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# CONTROL ROD MECHANISM CONDITION MONITORING

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## ABSTRACT

The Primary Shutdown System of the UK's Advanced Gas-Cooled Reactors involves inserting the control rods into the reactor core. The Control Rod Mechanism (CRM) is designed to ensure that the rods insert quickly enough to shut down the reactor with a sufficient safety margin, but slowly enough to prevent damage to the reactor core. The system is tested regularly in each of the reactors and a large amount of data has been collected. This, along with appropriate modelling techniques and a huge increase in computer processing power, gives an opportunitymeq12ms to understand and monitor the CRM performance at a more detailed level then was previously available.
A mathematical model of the system based on physical parameters (e.g. spring stiffnesses, friction coefficients) has recently been made. The aim of this paper is further develop this model as a condition monitoring tool for the CRM.
Bayesian system identification techniques are used to estimate probability distributions for parameter values given a set of test data from a single drop. This allows the values of parameters to be tracked over time in the reactor and gives the potential to identify the causes of poorly performing CRMs.

## INTRODUCTION

The Advanced Gas-cooled Reactor (AGR) is a design of nuclear power station unique to the United Kingdom, providing around 20% of its electricity. There are seven currently in operation, their construction was completed in the 1970s and 80s and they are now nearing the end of (or have already exceeded) their original design lives.

Condition monitoring is the process of monitoring the state of machinery, by interpreting signals produced as part of its operation. The motivation for using such techniques in nuclear power stations is obvious, as the consequences of equipment failure could be extremely serious.

Condition monitoring techniques have recently been developed to monitor the state of the graphite core, the deterioration of which is thought to be one of the main life limiting factors of the AGRs. In [4] and [8] various techniques for analysing the fuel-grab load trace data are investigated, and in [7] a technique is developed to assess the condition of the control rod channel walls by analysing the movement of the regulating rods as they as they are raised and lowered in order to control the reaction. The aim of the paper is to develop a condition monitoring tool for the primary shutdown system.

The control rods are used for the primary shutdown system; in order to stop the reactor the control rods are released and inserted into the core under gravity. A braking system prevents the control rods from inserting too fast and damaging the core, a schematic of the system is shown in figure 1. The system is tested regularly and the position of the control rods is recorded every 50 milliseconds. This data is currently only used to calculate the distances the rod has inserted after certain times (2, 3, 4.5 and 9 seconds) which are used as the performance indicators. The Control Rod Mechanism (CRM) was designed empirically and historically its performance has been extremely good. However due the importance of the system, the planned extension of the AGR lives provides a motivation to understand the CRM performance in more detail.

In [5] a mathematical model of the CRM was developed, based on physical parameters. Many of the model parameters (e.g. dimensions, masses and gear ratios) were either well known or straightforward to estimate from drawings. Other parameters such as spring stiffnesses and friction coefficients are inherently uncertain and difficult to estimate analytically. These parameters were estimated by using system identification techniques to fit the model output to test data.

System Identification is the basis of the condition monitoring technique used in this paper, for each set of insertion test data, a set of model parameter values are estimated, allowing any significant changes in parameter values to be monitored.

In [5] it was shown that large changes in parameter values can have a relatively small effect on the drop times, due to the nonlinear braking system which is able to compensate, keeping the rod at a fairly constant velocity. This means that the degradation of an individual components performance may not be apparent looking only at the distance the rod has fallen, however it may still be detectable in the shape of the curves of the test data plots.

The layout of the paper is as follows: The next section introduces the model and explains how the parameters to be monitored were chosen. The following section describes the MCMC techniques used to estimate model parameters, then some selected results are presented and discussed and the paper finishes with some conclusions.

## THE MODEL

A sketch of the system is given in figure 1, its performance is mainly controlled by a multi-stage brake mechanism, but it is also affected by bearing friction, gear and chain/sprocket efficiencies, drag forces from the coolant gas and friction between the core and the rods. Key assumptions made in the derivation of the model are:

- The effects of the chain friction, bearing friction, gear/sprocket efficiency and the friction between the side walls of the core and the rods are lumped together in a single, scaled friction parameter, $F_f$, which acts as a constant force resisting the rod motion.
- The coefficient of friction between the governor and the brake is a constant.
- The drag forces from the coolant gas are directly proportional to the velocity of the rods and do not depend on the displacement.
- All components are assumed to be fully rigid, except the springs in the brake mechanism.

The model was developed in [5] and consists of a series of 9, two degree of freedom differential equations. One degree of freedom represents the position of the rods and the other represents the position of the flyweights on the break mechanism. Each of the 9 sets of equations represent a stage of braking, the first stage being before the primary brake has engaged and the last is when the secondary brake has fully engaged. The points at which the model switches between stages are dictated by the positions of the rod and the flyweights. The equations describing the first stage of the rods motion are given as an example below.

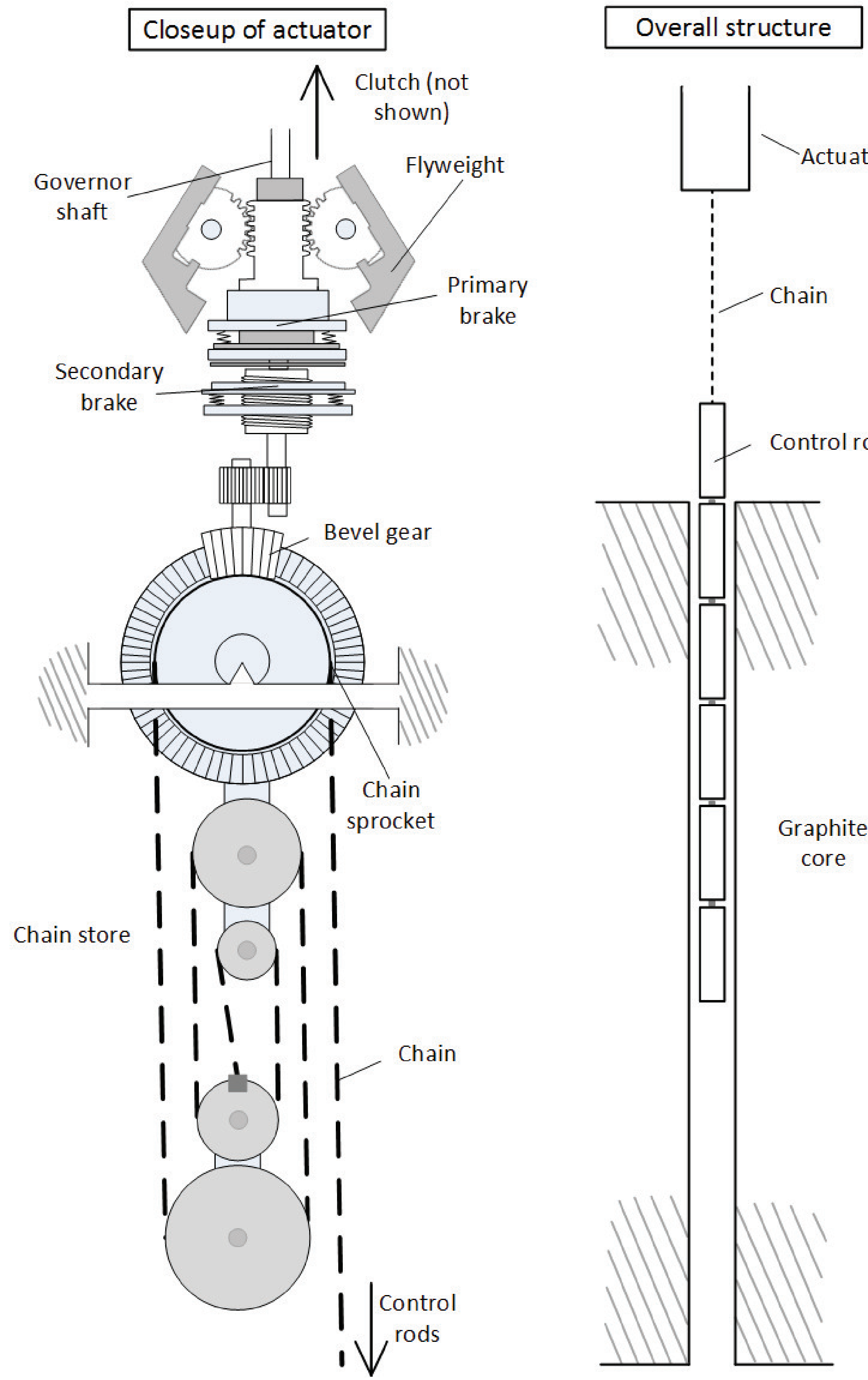


Figure 1. Schematic of control rod system.

The rod acceleration, $\ddot{x}$, is given by,

$$\ddot{x} = \frac{Mg + M_c g x - h\dot{x} - F_f}{M + M_c x + I}$$

The flyweight acceleration, $\ddot{\theta}$, is given by,

$$\ddot{\theta} = \frac{C_a \dot{x}^2 - M_f g c - (kb\theta - M_p g)b - F_u sgn(\dot{\theta})}{I_f + M_p b^2}$$

The model depends on 28 parameters representing physical attributes of the system. 20 of these parameters are either well known (e.g. masses, gear ratios) or were estimated using component drawings and material properties (e.g. dimensions, moments of inertia, masses). For the purposes of the current work it is assumed that the values of these parameters cannot change while the mechanism is in service. Although it is possible that some of these parameters could change in service, it is extremely unlikely and, as far as the authors are aware, this has never occurred during the lifetime of the reactors. However, some of these parameters, such as the pre-compression of the springs or the distance between brake disks, can be adjusted when the mechanism is removed and maintained, and therefore vary slightly between different mechanisms. The authors currently do not have access to information about how these parameters have been adjusted, so they are assumed to be the same across all mechanisms, the effects of this assumption will be explored further in the *results and discussion* section.

The eight remaining parameters are objectively uncertain; their values can, and are likely to change while the mechanism is in operation, depending on the conditions they are subjected to. In [5] the model was shown to be extremely insensitive to three of these parameters; the return spring stiffness, the viscous drag coefficient and the friction resisting the flyweight's motion. This leaves five parameters which are likely to dictate any changes to the performance of the system:

- The main spring stiffness, $k_1$, the main spring holds apart the primary brake disks.
- The reaction spring stiffness, $k_2$, the secondary brake disks are mounted on the reaction springs.
- The combined friction term, $F_f$.
- The brake friction coefficient, $\mu$.
- The clutch release delay time, $D_t$.

Tracking these five parameters is the basis of the condition monitoring technique developed in this paper.

## ESTIMATING PARAMETER VALUES

In [5] a Bayesian framework was used to estimate probability distributions for parameter values using a combination of prior knowledge and comparing the model output to a set of test data. Probability distributions are required for two reasons. Firstly, test data will have been contaminated by noise, and secondly, there may be several combinations of parameters which give an extremely similar model output.

A Markov Chain Monte Carlo method, the Metropolis algorithm [3] was used to generate the parameter distributions in [5]. It generates a Markov chain as follows: given an initial set of parameter values, a variation is proposed by randomly sampling from a multivariate Gaussian distribution with a mean equal to the initial set and a specified standard deviation, $S$. The relative probability, $R$, of the two parameter sets is then calculated. If the proposed set is more likely than the initial set (i.e. if $R > 1$ ) then it is accepted and the algorithm continues with the proposed set as the new initial set. If $R < 1$ then the new set will be accepted with a probability of $R$ . This process is repeated producing a "chain" of parameter values. If it is assumed that the model correctly represents the system, then the distribution of the stationary chain is equal to the probability distribution for the parameters [3]. An example of a Markov chain and a histogram of its distribution for the brake friction is given in figure 2.

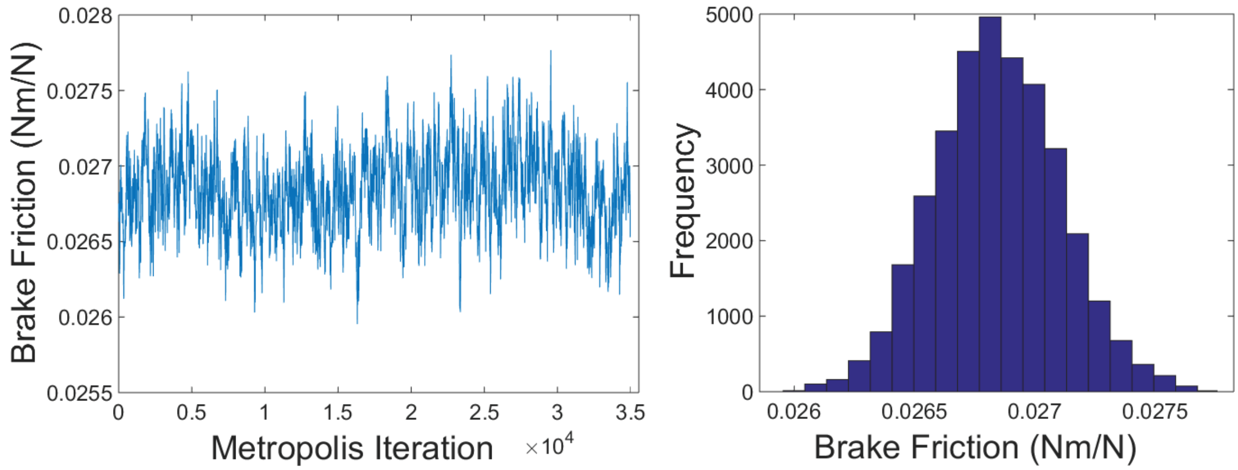

Figure 2. Markov chain and histogram of brake friction values.

While the Metropolis algorithm is a powerful tool, it has several drawbacks: the Markov chain can be slow to converge on its stationary distribution. It can become stuck in traps of locally optimal but globally sub-optimal regions of the parameter space, an appropriate initial parameter set is needed to avoid this. Choosing the correct proposal density width, $S$, is crucial to the speed of the convergence of the chain, but can be difficult to do.

In [5] a version of the Simulated Annealing algorithm developed in [1] was used to address these problems. It was successful in producing consistent results but is was still extremely slow, in the current work a different approach has been taken.

A variant on the Bee Swarm algorithm developed in [6] was used to find suitable initial parameter sets. It was chosen due to its speed and ability to escape local traps (solutions that do not correspond to the global optimum).
The initial iterations of the Metropolis algorithm were used to tune the width of the proposal distributions. For the first 3000 iterations, after every 100 the standard deviation of the entire Markov chain up to that point, $S_{MK}$, is calculated, the new value of $S$ is set at $0.35\, S_{MK}$. For this particular problem, 0.35 was found to be the optimum ratio of $S$ to $S_{MK}$ over the course of several tests across many different data sets.

One of the causes of the slow convergence of the algorithm is that some of the parameters are highly correlated, for instance $\mu$ and $k_2$ are highly negatively correlated. This leads to a low acceptance ratio because to have a good chance of being accepted, a proposed parameter set with an increase in $k_2$ must have a corresponding decrease in $\mu$ . A solution to this is to make a linear transformation into two less correlated parameters, $C_a$ and $C_b$ [2].

$$C_a = (5 \times 10^5 \mu) - k_2, \quad C_b = (5 \times 10^5 \mu) + k_2$$

Figure 3 show a plot of $\mu$ against $k_2$ and $C_a$ against $C_b$, which are clearly much less correlated.

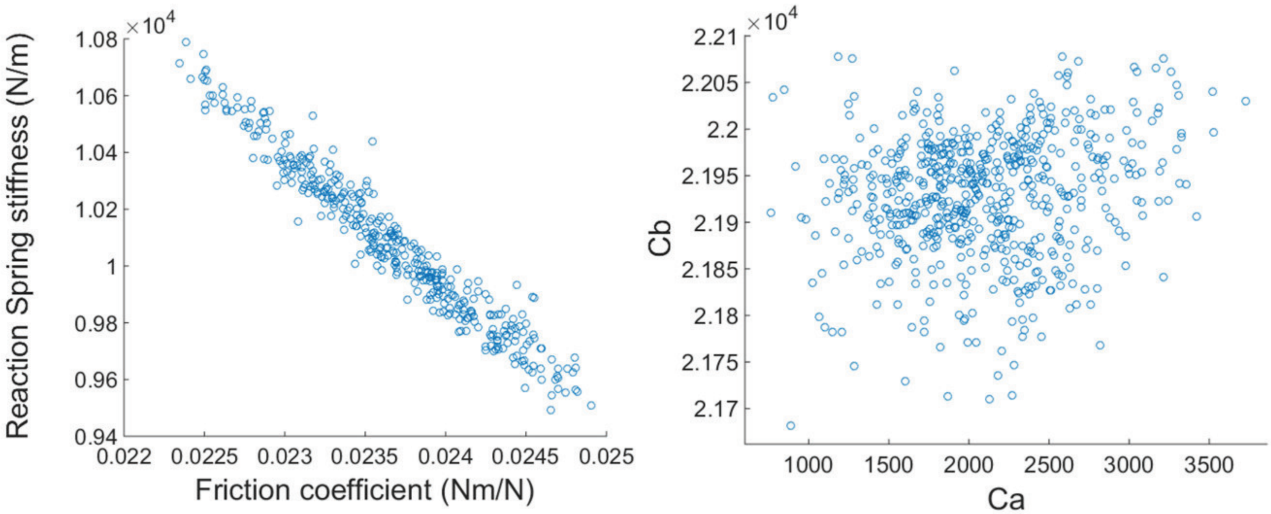


Figure 3. Plot of $\mu$ against $k_2$ and $C_a$ against $C_b$.

A transformation was also made with the parameters $F_f$ and $D_t$ which are highly positively correlated.

With the approach taken in [5], 18 hours (200000 metropolis iterations) were required to produce parameter distributions for a single set of test data. With the approach taken in the current work this has been reduced to about 3 hours (35000 iterations).

Using the mean values of a set of parameter distributions generated in this way, the model has always given a good fit to the test data, an example of this is shown in figure 4.

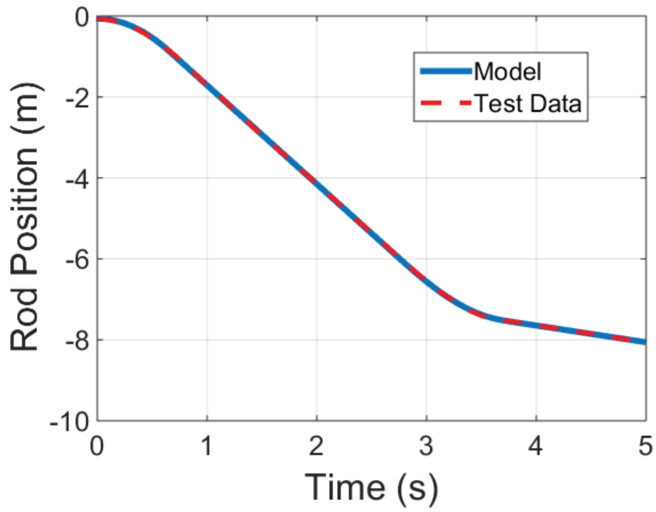


Figure 4. Plot of modelled and measured rod position during insertion test.

## RESULTS AND DISCUSSION

At Hinkley Point B power station, the full system of 81 CRMs in reactor three was tested 11 times, at full temperature and pressure between January 2009 and September 2013. Parameter distributions were estimated for each of these tests, for CRMs which showed an obvious variation in their performance over that period. A selection of these results are given below. Each chart (figures 4, 6, 7 and 8) shows all 11 distributions for a parameter, with each vertical bar representing a single distribution. The central, red line shows the mean value of the distribution. 90% of the values in the distribution are contained within the blue line and the highest and lowest 5% are contained within the green lines.

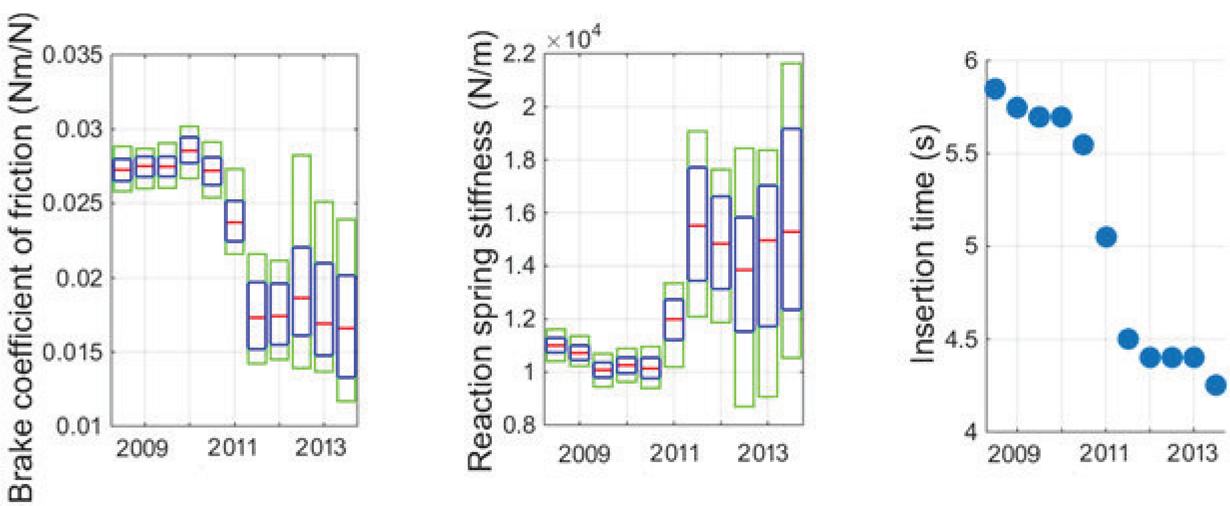


Figure 5. Estimated parameter distributions for rod VW28, between 2009 and 2013.

Figure 5 shows the estimated distributions for $\mu$ and $k_2$ for rod VW28, and a plot of its insertion times. This was one of the slowest rods for the first five tests, after which there is a dramatic reduction in insertion times. This coincides with a decrease in the brake friction ($\mu$) which would cause the reduction in insertion times. It also coincides with an increase in $k_2$ which should increase the insertion times. It is unlikely that these two changes would occur simultaneously while the mechanism is in service. It is more probable that $k_2$ appears to change as a result of the model failing to accurately represent the system.

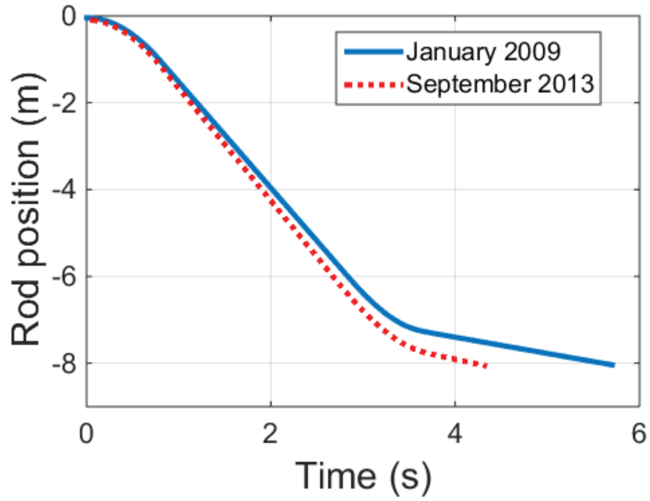


Figure 6. Plot of rod VW08 positions during insertion tests in Jan 2009 and Sep 2013.

This effect, a correlation between $\mu$ and $k_2$, is observed for some mechanisms but not for all. It is likely that the model represents some mechanisms better than others, since it does not currently take into account the fact that some parameters, such as the gap between the brake disks, are slightly adjusted when the mechanisms are maintained. Figure 6 shows a plot of the rod position from the first and last tests of VW28.

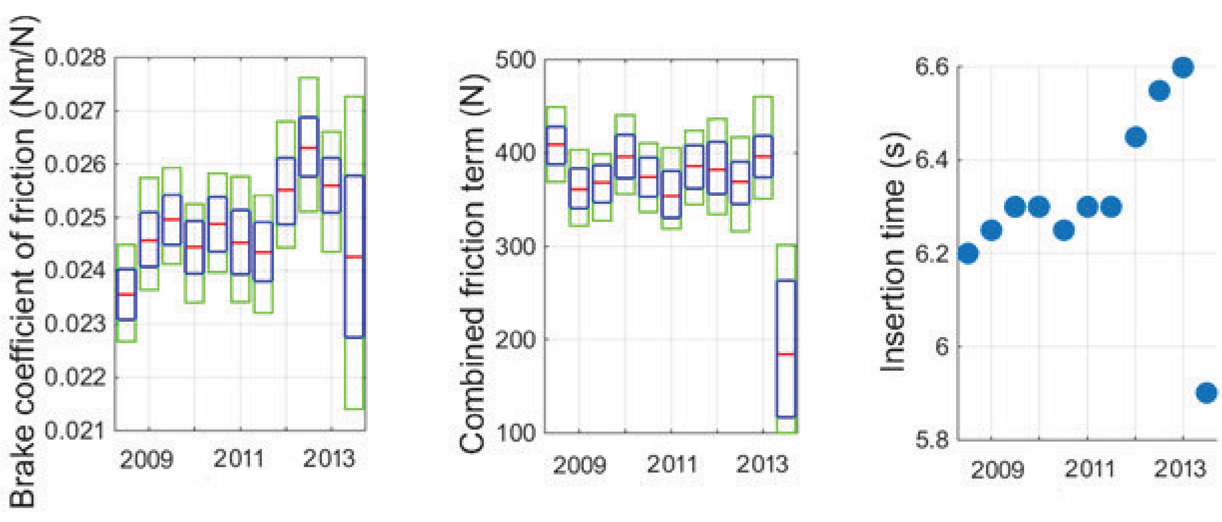


Figure 7 Estimated parameter distributions for rod TU16, between 2009 and 2013.

Figure 7 shows the estimated distributions for $\mu$ and $F_f$ from TU16, which is another of the slowest rods. The results suggest that a higher than average combined friction force ($F_f$) is partially responsible for the longer insertion times. The results also show a trend of increasing $\mu$, which coincides with rising insertion times, until the last test when a large drop in $F_f$ appears to cause a drop in insertion time. There were no significant trends in any of the other parameter distributions for TU16 over the tests.

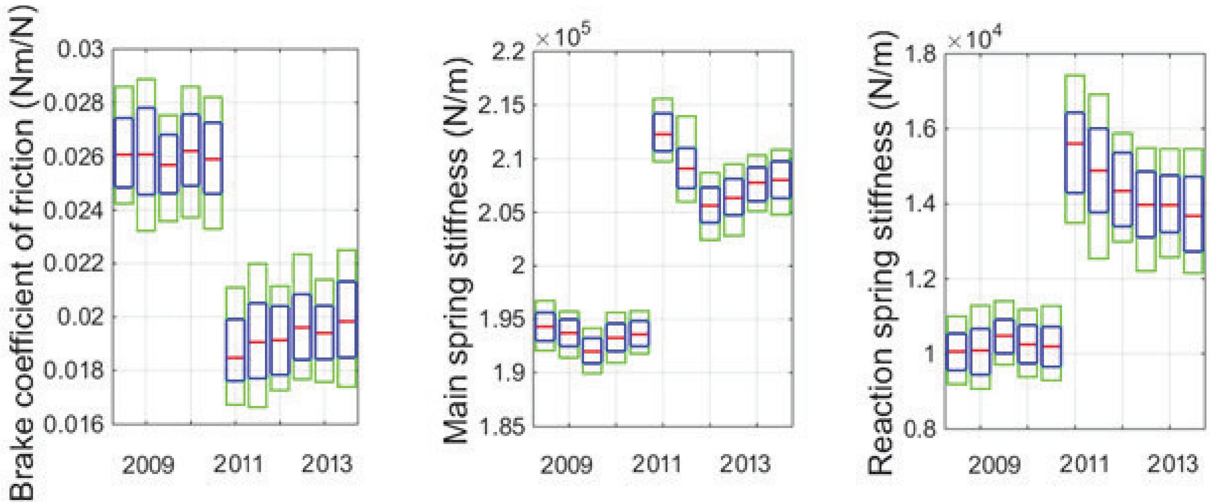


Figure 8. Estimated parameter distributions for rod BC24, between 2009 and 2013.

Figure 8 shows estimated distributions for $\mu$ , $k_1$ and $k_2$ from rod BC24, which has a fairly average performance. The results show a large step change in all three parameters. It is possible that only one parameter has changed, but there appears to be a change in the others due to the model not correctly representing the system. Another possible explanation is that the mechanism was maintained and either some parameters were adjusted, or some components were replaced. Similar step changes are observed in many of the results, with no consistent correlation between parameter values, i.e. an increase in one parameter can either coincide with an increase or a decrease in another.

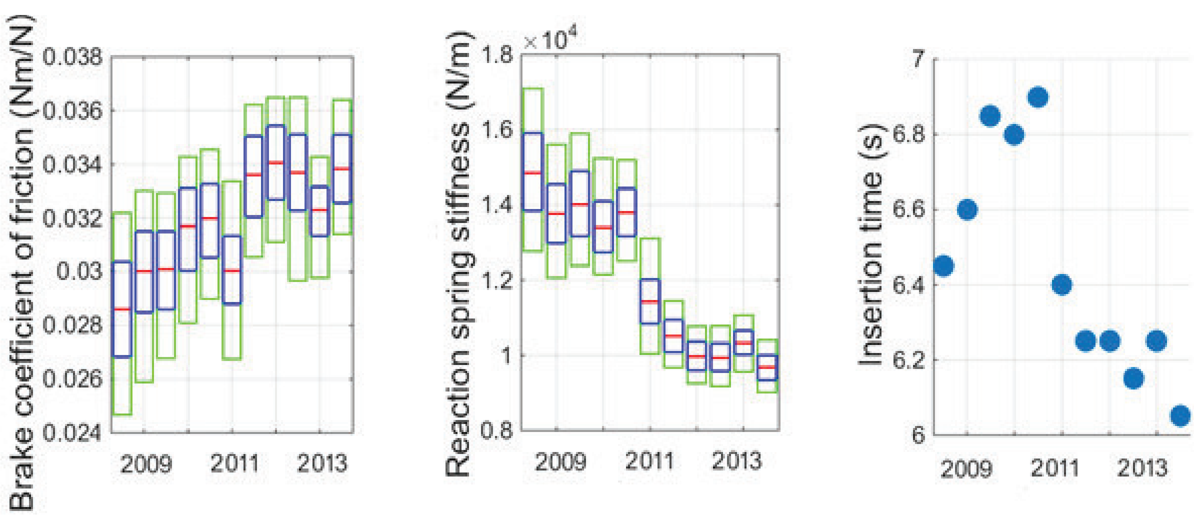


Figure 9. Estimated parameter distributions for rod KL08, between 2009 and 2013.

Figure 9 shows distribution for $\mu$ and $k_2$ for rod KL08, which was on average the rod with the slowest insertion times. The results suggest that this is due to a higher than average brake friction, $\mu$ . Typical values of $\mu$ are between 0.18 and 0.28. KL08 was the only mechanism where the mean value of the $\mu$ distributions exceeded 0.03. After the first five tests it appears as though the effects of the high brake friction are mitigated slightly by a drop in the reaction spring stiffness.

## CONCLUSION

The results suggest that a variety of reasons contribute to variations in control rod performance. The brake friction and reaction spring stiffness appear to be the most influential parameters, this is in agreement with the sensitivity analysis results in [5].

The technique developed here appears to have potential as a condition monitoring tool, but since the model is currently un-validated for the purpose of parameter estimation for the CRMs, these results can only be speculative. Fully validating the model will be expensive, but a straightforward way of providing some confirmation that parameter changes can be detected would be to investigate whether step changes in parameters match up to times when mechanisms have been maintained, and if the adjustments implied by the parameter changes have been made. Unfortunately the authors do not currently have access to this information.

The results imply that the model represents some mechanisms more accurately than others. A possible solution to this would be to find out how individual mechanisms have been adjusted and vary the model parameters accordingly for each mechanism.

[1] P. L. Green. A MCMC method for Bayesian system identification from large data sets. *Proceedings of IMAC XXXIII, Conference and Exposition on Structural Dynamics*, 2015.

[2] P. C. Gregory. Bayesian exoplanet tests of a new method for MCMC sampling in highly correlated model parameter spaces. *Monthly Notices of the Royal Astronomical Society*, 410:94–110, 2011.

[3] Nicholas Metropolis, Arianna W. Rosenbluth, Marshall N. Rosenbluth, Augusta H. Teller, and Edward Teller. Equation of state calculations by fast computing machines. *Journal of Chemical Physics*, 21:1087–1092, 1953.

[4] Y Pang, L Giovanini, M Monari, and M Grimble. Condition monitoring of an advanced gas-cooled nuclear reactor core. *Proceedings of the IMechE Part I: J. Systems and Control Engineering*, 221:833–843, 2007.

[5] M. Scott, P.L. Green, Don O'Driscoll, K. Worden, and N. D. Sims. Sensitivity analysis of an Advanced Gas-cooled Reactor control rod model (under review). *Nuclear Engineering and Design*, 2015.

[6] M. Scott and K. Worden. A bee swarm algorithm for optimising sensor distributions for impact detection on a composite panel. *Strain*, 51:147–155, 2015.

[7] C. Wallace, G West, G. Jahn, and S. McArthur. Conrol rod monitoring of advanced gas cooled reactors. *American Nuclear Society International Topical Meeting on Nuclear Plant Instrumentation, Control and Human-Machine Interface Technologies*, 2010.

[8] G. West, G.Jahn, S. Mcarthur, and J. Reed. *Graphite core condition monitoring through intelligent analysis of fuel grab load trace data*, pages 232–239. Royal Society of Chemistry, 2007.