Nonlinear Model-Based Condition Monitoring of Advanced Gas-cooled Nuclear Reactor Cores

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Abstract: *The graphite core is one critical component in gas-cooled nuclear reactors and it ages and degrades over time. As a result, the graphite core can dictate the life-time of a reactor in a nuclear power station. To support the safety cases and ensure the continued safe operation of an advanced gas-cooled reactor (AGR) nuclear plant, it is important to closely monitor the condition of its reactor graphite core to maintain the integrity throughout the life of the reactor. Toward this end, the fuel grab load trace (FGLT) measurements are currently used as main information sources to infer the core condition. Due to the fact that the FGLTs are masked by many effects in the refuelling process, the first principles models for nuclear refuelling process are promising to separate the information of interests to core condition from the masked FGLT measurements.*

To reliably and accurately obtain the unknown parameters existing in the developed first principles model for model-based condition monitoring of AGR nuclear graphite cores, this paper presents a nonlinear system identification approach. In this approach, a nonlinear first principles model is first developed to describe the refuelling process. A friction model is then investigated to mathematically deal with the frictional effects. The aerodynamic force is also modelled separately. Finally, the Trust-Region Reflective Newton method is used to find the optimal parameters in the nonlinear refuelling model. The real-world data from an AGR nuclear power plant is employed to demonstrate the effectiveness of the proposed nonlinear system identification approach for nonlinear model-based condition monitoring of graphite cores.

Keywords: *Process modelling, system identification, condition monitoring, nonlinear systems, advanced gas-cooled reactor (AGR), graphite core, nuclear engineering, energy and power*

1. INTRODUCTION

In the UK, a number of AGRs are operated by EDF Energy. In an AGR, the graphite core is the critical component and it can age and degrade over time. One mechanism of the core degradation is that the graphite bricks are under high neutron doses which cause changes in graphite properties and induce internal stresses. Therefore, with the ageing of an AGR graphite core, the individual channels within the core, each of which is composed of many graphite bricks, may develop distortion as a result of brick cracking. To support the safety cases of the AGR nuclear power plant and ensure its continuous, safe and economical operation, it is vital to closely monitor the condition of graphite cores in a timing and effective way (McLachlan, et al, 1995; Steer, 2007; Stephen, et al, 2009; West, et al, 2006; Yang, et al, 2010).

At present, the inspection of graphite cores to determine if brick cracking and channel distortion exist can only be carried out every few years by using a measurement and TV device during the planned station outages. In the inspection process during these outages, the internal measurement of brick bore dimensions and ovality can be made directly. However, these detailed and direct inspections only take place every two to three years. As the AGR core is aging and degrading, it is desirable to obtain other more frequently collected information which can be related to the health condition of the AGR graphite core. Graphite team members and station engineers in EDF Energy are very interested in taking advantage of the measurements that can be obtained during routine refuelling activities on individual fuel channels within the reactor core.(Bonivento, et al, 2007, 2008; Pang, et al, 2007; Stephen, et al, 2009; West, et al, 2006; Yang et al, 2010). The refuelling is the process by which the original fuel assembly is first removed and then a new fuel assembly is inserted to the same fuel channel by a refuelling machine.

A significant measurement obtained during the refuelling process is the fuel grab load trace (FGLT) data. The friction forces generated between the fuel channel walls and the moving fuel assembly directly contribute to the FGLT value. Cracks and/or distortions within the graphite core of any significance will normally change the friction forces experienced as the fuel assembly traverses the channel. As a result, this change should be reflected in the FGLT data. This is the main idea on using the FGLT to infer the condition of graphite cores.

However, the anomalies in the FGLTs are normally masked by many factors during the nuclear refuelling process. Masking of data occurs during removal or insertion of the fuel assembly where both brushes on the fuel assembly are within the graphite brick stack, or encounter various constrictions such as seals or events where the top brush enters the bottom of the reactor standpipe. Therefore,

an essential research question is how to separate the friction forces between the channel wall and brushes in the fuel assembly from weight, aerodynamic forces, and measurement noises embedded in the gathered FGLT data.

To unmask the FGLT measurements, currently a promising method is to develop and utilise the first principles models for nuclear refuelling process. However, in general there are many unknown parameters existing in the developed first principles models, which raise another challenging issue in model-based condition monitoring of AGR nuclear graphite cores, i.e., how these unknown parameters can be reliably and accurately identified. To solve this problem, this paper presents a nonlinear system identification approach. First, a nonlinear first principles model is developed to describe the refuelling process. Second, the friction effects are mathematically investigated. Finally, a nonlinear system identification method, i.e., trust-region reflective Newton is used to find the optimal parameters in the nonlinear refuelling model. The real-world data from an AGR nuclear power plant is employed to demonstrate the effectiveness of the proposed nonlinear system identification approach to model-based condition monitoring of the AGR nuclear graphite cores.

The rest of this paper is organized as follows. Section 2 briefly reviews the related work and points out the necessity of the study to be reported in this paper. The modelling of the nuclear refuelling process is presented in Section 3. The nonlinear system identification problem is formulated in Section 4. Section 5 gives the details on the trust-region reflective Newton method. Numerical experiments are carried out in Section 6, with the real-world data from an AGR nuclear power station. Finally, conclusions are made in Section 7.

2. RELATED WORK

The cores of AGRs consist of many graphite components which are joined together by graphite keys and keyways. The graphite failure can be resulted by the internal shrinkage and thermal stresses generated during operation. To extend the lifetime of an AGR nuclear plant, it is therefore paramount to understand the behaviour of nuclear graphite material. This is the research area from the point of view of materials and has been dominant in nuclear graphite research. For example, a continuum damage mechanics model was presented in (Zou, et al, 2004) to predict failures of nuclear graphite.

In recent years, there have been a number of research studies undertaken for the AGR refuelling process. An intelligent system for interpreting this process within an AGR reactor was developed in (Steele, et al, 2003). A software system called BETA (British Energy Trace Analysis) is being developed to evaluate the condition of individual bricks and channels within the graphite cores (West, et al, 2006). A data mining approach was also proposed to support graphite core condition monitoring by taking the FGLT data as the main source of information.

The use of hidden Markov models (HMM) for anomaly detection in graphite core condition monitoring was published in (Stephen, et al, 2009). Two benchmarking techniques were used in (Pang, et al, 2007) to support the use of the FGLT data for the condition monitoring of graphite cores. To separate the friction forces from the masked FGLT data, model-based condition monitoring methods have attracted much attention over the last few years (Bonivento, et al, 2007, 2008; Yang, et al 2010).

Due to the unknown properties of the aerodynamic forces involved in the model and filter as described in (Bonivento, et al, 2007, 2008), the accuracy of estimating the friction forces is affected significantly. A new approach is therefore required to simultaneously estimate/filter the friction and aerodynamic forces from the masked FGLT data obtained during the routine refuelling process. To this end, a novel analytical approach to model-based condition monitoring of the AGR nuclear graphite core was recently presented in (Yang, et al, 2010). By using an analytical first principles model for the refuelling process, the friction force is not only estimated, but also the aerodynamics-related forces for the whole core region can be separated from the masked FGLT data gathered during the charge and discharge stages. Moreover, both the estimated friction and aerodynamic forces can be filtered further to remove any potential noise and modelling error by taking advantage of an efficient filtering algorithm under a three-stage filtering procedure.

In the first stage, the estimated frictional and aerodynamic forces are obtained by using the developed analytical first principles model. Due to the measurement noises and unmodelling effects on the estimated frictional and aerodynamic forces, the filtering algorithms are used to get clearer frictional and aerodynamic forces in the second stage. In the third stage, the filtered FGLT is directly obtained through a reconstruction process, which also directly uses the developed analytical first principles model.

As a result of the abovementioned three-stage approach, the filtered FGLT data can be directly obtained from this process rather than using a separate filtering procedure which normally involves an operation directly on the raw FGLT data. This is another advantage of the proposed three-stage approach.

However, the abovementioned analytical approach was developed by taking advantage of the fact that the fuel assembly travels at a constant speed in the core region. Therefore, the basic condition for the use of the analytical model-based approach is that the speed of the fuel assembly is constant. This is fully satisfied in practice because: 1) In the core region, the speed is 2 ft/min constantly. 2) Outside the core region, the constant speed is 20 ft/min.

To deal with the dynamics and nonlinearity of the refuelling process, a nonlinear first principles dynamic model is unavoidably needed. The nonlinear model is developed to deal with the regions with varying refueling speed. These regions mainly include the stoppage points-related sections, and where the refueling speed changes from 2 ft/min to 20 ft/min or vice versa.

The objective of this paper is to develop such a nonlinear system identification approach for monitoring the condition of AGR graphite cores. The frictional and aerodynamic components will be mathematically modelled in the nonlinear first principles dynamic model.

3. PROCESS MODELLING

The refuelling process has two stages, i.e. charge (insertion) and discharge (vacation). In the charge stage, the fuel assembly is lowered by a charge machine into a fuel channel. The discharge stage is opposite, namely, the exhausted or part exhausted fuel assembly is removed from the channel by the charge machine.

3.1. Fuel Assembly Dynamics

During the refuelling process each time the fuel assembly is inserted or removed, two load cells directly measure and record the grab load. The height of the fuel assembly in the brick stack is also recorded. The value of measured load is usually affected by a number of factors, such as the weight of fuel assembly, frictional forces, the downthrust from the cooling gas in refuelling machine, and the upthrust of the gas circulating through the core, etc.

Considering all the above factors, the general dynamics of the refuelling process is governed by the following equations:

$$\dot{h} = v \tag{1}$$

$$\dot{v} = \frac{1}{m}[mg - F + \mathrm{sgn}(v)F_f - F_a] \tag{2}$$

where sgn(v) denotes the discharge ("+") and charge ("–") stage, respectively, h, v, and m denote the height, velocity, and mass of the fuelling assembly, respectively, F represents the grab load force, F_f and F_a denote the frictional and aerodynamic force, respectively.

3.2. Aerodynamic Model

The net between the upthrust and the downthrust is the main aerodynamic force experienced by the fuel assembly. Because the downthrust is much smaller than the upthrust during the normal operation of an AGR power plant, the upthrust is therefore considered as the main aerodynamic force in this paper.

The aerodynamic force in this study is modelled by

$$F_a = \frac{1}{2}\rho C_d A[U + \mathrm{sgn}(v)v]^2 \tag{3}$$

where ρ and U are the mass density and speed of the coolant gas, respectively, A is the cross-sectional area, and C_d is the drag coefficient.

If all the parameters ρ, C_d, and A are unknown and need to be identified, then it is unlikely to separately estimate them by only using input-output data set. However, for the purpose of condition monitoring we can treat the term $\rho C_d A/2$ as a new parameter, i.e., generalised aerodynamic coefficient ψ,

$$\psi = \frac{1}{2}\rho C_d A \tag{4}$$

3.3. Friction Modelling

In order to reliably derive the estimates of the core cracking conditions from the FGLTs, it is critical to understand how the friction force between the fuel assembly's guide brushes and the fuel channel walls can be mathematically modelled and analysed.

Currently, there have been many friction models available in different engineering domain to deal with diverse application problems (Dahl 1975; Canudas de Wit, et al, 1995; Madi, 2004; Lampaert et al, 2002). In 1995, Canudas de Wit et al proposed a new dynamic friction model, i.e., the LuGre friction model. It is given as follows (Canudas de Wit, et al, 1995):

$$\begin{aligned} \frac{dz}{dt} &= v - \sigma_0 \frac{|v|}{s(v)} z \\ s(v) &= F_c + (F_s - F_c)e^{-\left|\frac{v}{V_s}\right|^{\delta}} \\ F_f &= \sigma_0 z + \sigma_1 \frac{dz}{dt} + \sigma_2 v, \end{aligned} \tag{5}$$

where F_f is the friction force, z is the average deflection of the bristles, v is the relative velocity between the two surfaces; σ_0 is the stiffness, σ_1 is the damping coefficient, σ_2 is the viscous coefficient, F_s is the static force, F_c represents the Coulomb force, V_s is the Stribeck velocity, and δ is a shape factor.

The LuGre friction model is able to describe both the presliding and sliding regime. Therefore, it is popular in control engineering, mechanical engineering, and robotics, etc. The internal state variable z is used to represent the average deflection of the bristles. The first-order nonlinear part in the above equations describes the friction lag in sliding regime. Unlike the static and Dahl friction model (Dahl 1975; Lampaert et al, 2002), there are seven

parameters in the LuGre friction model. Therefore, it often raises more challenging issues in identifying these parameters in practice due to its hysteresis-like behaviour in presliding and varying breakaway force (Madi, 2004; Lampaert et al, 2002). Since the LuGre friction model cannot be transformed into a linear form of its unknown parameters, the traditional linear system identification methods cannot be applied (Unbehauen and Rao, 1998).

In this paper, the friction model is used to separate the frictional forces from the masked FGLT data which are collected during the routine refuelling activities in the AGR nuclear power stations. However, they can also be expected to be used for other purposes, such as model-based filtering and state estimates in the nuclear refuelling process.

4. NONLINEAR SYSTEM IDENTIFICATION

Since there are a number of unknown parameters in the nonlinear dynamic model developed for the refuelling process, it is paramount to identify these parameters from noisy input/output data to implement the nonlinear first principles model in the condition monitoring of nuclear graphite cores.

The nonlinear system can be described by the following continuous-time SISO (single-input single output) form:

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}, u, \mathbf{p}) \\ y &= h(\mathbf{x}, u, \mathbf{p}) \end{aligned} \tag{6}$$

where $\mathbf{x}$ is the state vector, y and u are the scalar output and input, respectively; $\mathbf{f}(\cdot)$ is a nonlinear vector field, $h(\cdot)$ is a nonlinear scalar function; $\mathbf{p}$ is a parameter vector with an appropriate dimension.

In this study, the nonlinear system identification is directly performed in continuous-time domain. It will provide many advantages outlined as follows:

1) The model of the nuclear refuelling system is derived from the first principles. They are inherently continuous in time.
2) The parameters in the continuous-time model are strongly linked with the physical properties of the nuclear refuelling system.
3) The continuous-time model can allow us to have a better understanding of the physical behaviour of the nuclear refuelling system under consideration.
4) The physical meanings of the model parameters can be lost after the continuous-time model is discretised.
5) etc.

However, the main difficulty in dealing with the continuous-time system with conventional methods is the presence of the derivative operators associated with the noisy input and output data (Unbehauen and Rao 1998; Niethammer, et al, 2001). To avoid this difficulty in the nonlinear system identification of the continuous-time nuclear refuelling model, a simulation-based optimization method is adopted in this study. The optimization method will be detailed in the next section.

5. TRUST-REGION REFLECTIVE NEWTON METHOD

The nonlinear system identification problem can be solved by finding the solution to the nonlinear constrained optimization with the following form:

$$\begin{aligned} &\min_{\mathbf{x}\in R^n} f(\mathbf{x}) \\ &s.t. \quad l_i \le x_i \le u_i, i = 1, 2, \cdots, n \end{aligned} \tag{7}$$

where $f(\mathbf{x})$ is a real scalar function to be minimized, l_i and u_i are the lower and upper boundedness for the optimization variable x_i, respectively.

To solve the above optimization problem, the classic methods are line search algorithms. In these algorithms the better point for solution is obtained by following a descent search direction. The descent direction can be found by solving a sub-problem which approximates the original optimization problem near the current iteration. Therefore, the major drawback for the line search methods is that they cannot guarantee a descent direction can be always found.

Trust-region methods are simple, yet robust and powerful for nonlinear optimization problems (Moré and Sorensen,1983; Byrd, et al,1988; Branch, et al, 1999). Trust-region algorithms are based on the simpler function $q(\mathbf{x})$ which is constructed near the current solution point $\mathbf{x}$. The simpler function $q(\mathbf{x})$ reasonably approximates the behaviour of function $f(\mathbf{x})$ in the *trust region*, i.e., a neighbourhood N around the current point $\mathbf{x}$. A trial step $\mathbf{s}$ is obtained by solving the following trust-region sub-problem:

$$\begin{aligned} &\min_{\mathbf{s}\in N} q(\mathbf{s}) \\ &s.t. \quad l_i \le s_i \le u_i, i = 1, 2, \cdots, n \end{aligned} \tag{8}$$

If $f(\mathbf{x}+\mathbf{s}) < f(\mathbf{x})$, then the $\mathbf{x}+\mathbf{s}$ becomes the current point; otherwise, the current point remains unchanged and the trust region is shrunk to compute a new trial step $\mathbf{s}$. This process is repeated until a point can be accepted as a solution.

In trust-region algorithms (Moré and Sorensen,1983; Byrd, et al,1988; Branch, et al, 1999), the key questions are how to construct the approximation $q(\mathbf{x})$ at the current point $\mathbf{x}$, how to decide whether a trial step $\mathbf{s}$ should be accepted, how efficiently to solve the trust-region sub-problem, and how to choose and adjust the trust region N. Because the trust region N is bounded, the non-convex approximate models can be used in trust-region algorithms.

In the standard trust-region algorithm (Moré and Sorensen, 1983), the trust-region sub-problem is defined by

$$\min\{\frac{1}{2}\mathbf{s}^T\mathbf{H}\mathbf{s}+\mathbf{s}^T\mathbf{g}, \|\mathbf{D}\mathbf{s}\| \le \Delta\} \tag{9}$$

where $\mathbf{H}$ is the Hessian matrix, $\mathbf{g}$ is the gradient of $f(\mathbf{x})$ at the current point $\mathbf{x}$, $\mathbf{D}$ is a diagonal scaling matrix, and Δ is a positive scalar. The algorithms used for solving the above trust-region sub-problem normally involve the computation of a full eigensystem and a Newton process to the following secular equation:

$$\frac{1}{\Delta}-\frac{1}{\|\mathbf{s}\|}=0 \tag{10}$$

To reduce the computation time when the standard trust-region algorithm is applied to solve large-scale problems, a number of new approximation and heuristic strategies have been proposed in the literature. In this study, a two-dimensional subspace strategy (Branch, et al, 1999; Byrd, et al, 1988) is adapted to solve the nonlinear system identification problem for the nonlinear model-based condition monitoring of AGR nuclear graphite cores. The key idea is to restrict the trust-region sub-problem to the two-dimensional subspace S which is determined with the aid of a preconditioned conjugate gradient process. S is linearly spanned by $\mathbf{s}_1$ and $\mathbf{s}_2$, where $\mathbf{s}_1$ is the direction of the gradient $\mathbf{g}$. $\mathbf{s}_2$ is determined to be either in the direction of negative curvature

$$\mathbf{H}\times\mathbf{s}_2=-\mathbf{g} \tag{11}$$

or an approximate Newton direction found by solving the following equation:

$$\mathbf{s}_2^T\cdot\mathbf{H}\cdot\mathbf{s}_2<0 \tag{12}$$

By constructing such a two-dimensional subspace S, the global convergence can be reached via the steepest direction or negative curvature. Through the Newton step, a fast local convenience can also be achieved. The trust region is reflectively adjusted from iteration to iteration. It is reduced if the approximation function is not good enough; otherwise, the trust region needs to be enlarged.

6. Numerical Experiments

In this section, a case study for the fuelling system is performed. In all the numerical experiments, the cost function to be minimised is defined as the sum of squares of the errors between the measured and simulated outputs. Because the fuel assembly system is considered in this case study, the input and output are the FGLT and height, respectively, which can be measured and collected for each fuel channel during the routine refuelling activities.

The FGLT and height data used in this case study are chosen from one channel in an AGR nuclear power station, as shown in Fig. 1. If the parameters in the developed model are not correctly estimated, then the model will not be able to properly describe the true output (height measurements) under the true, noisy input (FGLT data traces). Therefore, the key issue in applying the developed first principles model to the condition monitoring of AGR graphite cores is to correctly estimate these model parameters by taking advantage of proper nonlinear system identification method.

Three numerical experiments are carried out in this study. Among the three numerical experiments, the first and third are used for nonlinear system identification purpose, the second experiment is for validating the nonlinear model with identified parameters.

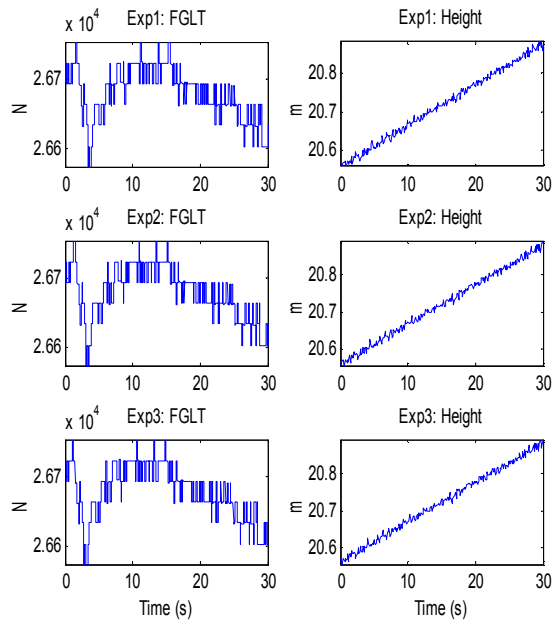


Fig. 1. FGLT and Height data set for numerical experiments

The LuGre friction model is designed to describe the dynamic behaviour of frictional phenomena. It has seven parameters, i.e., the stiffness coefficient σ_0, the damping coefficient σ_1, the viscous coefficient σ_2, the Coulomb force F_c, the static force F_s, the Stribeck velocity V_s, and the shape factor δ. From the aerodynamic force model, there are another two parameters to be identified, i.e., aerodynamic coefficient ψ and gas velocity U. In addition, the mass of the fuel assembly m can also be identified in the case that only one FGLT trace is available. If the shape

factor is fixed, there are 9 parameters to be identified by using the proposed nonlinear system identification approach.

Figure 2 shows the evolutions of the cost function in the system identification with the LuGre friction model. It can be clearly seen that the convergence of the optimisation process with the LuGre friction model was very fast. From the figure, the cost value can be quickly reduced to the value less than 0.0001 within 6 iterations.

Table 1 gives all the obtained parameters of the fuel assembly system with the LuGre friction model and the aerodynamic model. For all the three numerical experiments, the measured and simulated outputs are compared in Fig. 3 over the input-output data sets.

TABLE 1

SYSTEM PARAMETERS UNDER THE LUGRE FRICTION MODEL AND THE AERODYNAMIC MODEL

Parameter	Symbol	Unit	Value	Range	Note
Mass	m	kg	2859.92	[2800, 2900]	Identified
Stiffness coefficient	σ_0	N/m	18.8273	[0, ∞]	Identified
Damping coefficient	σ_1	N.s/m	2.012	[0, ∞]	Identified
Viscous coefficient	σ_2	N.s/m	22007.9	[0, ∞]	Identified
Coulomb force	F_c	N	14.1654	[0, ∞]	Identified
Static force	F_s	N	15.0422	[0, ∞]	Identified
Stribeck velocity	V_s	m/s	0.00100161	[0, ∞]	Identified
Shape factor	δ	N/A	2	Fixed	Fixed
Aerodynamic coefficient	ψ	$N.s^2/m^2$	10.3139	[0, ∞]	Identified
Gas velocity	U	m/s	10.3385	[0, ∞]	Identified

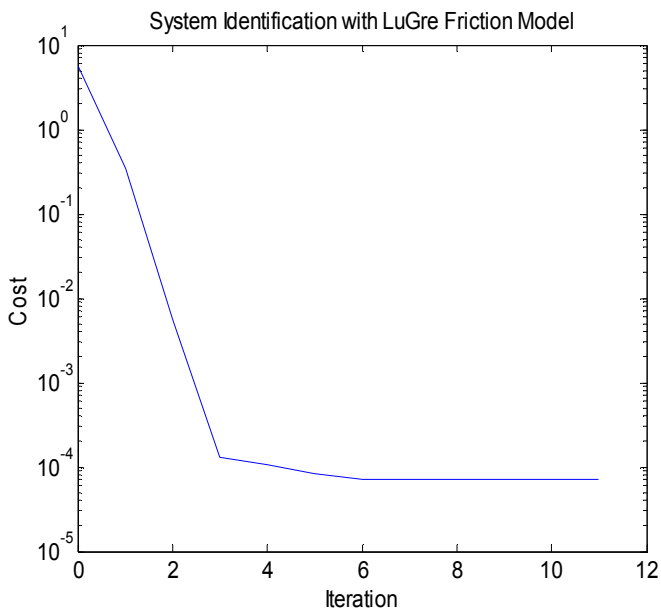
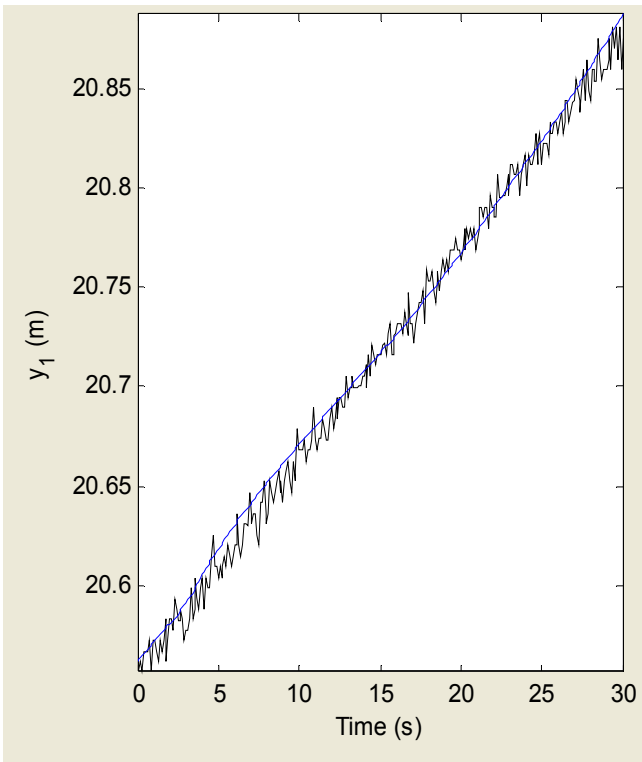
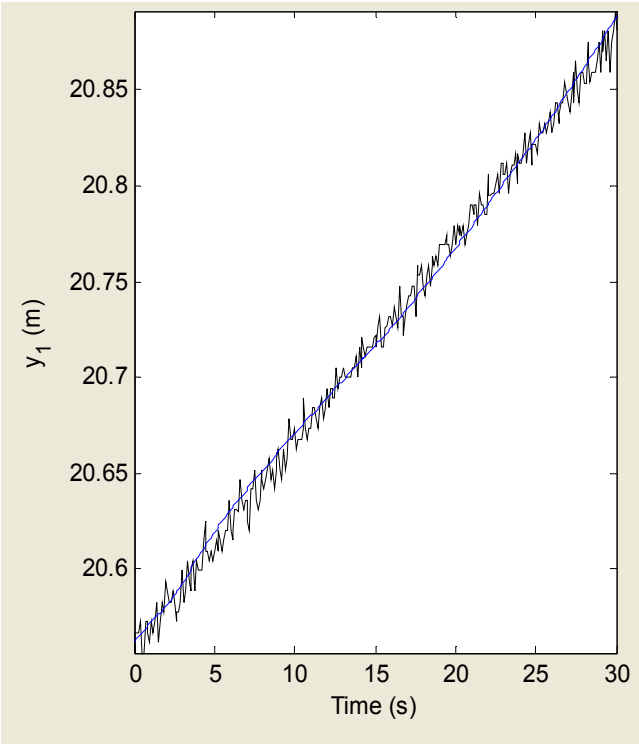


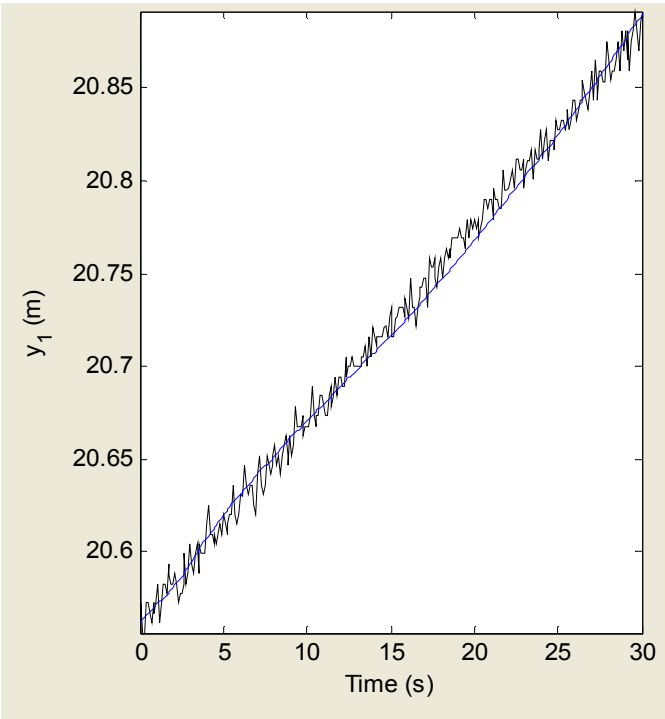
Fig. 2. The evolutions of the cost function in the nonlinear system identification with the LuGre friction model.



(a) Experiment 1 with modelling accuracy: 90.78%



(b) Experiment 2 with modelling accuracy: 91.62%



(c) Experiment 3 with modelling accuracy: 91.35%

Fig. 3. Numerical experiments for the LuGre friction model. In the figure, the black, noisy line is for the measured data, the blue, smoother line depicts the model outputs.

Having applied the input-output data sets to the assembly system with the frictional and aerodynamic models, an obvious question now is how good are these models? To answer this question, the performance is investigated by comparing the true outputs with its simulated outputs. If the absolute error between the measured output and the simulated output is less than the specified tolerance, then the modelling accuracy is satisfied at that point. The total modelling accuracy is defined as the percentage (%) of the total satisfaction points against the whole points.

The modelling accuracy under the LuGre friction model and aerodynamic model is also given in Fig.3. From Figs.2 and 3, it is obviously seen that in this case study the LuGre friction model achieved very good performance in terms of both computation time and modelling accuracy. In the given input-output data sets as shown in Fig 1, the velocity of the fuel assembly seems nearly constant. However, it still exhibits some dynamics. Because the LuGre friction model fully considered this weak dynamics in the nonlinear system, it performed very well.

7. Conclusion

In recent years a lot of research efforts have been made towards extending the lifetime of AGR nuclear power stations in the UK. There is an increasing need to closely monitor the condition of the graphite core within the reactor to ensure its continued safe operation. To use the FGLT data for core condition monitoring, one essential and key challenge is how to reliably and accurately separate friction forces from the masked FGLT measurements. As the FGLT is more frequently available than other inspection data, the model-based condition monitoring can provide a new approach to more frequently monitor the core condition. There are many unknown parameters in the nonlinear dynamic model of the refuelling process for dealing with varying speed regions such as stoppage points, speed change from 2 ft/min to 20 ft/ min, etc. To indentify these parameters in the nonlinear dynamic first principles model for the condition monitoring of AGR nuclear graphite cores, a nonlinear system identification approach has been proposed in this paper.

The approach developed in this paper, along with other developed model-based methods, new inspection devices and monitoring strategies will provide EDF Energy with alternative methods to satisfactorily respond to the current and future monitoring requirements in AGR core safety cases.

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