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The Role of Simulation

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MATHEMATICAL MODELLING OF POWER STATION PLANT

THE ROLE OF SIMULATION

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ABSTRACT

The role of simulation in an exercise aimed at identification and verification of mathematical models of the principal control loops of pulverised fuel mills feeding the furnace of a large coal-fired power station is described. Models of this type are an essential precursor to decision of control strategy, controller design and optimization, and to development of monitoring and alarm systems for operator assistance. Design of the experimental program and choice of excitation sequence is described, together with detection of the plant structure and estimation of the model coefficients. Development of a simulation incorporating a range of plant constraints, including representation of associated control systems, is discussed and uses to which the simulation may be put are reviewed.

INTRODUCTION

Nine pulverised fuel mills feed the furnace of the 500 MW generator at the coal-fired power station on which this identification exercise was conducted. Coal enters at a controlled rate via a conveyor and is ground within the body of the rotating mill by impact with steel balls. Air is forced through the mill under the influence of the primary air (PA) fan, conveying lighter particles to the burners, whilst heavier particles fall, recombine with the feed, and undergo further grinding. Pulverised fuel output, unobservable on a routine basis, is regulated principally by adjustment of the PA flow, which is in turn regulated by manipulation of a vane enabling or inhibiting flow of air to the PA fan. Rate of raw coal feed is controlled by the speed of the conveyor, whilst a further, independent vane controls the proportion of hot and cold air fed to the mill to preserve a desired output temperature for the air/fuel mixture.

Plant variables available for monitoring and control are the pressure drop developed across the PA fan, termed the PA differential pressure (PAD), which is strongly related to air flow, and the pressure drop across the whole mill, the mill differential pressure (MDP), which has a component related to fuel outlet flow. Also available are the current driving the fan, the mill motor current, the temperature of the air/fuel mixture leaving the mill and the air inlet temperature. Inputs to the mill comprise the PA vane position, the feeder speed and the tempering air vane position. Mathematical models are sought which include only physically existing, accessible variables, which are routinely available for plant monitoring and control.

PRELIMINARY MODELLING

A reduced-order state-variable system model (Maples and Ghosh 1982; Cheetham et. al. 1985) was simulated to assist in plant familiarization and with development of the experimental program. Normal operating records were obtained by monitoring plant output without injection of disturbances; variables to be monitored during full experiments were chosen from cross-correlation analysis of the ensuing multi-channel data.

Actuator step tests were conducted in the three principal control loops (primary air, feeder, and outlet temperature) of which models were sought. PA and tempering air vane positions, and feeder speed, were manually adjusted in a series of separate experiments with the mill under test isolated from the remainder of the plant, yet otherwise operating routinely. Effects of step changes in actuator positions were assessed using the state-variable model before being undertaken in the power station. From the results of the step tests, correlation analysis revealed the major links between recorded variables. A first-order model was fitted between each pair of strongly-linked variables, and simulated using a Runge-Kutta procedure, with the gain, time-constant and time-delay fine-tuned using the simulation to minimise the sum-of-squares of errors between model outputs and corresponding recorded plant data.

Ensuing preliminary models were used in choice of excitation sequence for the main experimental program. It is desirable to conduct experiments whilst the plant operates routinely, both for economic reasons and to generate representative data on which modelling may be based. Input sequences are sought which maximise information whilst minimising plant disturbance, fulfill statistical constraints on admissible inputs, and which require a relatively short experiment time without specialist equipment. Pseudo-Random Binary Sequence (PRBS) excitation is selected as the best available means; the sequence is generated by an on-site mini-computer and applied to the plant to perturb actuator positions via modified versions of the existing station control software, whilst the minicomputer records sixteen variables simultaneously using custom-designed software. Choice of PRBS parameters, sequence length, bit interval and amplitude are chosen on the basis of the first-order preliminary models: specifically, the PRBS bit interval is chosen to give a flat spectral-density over the system bandwidth, and the sequence length is chosen to exceed the plant settling time; amplitude of the perturbation is chosen in accordance with operating constraints and may be modified on-line. PRBS experiments and parameters are described in Cheetham and Billings, 1986. All PRBS sequences to be generated on-site were applied to the reduced-order simulation and their effects gauged, demonstrating the maximum anticipated disturbance to output variables. Considerable precautions were taken to avoid overlarge plant disturbances, and safeguards were built into the software, which was extensively tested before the experimental program commenced.

ANALYSIS OF PRBS DATA

Sections of data containing around 500 data points were selected for the identification exercise, free from extraneous disturbances, without drift in the mean levels, and which exhibited the lowest levels of plant noise. In this study one such data set is used to identify the model, another independent set is retained for verification; mean levels were subtracted from all data sequences and trends were removed. Variables included in the model are chosen on the basis of advance plant intuition, preliminary experimentation and modelling, together with significance testing. Fig. 1 shows the cross-correlation functions between PA vane position, the perturbed variable, and three available plant signals; strong correlation is noted with PA differential pressure (PAD), fan current and mill differential pressure (MDP), whilst low correlation is detected between PA vane position and outlet temperature. On the basis of a series of such tests, PAD, MDP and fan current are selected for inclusion in the model of the PA loop. In the temperature and feeder loops similar tests are conducted, with the significant variables similarly selected for inclusion.

Three outputs are thus principally affected by perturbation of the PA vane position, and tests reveal that the outputs are strongly correlated, requiring a multivariable model. The system is decomposed into three strongly-interacting sub-systems, the output of each being one of the principally affected variables. Inputs to each subsystem comprise the overall plant input, PA vane position, together with the outputs of the other two sub-systems. In this way the multivariable system is represented by identifiable component sub-systems, comprised solely of accessible, physically existing plant variables, containing a manageable number of coefficients.

Recursive Least-Squares (RLS) (Goodwin & Payne, 1977) was first employed to identify each sub-system, but examination of the ensuing modelling errors reveals that the estimates contain bias. Recourse was made to Recursive Extended Least-Squares (RELS) (Ljung & Soderstrom, 1983) where a system and noise model are fitted to the experimental data with computational efficiency; in this case a fifteenth-order noise model was fitted. The order of polynomial required to represent the relationships between variables is selected by successively increasing the order until the sum of squares of modelling errors ceases to be significantly reduced by each increase. Time-delays between related sequences are determined by examination of cross-correlation functions.

Following decision of model structure, RELS was used to identify a multiple-input single-output linear difference equation model of each sub-system in each of the control loops, a total of nine multiple-input single-output sub-systems. An example of the outcome of the modelling exercise conducted within the PA loop is presented in Fig. 2: the three model outputs are compared with the corresponding experimental data, revealing close agreement. If all information contained in the plant output is not captured by the model, the sequence of modelling errors will be correlated: examination of Fig. 3, in which the auto-correlation function (ACF) of each error sequence is plotted, reveals no correlation in this case. Parameter estimates are demonstrated to be unbiased by examination of the CCF between inputs and errors, and between the error sequences of each sub-system. Extracts from the CCF plots are presented in Fig. 4, showing no correlation.

SIMULATION

Together with similar identified models of the temperature and feeder loops, the PA model described in the preceding section was simulated using the Advanced Continuous Simulation Language (ACSL). Each discrete-time loop model operates at a different sampling rate and each is represented by an ACSL DISCRETE block, with outputs appearing in more than one model summed within a separate fast-running block. The model equations are written using normalised variables; conversion to and from plant variables, in engineering units, is performed using ACSL macros; starting conditions for the simulation are taken to be those setting model outputs to the mean levels observed during the experiment. Models identified on the basis of PRBS tests describe the relationships between actuator positions and plant outputs; the operation of the actuator, linking the controller-generated input signal and the actuator position used as model input, is represented in each case by a first-order model with an experimentally-determined gain and time-constant. Constraints on actuator position, and rate of movement, are incorporated, together with representation of actuator backlash and deadzone.

Relevant sections of the existing plant control software have been reproduced as closely as possible in the simulation. Macros fulfill the functions of software commands and utilities, rendering the simulation subject to constraints similar to those occurring in the plant. Real-time control problems are represented by macros, using combinations of functions available with the ACSL system, supplemented by custom-written functions, including the effects of measurement and quantization noise, propagation delays between interacting modules, actuator constraint, look-ahead-to-limit checks, facilities for avoidance of actuator wind-up and provision for contingency action by one controller if another loop is inactive or in constraint. Simulated controllers, with an incremental three-term (PID) configuration, operate with the same sampling intervals (relative to the plant), and with the same coefficients, as those employed in practice.

Actuator step tests conducted on the simulation reveal close agreement with the preliminary experiments conducted on plant, in terms of deduced gains and time-constants. An example of a step-change in PA desired value is shown by Fig. 5: plant noise, effects of actuator constraint and effects on variables in other loops may be noted; a wide range of effects on both software and hardware can be studied both graphically and by printing out detailed numerical data at user-selected data intervals.

The simulation has been employed in controller design, in that a state-space equivalent representation has been constructed and used as a basis for optimal control (Cheetham & Wilson, 1986). State and control weightings in the quadratic criterion are initially chosen according to plant intuition and fine-tuned by experiments on the simulation; the latter contains representations of non-linearities and real-time constraints not included in the state-space model.

Strategies for plant monitoring and control may also be developed and optimized using such simulations. Interest has been shown by industrial partners in development and testing of intelligent alarm systems for operator assistance, supplementing existing systems. As a precursor to this work a self-tuning predictor has been implemented on the simulation, Fig. 6; PA vane position and PA differential pressure are taken as system input and output respectively. A linear difference equation is recursively fitted and used to predict system outputs. Significant departure of measured output from prediction, or sudden changes in estimated coefficients, is taken as an indication of fault condition.

CONCLUSION

An exercise has been described in which simulation is not only the end product, but is used extensively at several intermediate stages. Preliminary simulations have been used to develop and verify a comprehensive experimental program which was subsequently conducted in a large coal-fired power station during routine operation. Multivariable plant models have been identified and verified on the basis of the experimental data and simulated using ACSL. Representations of associated control systems, and of problems inherent in real-time control, have been included in the simulation which has been used in controller design and testing, and as the basis for development of monitoring and alarm systems, including use of a self-tuning predictor.

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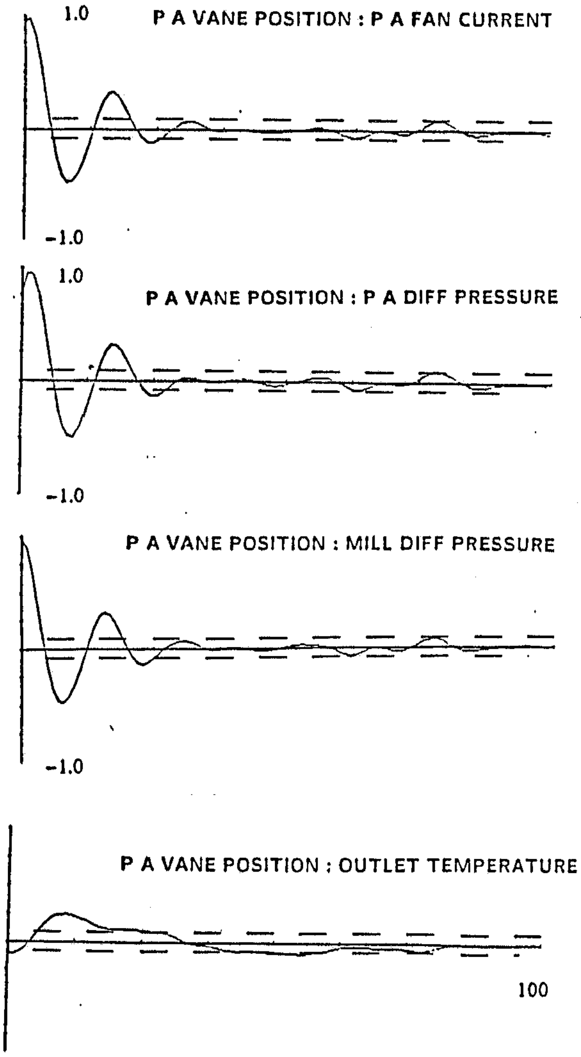

Fig. 1 Significance Tests

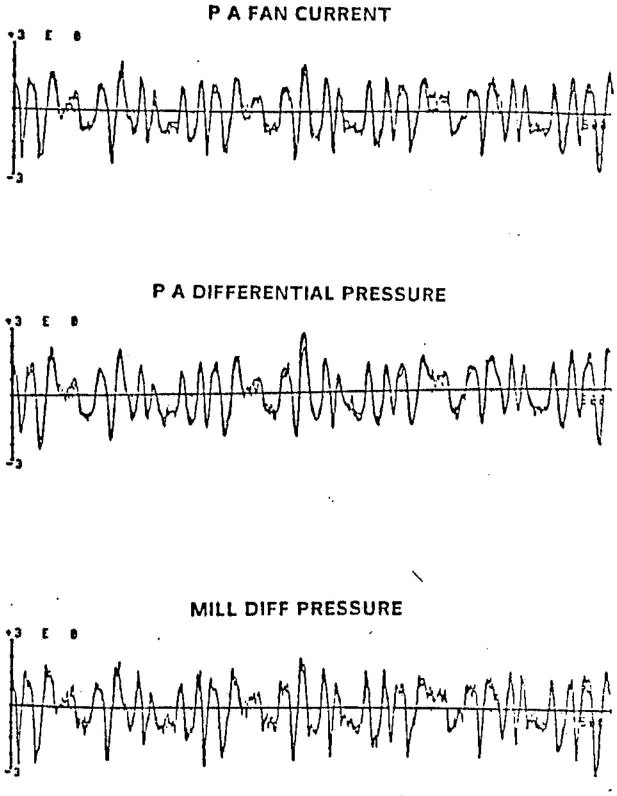

Fig. 2 Model / System Comparison

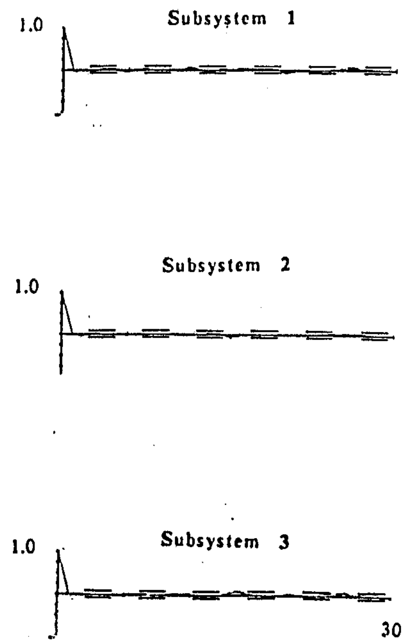

Fig. 3 Autocorrelation Tests

Modelling Errors

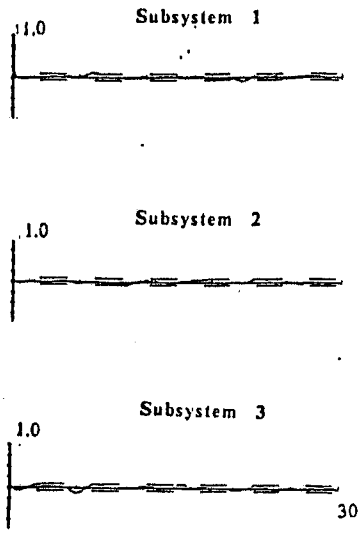

Fig. 4 Autocorrelation Tests

Modelling Errors / Inputs

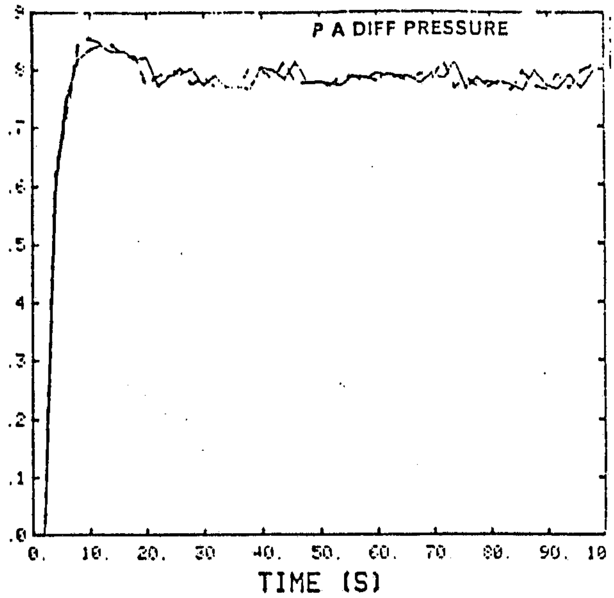

Fig. 6 Self–Tuning Predictor

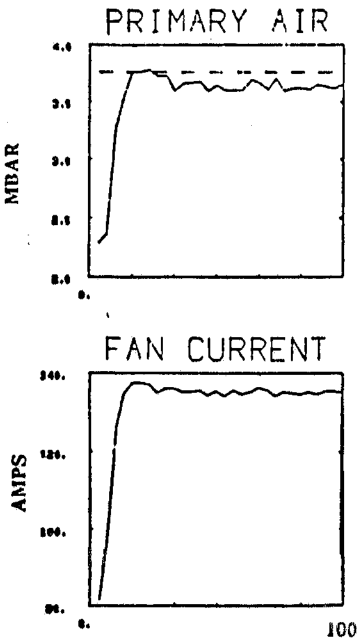

Fig. 5 Step Change in PA Reference