall. The magnitude of the frictional component will directly depend on the channel wall geometry, which means that any distortion in the channel geometry will be reflected in the friction force. The sign of the frictional component depends upon the direction of travel of the fuel assembly. During the reactor discharge by removal of the old fuel assembly from the core, friction opposes the movement of the assembly and therefore a narrowing of the channel will result in an increase in the apparent load of the fuel assembly. During the reactor charge of new fuel insertion, the frictional force supports the weight of the fuel assembly, resulting in a decrease in the apparent load from a narrowing of the fuel channel.

Cracks represent the extremes of graphite brick distortions and although the nature and causes of the cracking are beyond the scope of this paper, a brief overview of what they are and how they may appear on a load trace is given. Circumferential cracking occurs around the diameter of the brick. Deformations of graphite associated with the crack result in a reduction in diameter at the crack location. This reduced diameter will result in more friction between the fuel assembly and the channel, which will appear as a peak on a discharge load trace and as a trough on a charge trace. Axial brick cracking is where a brick cracks along its entire length, which may cause the brick to open up, resulting in a larger-than-expected internal diameter. It is also possible that the bricks may doubly crack and shear, causing a reduction in the effective internal diameter across the brick. Either of these effects would be likely to result in a step change in the friction and hence load across a brick layer. The magnitude and direction of this step change would depend upon the severity of the dimension change and the direction of travel of the fuel assembly.

Finally, the circulated gas through the core produces a *buoyancy force* that makes the fuel assembly appear lighter. The buoyancy force is defined using the sign convention that an up-thrust is positive because, in both cases, reactor charge or discharge has the same effect. The sign convention for brush friction depends on the refuelling operation being represented. For a discharge, brush friction acts to increase the grab load (i.e. it is negative); for a charge, brush friction acts to reduce the grab load (i.e. it is positive). During the refuelling process, the fuel assembly motion is governed by the interaction of forces that act on the fuel assembly simultaneously. Applying Newton's law gives

$$ma = \sum f \tag{1}$$

where m is the fuel assembly mass and a is its acceleration. The forces acting on the fuel assembly are its own weight, the brush friction force, and the aerodynamic force due to the gas flow. Applying these forces, equation (1) can be expressed as

$$ma = f_l - mg + f_a \pm f_f \tag{2}$$

where f_l is the grab load, m is the fuel assembly mass, a is the fuel assembly acceleration, f_f is the friction force, f_a is the aerodynamic force, and g is the acceleration of gravity ($g = 9.8\ \mathrm{m/s^2}$). This model does not include any allowance for the dynamics of the fuelling machine hoisting system as these are beyond the scope of the development task. These phenomena may influence the grab load at lift heights where the load changes rapidly, such as during a charge when the nose of the assembly first enters the guide tube and immediately following a dropped stringer during the initial phase.

During the refuelling process, measurement of the position of the grab in the channel and grab load are recorded along with elapsed time. Let the continuous variables $x_1(t)$ and $x_2(t)$ denote the displacement and velocity of the fuel assembly respectively. According to equation (2) the model can be built as

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ f_l(t)/m - g \end{bmatrix} - \begin{bmatrix} 0 \\ 1/m \end{bmatrix} f_f(t) + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} w(t) \tag{3a}$$

$$y(t) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + v(t) \tag{3b}$$

where $w(t)$ is system noise and $v(t)$ is measurement noise. Given the fact that the mass of the fuel assembly is known, the real input to the system $u(t)$ can be defined as

$$u(t) = \frac{1}{m} f_l(t) - g \tag{4}$$

Then the dynamic model of the refuelling process is given by

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_1(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u(t) - \begin{bmatrix} 0 \\ 1/m \end{bmatrix} f_f(t) + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} w(t) \tag{5a}$$

$$y(t) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + v(t) \tag{5b}$$

The main source of process noise $w(t)$ is the turbulent behaviour of the coolant gas and can be neglected due to its magnitude, which is much smaller than the weight of the fuel assembly. Similar assumptions can be made about the measurement noises $v(t)$ due to sensors and instruments. Therefore, the main source of noise is the effect of quantization phenomena introduced by the digital acquisition system [**15**, **16**]. This problem originates from two completely different facts: (a) old records of the refuelling processes recorded on paper and (b) the relationship between the full and deviation ranges of the monitored variables of the fuel assembly. In the first case, the data available on the paper records is not quantized, but the digitalization process introduced quantization in the digital records. In the second case, the small-amplitude ranges of the monitored variables, compared with their full range, leads to a quantization phenomena introduced by the use of just a few of all quantizer levels available in the analogue-digital converters used by the instrumentation equipment. The quantization of recorded variables not only introduces uniformed distributed noises in the variables but also distorts the data, reducing the amount of information available in it [**16**] if the analogue/digital converters are not properly selected, leading to poor estimates of system parameters [**15**]. In other words, the one-to-one connection between the statistical description of input and output signals of the quantizer need to be guaranteed.

In order to estimate the distortion in the fuel channel the data needs to be split from full trace data into layer data so that their relative loads can be tested. It is also thought that any variation due to effects other than change in the channel diameter, such as gas up-thrust, as well as the effects of the fuelling machine hoisting system will be reduced when considering a smaller, single brick layer data trace as opposed to the full trace. Finally, the effect of the quantization will be addressed in two ways.

1. The quantization on the system input $f_l(t)$ (grab load) will be addressed by modifying the statistical characteristic of the process noise, which will be assumed to be uniformly distributed instead of a Gaussian distribution. This will lead to an increment in the value of the covariance matrices of noises $w(t)$ [**16**].
2. The quantization on the system output $y(t)$ (fuel assembly position and velocity) will be addressed through a recursive procedure for estimation by maximum likelihood [**17**].

4 UNKNOWN INPUT ESTIMATION WITH QUANTIZED MEASUREMENTS

Given the fact that the friction force f_f is an unknown input of the system, a Kalman filter for the unknown input estimation can be employed to estimate it. The first step to develop such a filter is to rewrite the model in such a way that f_f appears explicitly in the output. Therefore, consider a stochastic linear dynamic system as follows

$$x(k+1) = \mathbf{A}x(k) + \mathbf{B}u(k) - \mathbf{F}f_f(k) + \mathbf{G}w(k), \qquad x(0) = x_0 \tag{6a}$$

$$y(k) = \mathbf{C}x(k) + v(k) \tag{6b}$$

where $x(k) \in R^2$ is the system state (the position and velocity of the fuel assembly), $x(0)$ is the system initial conditions described by a stochastic variable with a Gaussian distribution, zero mean, and covariance P_0, $y(k) \in R^2$ is the vector of available system's measurements (position of the fuel assembly), $f_f(k) \in R$ is the vector of unknown deterministic disturbance input acting on the system (the friction force), $w(k) \in R^2$ is system noise of zero mean and covariance Q, and $v(k)$ is the independent measurement noise of zero mean and covariance R. The process and measurement noises ($w(t)$ and $v(t)$), as well as the initial condition $x(0)$, are statistically independent of each other. The matrices **A**, **B**, **C**, **F**, and **G** are the model of the system given by

$$\mathbf{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}, \quad \mathbf{C} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$
$$\mathbf{F} = \begin{bmatrix} 0 \\ -1/m \end{bmatrix} \quad \text{and} \quad \mathbf{G} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{7}$$

The conditions for the existence of a solution for the optimal estimation problem ((**A**, **C**) is fully observable) are isolability of the unknown input $f_f(k)$ (the number of states (two) and outputs (two) bigger than the number of unknown inputs (one)) and the directional residual generation problem (the matrix **B** is full column rank and the matrix **C** is full row rank). Under this condition, the estimator of the refuelling process can be decomposed into an unknown input-dependent subsystem and an unknown input-free subsystem if the decoupling gains Π and Σ satisfied [**14**]

$$\begin{aligned} F\Pi &= \mathbf{I} \\ F\Sigma &= \mathbf{0} \end{aligned} \tag{8}$$

The unknown input estimator is given by

$$\begin{aligned} \hat{x}(k+1) &= \mathscr{A}(k)\hat{x}(k) + \mathbf{B}u(k) + \mathscr{K}(k)y(k) \\ \hat{f}_f(k) &= \Pi(y(k) - \mathscr{C}\hat{x}(k)) \end{aligned} \tag{9}$$

where

$$\begin{aligned} \mathscr{A}(k) &= \mathbf{A} - \mathbf{F}\Pi C - \mathbf{K}(k)\Sigma\mathbf{C} \\ \mathscr{K}(k) &= \mathbf{K}(k)\Sigma + \mathbf{F}\Pi \\ \mathscr{C} &= \Sigma\mathbf{C} \end{aligned} \tag{10}$$

and the observer gain $\mathscr{K}(k)$ is given by

$$\mathscr{K}(k) = \mathscr{A}\mathscr{P}(k|k-1)\mathscr{C}^{\mathrm{T}}(\mathscr{C}\mathscr{P}(k|k-1)\mathscr{C}^{\mathrm{T}} + \Sigma\Sigma^{\mathrm{T}})^{-1} \tag{11a}$$

$$\begin{aligned}\mathscr{P}(k|k) = {} & [\mathscr{A} - \mathscr{K}(k)\mathscr{C}]\mathscr{P}(k|k-1)[\mathscr{A} - \mathscr{K}(k)\mathscr{C}]^{\mathrm{T}} \\ & + W + F\Pi\Pi^{\mathrm{T}}F^{\mathrm{T}} + \mathscr{K}(k)\Sigma\Sigma^{\mathrm{T}}\mathscr{K}(k)^{\mathrm{T}}\end{aligned} \tag{11b}$$

The unknown input estimator was modified to tackle the available quantized measurements. The modifications of the unknown estimator are based on the *quantization regression* algorithm proposed by Ziskand and Hertz [**18**]. This is an iterative algorithm based on the maximum likelihood criterion, and was developed by combining the *Gaussian fit* algorithm [**19**], the *expectation–maximization* algorithm [**20**], and a Kalman estimator. The *quantization regression* algorithm is a general technique for finding maximum likelihood estimates from incomplete data [**21**]. The *quantization regression* algorithm comprises two steps: in the first step the expectation $(E(\hat{y}(k)|y(k)))$ of the system output estimation without quantization $\hat{y}(k)$ given a quantized measurement $y(k)$ $(E(\hat{y}(k)|y(k)))$ for the maximum likelihood step is computed using the Gaussian fit method [**19**]. This method was proposed by Curry [**19**] for a discrete-time non-linear filter that recursively fits a Gaussian distribution to the first two moments of the conditional distribution of a system state vector. The Gaussian fit algorithm is easy to compute, can handle non-stationary data, and its operation is independent of the quantization scheme used. Then, in the second step, the likelihood of the estimates is maximized using the expectation–maximization algorithm [**17**]. The expectation–maximization algorithm was developed by Shumway and Stoffer [**17**] to smooth and forecast time series with incomplete observations. It is an iterative algorithm based on a Kalman smoother that successively maximizes the conditional expectation of the log likelihood function of the unobserved data.

Given these modifications, the friction force estimator is given by the following iterative procedure.

Step 1. Initialize the estimator parameters $P(0)$, $Q(0)$, and $R(0)$.

Step 2. Use the unknown input estimator (28) to estimate the friction force $f_{\mathrm{f}}(k)$, $k = 1, 2, \ldots, N$, and update the state estimates using the following calculations

$$\begin{aligned}\hat{x}_n(k|k) &= \hat{x}_n(k|k-1) + \mathscr{K}_n(k) \\ &\quad \times [E(\hat{y}_n(k)|y(k)) - C\hat{x}_n(k|k-1)] \\ \mathscr{P}_n(k|k) &= \mathscr{P}_n(k|k-1) + \mathscr{K}_n(k)\mathscr{C}\mathscr{P}_n(k|k-1) \\ &\quad + \mathscr{K}_n(k)\,\mathrm{cov}[\hat{y}_n(k)|y(k)]\mathscr{K}_n^{\mathrm{T}}(k)\end{aligned} \tag{12}$$

where the expectation $E(\hat{y}_n(k)|y(k))$ is computed using the Gaussian fit approximation [**19**].

Step 3. Maximize σ_v^2 and σ_0^2 by iterative adjustment of the estimated signal $\hat{x}(k|k)$, assuming that $f_{\mathrm{f}}(k)$ does not change, using a smoother

$$\begin{aligned}\mathscr{K}_n(k) &= \mathscr{A}\mathscr{P}_n(k|k-1)\mathscr{C}^{\mathrm{T}}[\mathscr{C}\mathscr{P}_n(k|k-1)\mathscr{C}^{\mathrm{T}} + \Sigma\Sigma^{\mathrm{T}}]^{-1} \\ \mathscr{P}_n(N|k-1) &= \mathscr{P}_n(k-1|k-1) + \mathscr{J}_n(k-1) \\ &\quad \times [\mathscr{P}_n(N|k) - \mathscr{P}_n(k-1|k)]\mathscr{J}_n^{\mathrm{T}}(k-1) \\ \mathscr{P}_n(k|k-1,\, k-2) & \\ &= \mathscr{P}_n(k-1|k-1)\mathscr{J}_n^{\mathrm{T}}(k-2) + \mathscr{J}_n(k-1) \\ &\quad \times [\mathscr{P}_n(N|k,\, k-) - \mathscr{A}\mathscr{P}_n(k-1|k-1)]\mathscr{J}_n^{\mathrm{T}}(k-2)\end{aligned} \tag{13}$$

and the loop in the lag-one covariance calculation was for $k = N, N-1, \ldots, 2$.

Step 4. Evaluate the log likelihood

$$\begin{aligned}\Delta(\log L)_n = {} & -N\log(\sigma_0^2) \\ & - \frac{1}{2\sigma_0^2}\sum_{k=1}^{N}[y(k) - Cx_n(k|k-1)]^{\mathrm{T}} \\ & \times [y(k) - Cx_n(k|k-1)]\end{aligned}$$

and check whether the terminal condition is satisfied and then end the iteration; otherwise $n = n+1$, $\hat{x}_{n+1}(0|0) = \hat{x}_n(N|0)$, update the initial variance of the noise σ_0^2, and go to Step 2.

5 RESULTS

In this section the estimation algorithm developed in section 4 is applied to a data-set obtained during the refuelling process of a nuclear reactor in order to estimate the friction force due to the channel geometry. This information will be used by the diagnosis module to determine the presence and magnitude of any distortion in the fuel channel. The raw data employed in this work, the grab load $f_1(k)$, and the position of the fuel assembly $x_2(k)$ are shown in Fig. 5.

In Fig. 6 a detail of less than a thousand samples of the refuelling process can be seen and the effect of quantization phenomena on the grab load data can be easily appreciated. As explained in previous sections, resolution of the acquisition data system is

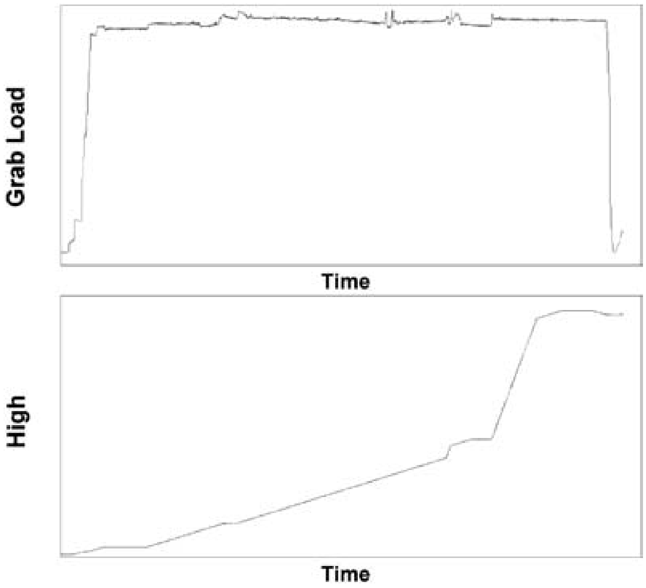

Fig. 5 Recorded raw data: (a) grab load and (b) height of the fuel assembly

enough to cover the entire range of the measured variables with good fidelity. However, when the fuel assembly moves through the channel the range of the grab load was reduced significantly (Fig. 5), increasing the effect of the quantization process (Fig. 6).

In Fig. 7 the results of the application of the proposed monitoring algorithm can be seen. In this figure the effect of the quantization regression algorithm on the estimation of the friction force can be appreciated. The effect of quantization on the variables has been significantly reduced without a significant deterioration in the performance of the filter and the loss of information has been minimized. The use of the iterative process allows all of the information available in the data to be extracted, improving the resulting estimation.

The results obtained using the proposed algorithm were compared with a standard unknown input observer. In this case, the quantization phenomena was addressed through an increment in the covariance of the process and measurement noise. The results of both estimators are shown in Fig. 8. In this figure the improvement obtained using the proposed algorithm is clearly shown. The standard unknown input observer is sluggish due to the high value of the covariance matrices.

6 CONCLUSIONS

This paper has described the use of fuel grab load trace data and estimation techniques to provide information relating to the core condition from a source not originally intended to provide condition-monitoring information. This has resulted in the development of an unknown input observer for quantized measurements that estimates the friction force resulting from the interaction of the fuel assembly and the core channel. This parameter allows a deeper understanding of the condition of the reactor core, allowing quick identification of major distortions (brick cracks) in the channel as well as the geometry of the channel. It also provides the means to visualize and explore fuel grab load trace data in a quick and repeatable manner and as a result to define models of expected behaviour.

This procedure allows existing data sources to be leveraged to provide information relating to the condition of a channel following a refuelling event,

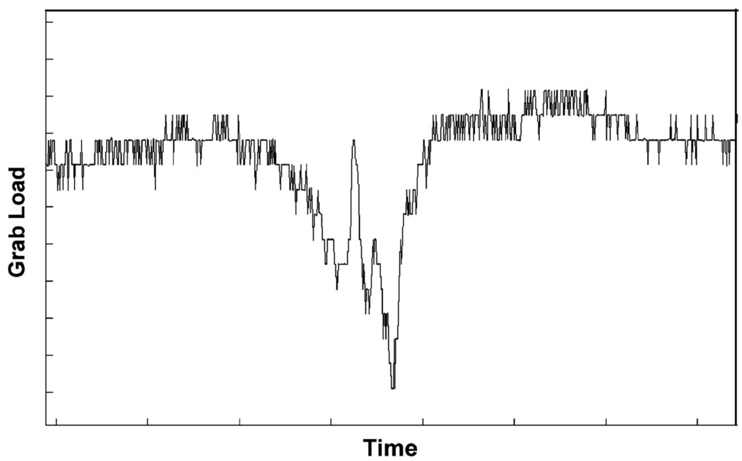

Fig. 6 Detailed grab load data for a portion of the refuelling process

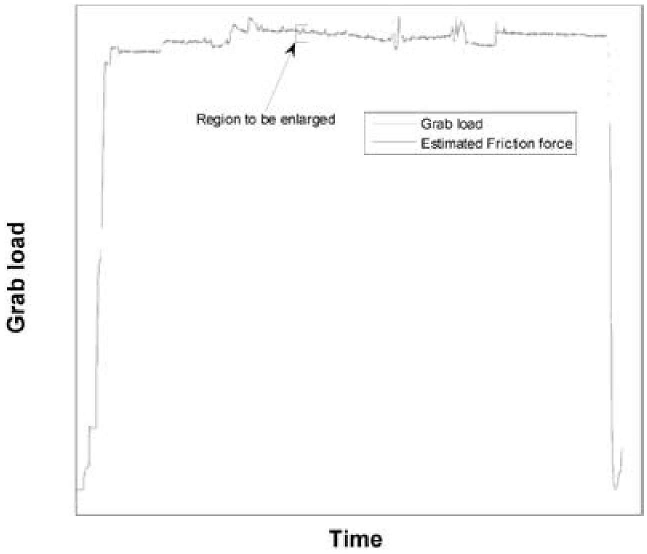

Fig. 7 Grab load data (grey) and rescaled friction force data (black)

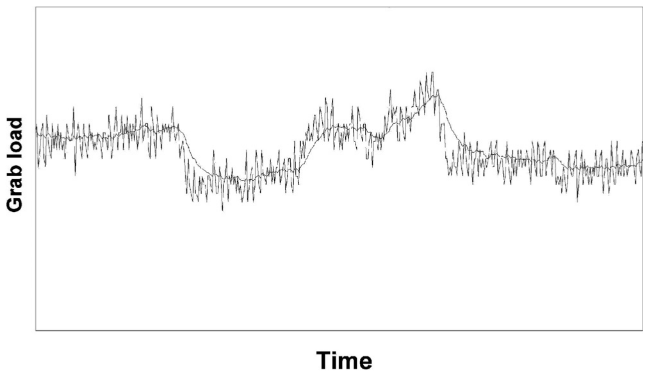

Fig. 8 An expanded view of the rectangular area shown in Fig. 7

which occurs with a far greater frequency than the existing detailed inspections undertaken during outages. In addition, gathering existing and historical data in a single location and through the use of the profiling software, patterns, and relationships between different refuelling events can rapidly and consistently be explored to determine whether time, location, stringer condition, and load conditions have an effect on the trace, ultimately increasing understanding of the existing, and possibly future, condition of the core.

Future work will include the development of new estimation algorithms capable of integrating constraints in the states and parameters, as well as historical information, in order to improve the accuracy of the estimations.

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