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Power System Plant Modelling from PRBS Experiments

by

R. G. Cheetham *

S. A. Billings +

* Department of Electrical Engineering
University of Leeds.

+ Department of Control Engineering
University of Sheffield
Mappin Street
SHEFFIELD
S1 3JD

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Power system plant modelling from PRBS experiments

*R.G. Cheetham*¹ and *S.A. Billings*²

This work is part of a collaborative exercise between the Department of Control Engineering, University of Sheffield, the Department of Electronic Engineering, University of Leeds and the CEGB Scientific Services Department, N.E. Region.

1. Introduction

Increasing availability of cheap, fast, reliable, localised computing power renders feasible the on-line control of a broad class of systems. Whether as a precursor to decision of control strategy, a tool for simulation studies or a means of fault detection, system identification is being increasingly pursued. This paper describes the process of experiment and identification conducted within an industrial context. An input test sequence is designed and used to perturb one of the inputs to a pulverised fuel mill supplying the furnace of a 500 MW boiler-turbine unit. On the basis of the observed response, a multivariable plant model is identified using linear difference equation [1] representations of a number of interacting sub-systems, the inputs and outputs of which are accessible plant variables. The model is validated by statistical tests conducted on the modelling errors and by favourable comparison of the model prediction with experimental results.

2. Plant description

Nine pulverised fuel mills supply the furnace of the 500 MW Unit 2 boiler-turbine unit at Thorpe Marsh Power Station. Coal enters each mill at a controlled rate via a conveyor and is ground within the vertical spindle mills by rotating steel balls. Air is forced through the mill by primary air fans conveying finer coal particles to the burners, the larger particles remaining for further grinding.

Plant operation is under the control of a distributed computer system running a suite of interacting programs written in the CEGB's CUTLASS software which consists of a suite of CORAL-based engineer-orientated applications packages for process control [5]. Boiler steam pressure is regulated to an operator-set level. Discrepancies between actual and desired pressure are converted by the master control program into fuel-demand changes and divided between the available mills. Fuel output from each mill is regulated principally by controlling the air flow through the primary air fans, with denormalisation to account for individual mill characteristics. It is also necessary to ensure that the air/fuel ratio in the mill and associated pipework remains within safe bounds, and consequently the coal feed to the

¹Dept. of Electronic Engineering, University of Leeds

²Dept. of Control Engineering, University of Sheffield

200041125



mill is regulated to maintain a specified ratio of mill differential pressure to primary air differential pressure. Mill outlet temperature is controlled by adjustment of the tempering air damper position, regulating the flow of hot/cold air to the mill. The identification exercise reported here was undertaken on experimental data generated by perturbation of this damper.

3. Experiment design

Choice of appropriate perturbation is a crucial element of the identification process. The following factors motivated selection of a Pseudo-Random Binary Sequence (PRBS) as the input perturbation in this investigation:

The experimental programme does not necessitate removal of the plant from operation

Information sufficient for system identification may be generated using a low level of perturbation in a short-duration experiment

PRBS signals may easily be generated using available equipment and readily applied without violating operational constraints

Sequence characteristics may be selected, on the basis of existing plant knowledge, to fulfil the statistical requirements on the input signal over the relevant frequency range

It has been shown [2] that an input sequence may be selected to have a frequency-independent power spectrum over a fixed frequency range, chosen to exceed the bandwidth of the plant under investigation, thereby fulfilling the statistical requirements on the input. It is further required that the sequence duration, the time-interval before the input repeats, is greater than the plant settling time. The amplitude of the perturbation is generally chosen as the maximum possible consistent with maintenance of the output within the linear region; in this investigation operating constraints imposed more stringent restrictions on perturbation amplitude than considerations of linearity. Effective choice of PRBS characteristics is hence dependent upon pre-experiment information regarding the bandwidth and settling time of the process to be identified. A series of actuator step tests was conducted leading to selection of the PRBS bit-interval as 60 seconds, and a sequence duration exceeding 1600 seconds, a requirement necessitating a 31-element PRBS. Eight repetitions of the sequence were used, a total experiment time of 248 minutes, with sixteen data channels sampled simultaneously at five-second intervals.

The PRBS sequence is applied to the plant via modified versions of the existing CUTLASS control software. In the temperature loop the PRBS is superimposed on the pre-set desired value to which the outlet temperature is controlled, thereby perturbing the tempering air damper position. During temperature tests the mill was disconnected from the master boiler steam pressure control with the primary air fan running on manual, with a constant vane position. The feeder control was retained in auto mode to

maintain the pre-set air/fuel ratio. Temperature desired value is driven symmetrically about the 70°C level by the PRBS, with an amplitude of ±0.5°C, rate limited to ±0.25°C per second. The effect is to drive the damper position over approximately ±7.5 per cent of its range, movement sufficiently small to maintain the air/fuel ratio within acceptable limits. Additional safety constraints are incorporated into the software used during PRBS tests, with facilities for rapid return of the plant to normal operation on conclusion or abortion of an experiment. Such safety features were extensively tested before the programme reported here began.

4. Model identification

The perturbed input, temperature damper position, and the principally affected variables, outlet temperature, primary air differential pressure and mill differential pressure, are shown with their mean levels removed in Fig. 1. Since the variables affected by the perturbation are correlated, the approach has been adopted of decomposing the mathematical representation of the system into three component multiple-input, single-output sub-systems, as shown in Fig. 2. The output of each sub-system is one of the principally affected variables, whilst inputs to each sub-system are the overall system input (temperature damper position) and the outputs of the other sub-systems.

A linear difference equation of the form

$$y_i(k) = a_{i11}y_1(k-j_{i1}-1) + a_{i12}y_1(k-j_{i1}-2) \dots + a_{i21}y_2(k-j_{i2}-1) + \dots \\ + a_{i31}y_3(k-j_{i3}-1) + \dots + b_{i1}u(k-j_1-1) + \dots + c_{i1}e_i(k-1) \dots$$

represents the input/output relations of the i-th sub-system, with $y_1(k)$ the output of sub-system 1 at the k-th sampling interval, $u(k)$ the damper position, $e_i(k)$ the system noise; j_{mr} is the number of sampling intervals delay between the output of the r-th sub-system and its effect on the output of the m-th. The sampling interval is 5 seconds. Time delays between input and outputs are deduced from correlation analysis.

Recursive Extended Least Squares (RELS) [3] is employed to generate estimates for the coefficients of each sub-system; a noise model is fitted to the experimental data, fulfilling the random, uncorrelated requirement on the input for generation of unbiased parameter estimates. Model order is determined by evaluation of the sum of squares of modelling errors for ascending model order until the reduction ceases to be significant. Fig. 3 shows the outcome, for each sub-system, of application of this procedure: Fig. 3(a) compares the outlet temperature predicted by the model, when excited by the input used in the test, with the corresponding experimental data, modified by removal of mean level; the sequence of modelling residuals is also shown. Figs. 3(b) and 3(c) similarly compare the PA and mill differential pressures as given by the model with those recorded in the

experiment. In all cases good agreement between model and plant response is noted.

5. Model validation

Properties of the sub-systems' residual sequences are investigated statistically, with the results displayed in Fig. 4. The impulse nature of each autocorrelation function (ACF) demonstrates that the residual sequences are random, with all information contained in the sub-system outputs. Remaining plots in Fig 4 show that the crosscorrelation functions (CCFs) both between system input and each residual sequence, and between residual sequences, lie exclusively within the five per cent confidence limits. In all cases the validity of the model structure and estimated coefficients is demonstrated. Model outputs, when excited by an input sequence recorded during a different part of the test, are compared with the corresponding experimental data in Fig 5., from which good agreement may be noted, further validating the model.

6. Conclusions

An input sequence has been designed and applied to a system operating in an industrial setting. Ensuing experimental data forms the basis for identification of a multivariable mathematical model consisting solely of accessible plant variables. Reconstitution of the outputs, by application of the test input sequence to the model, reveals good agreement with the experimental data. Statistical tests on the modelling errors validate the identified structure. The model identified on the basis of one data set, when excited by an input sequence from another data set, predicts outputs which compare favourably with the recorded data.

The procedure outlined here has been applied to the three mill control loops: temperature, feeder and primary air. An integrated system simulation based on these identified transfer functions is under development and will be used in conjunction with emerging data on coal-flow failure incidents. An application of this work is the use of expert systems concepts to develop rules for enhanced alarm generation. The different possible operational modes of pulverised fuel mills present complications when structuring a rules-based system and it is envisaged that the model will contribute to the development and testing of such a system.

7. Acknowledgement

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M. C. Greenslade in operating the computer packages. This paper is published with the permission of the Executive Director, North Eastern Region, CEGB.

8. References

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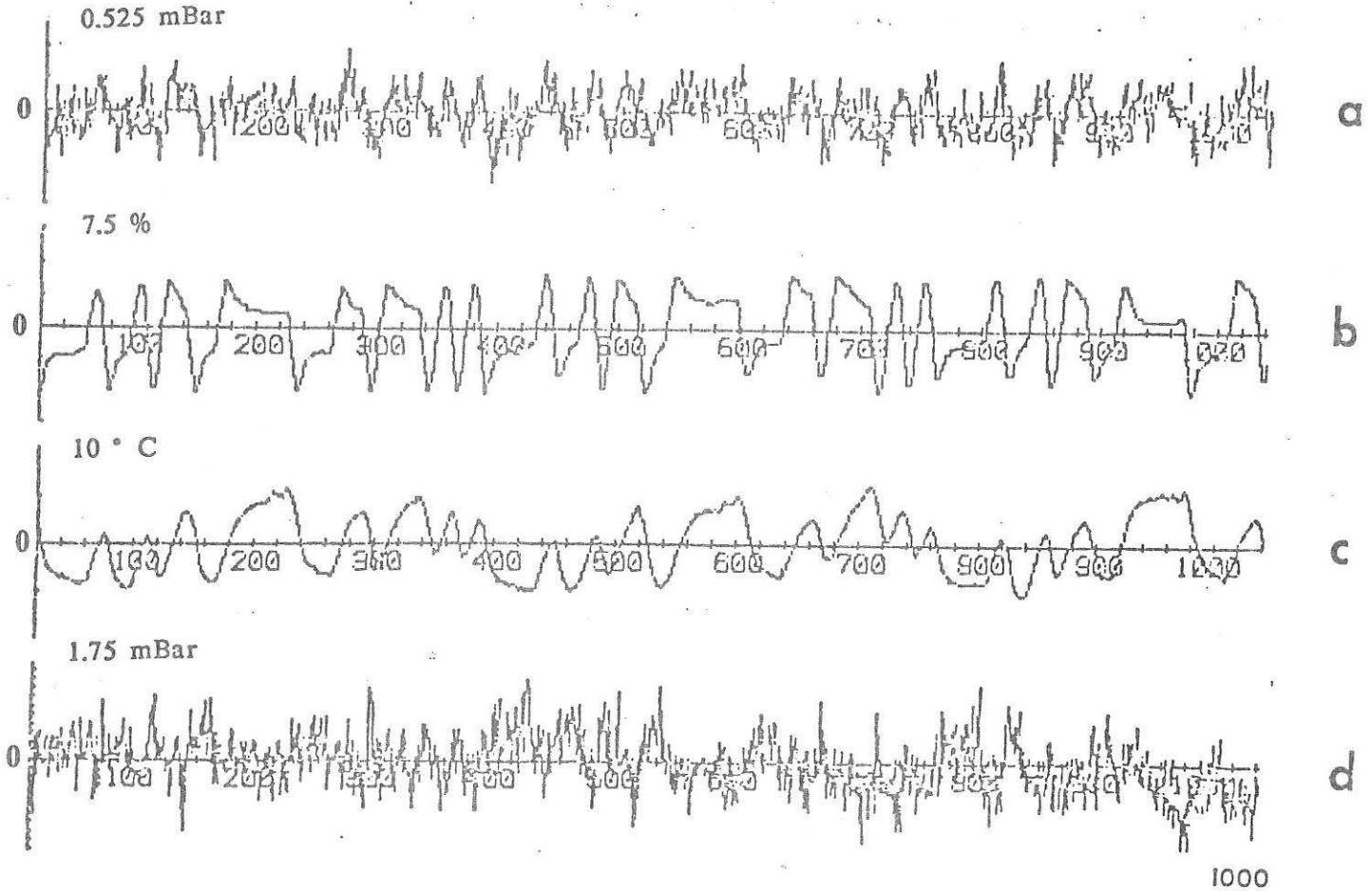


Fig. 1 PRBS applied to temperature damper position

- (a) Primary air differential pressure
- (b) Temperature damper position
- (c) Outlet temperature
- (d) Mill differential pressure

Sampling interval = 5.0 secs.

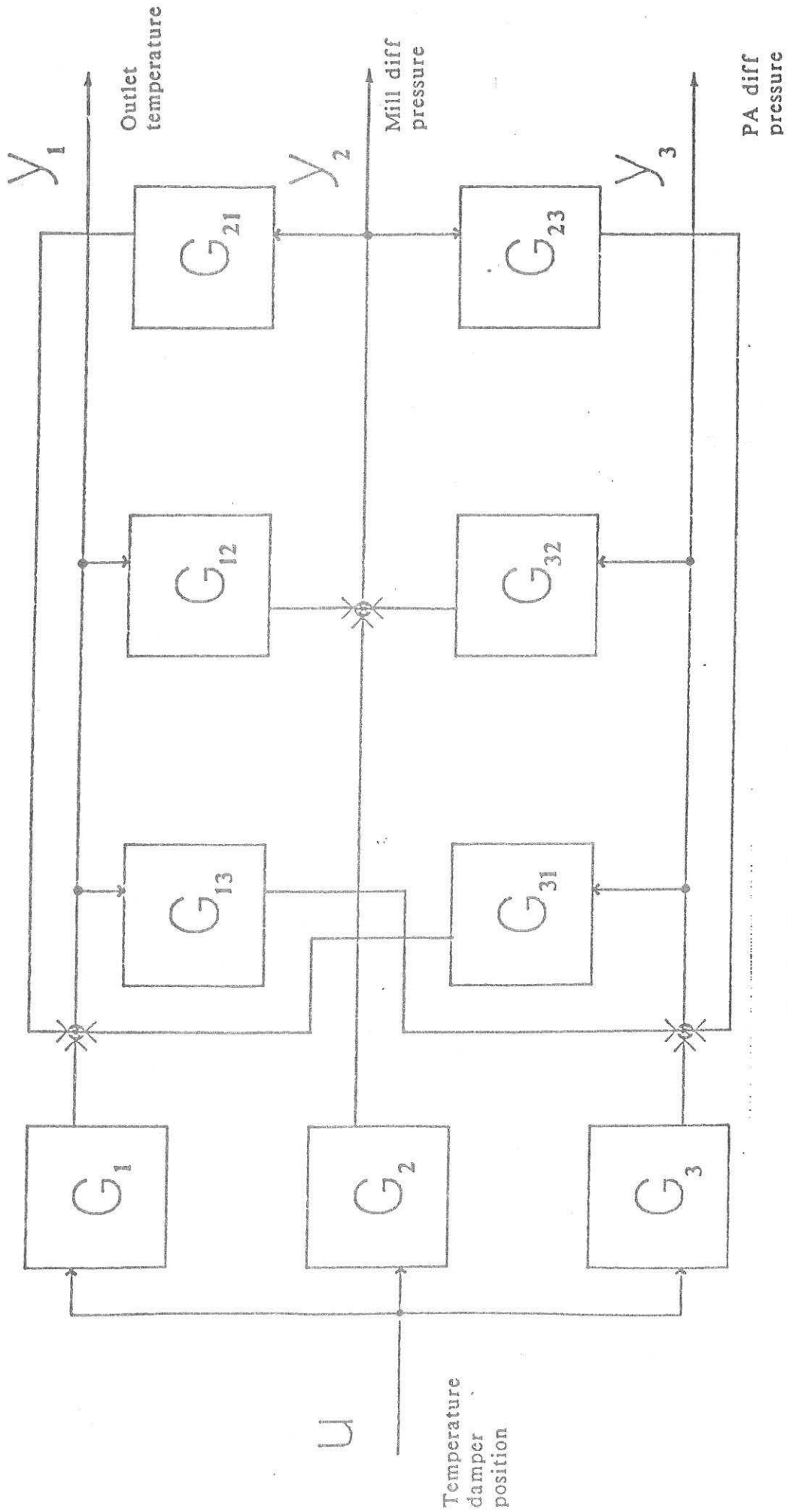


Fig. 2 Multiple-input, single-output sub-system representation

Temperature Loop

- y_1 sub-system outputs
- y_2 overall system input
- y_3 model governing interaction between i and j -th sub-systems
- u overall system input
- G_{ij} model governing interaction between i and j -th sub-systems

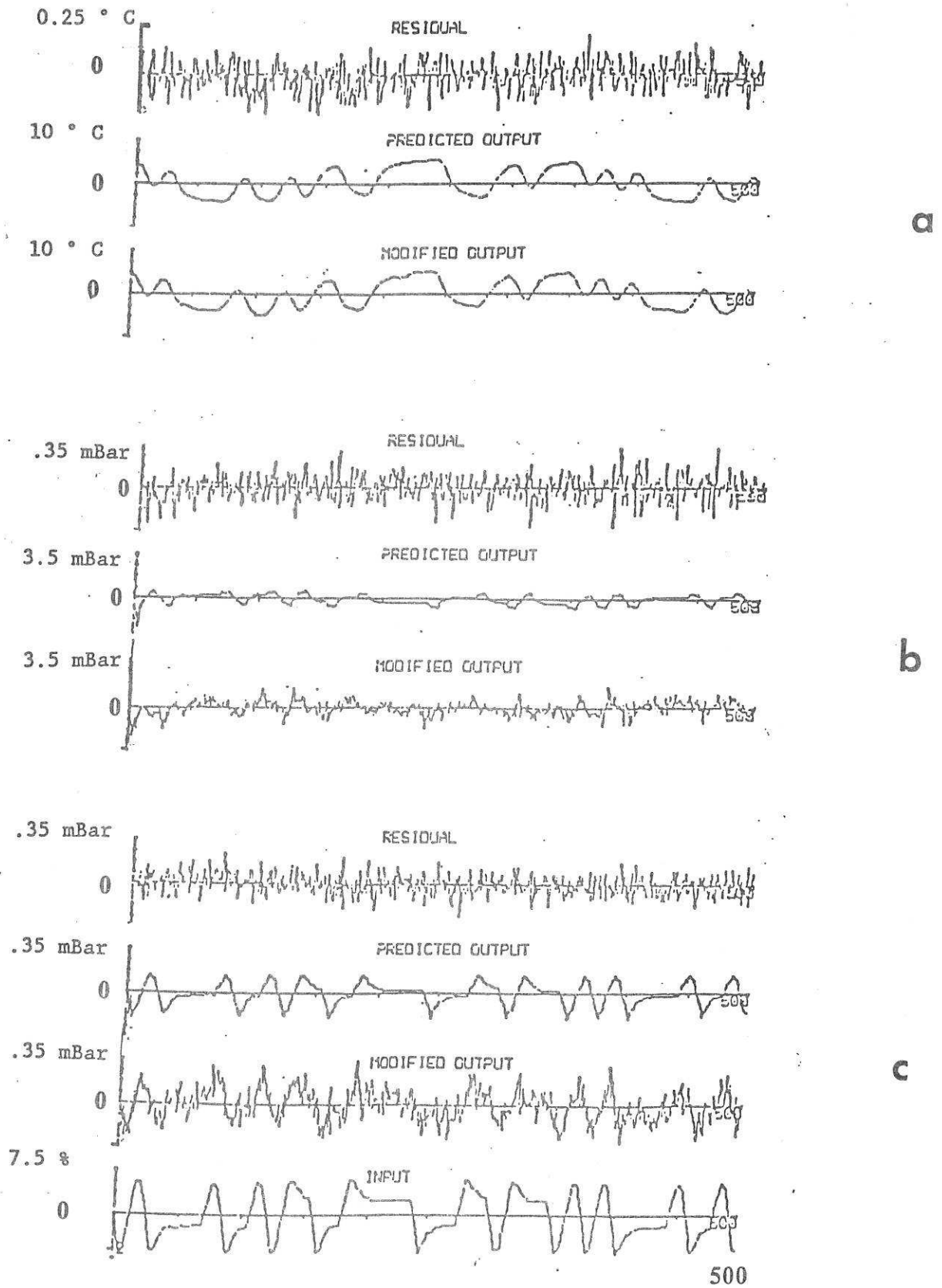


Fig. 3 Multivariable system model
Comparison of system and model outputs

- (a) outlet temperature
- (b) mill differential pressure
- (c) PA differential pressure

Subsystem 1

Subsystem 2

Subsystem 3

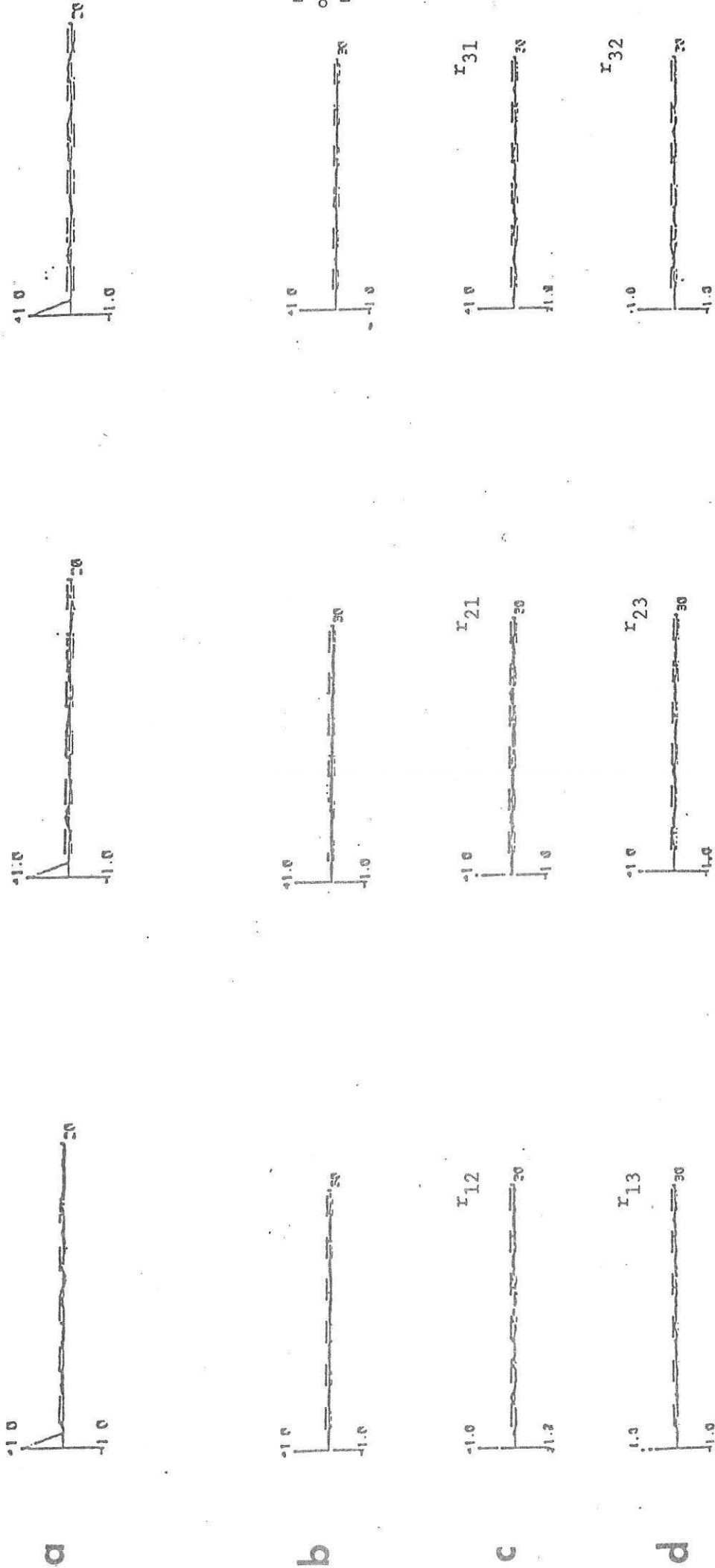


Fig. 4 Model validity tests

- (a) auto-correlation functions of residual sequences
- (b) cross-correlation functions residuals/input
- (c) cross-correlation functions residuals/residuals
- (d) cross-correlation functions residuals/residuals

r_{ij} - cross-correlation function between sub-systems i and j

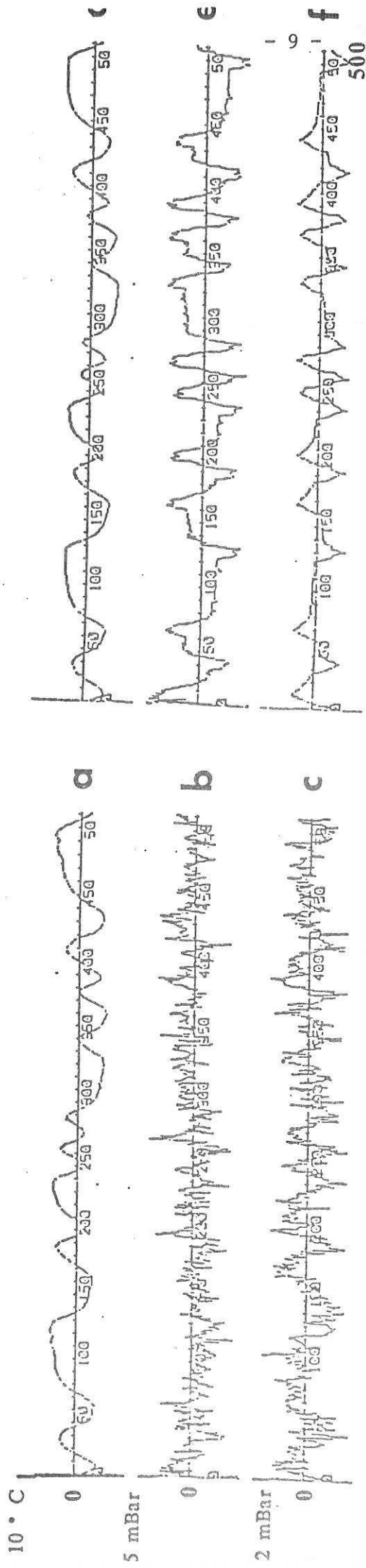


Fig. 5 Cross-validation of identified model with alternative data

- (a) experimental outlet temp.
- (b) experimental mill diff. pressure
- (c) experimental PA diff. pressure
- (d) model outlet temp.
- (e) model mill diff. pressure
- (f) model PA diff. pressure