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# IDENTIFICATION AND FEEDBACK CONTROL OF AN INDUSTRIAL GLASS FURNACE

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*A feedback identification method is applied to determine a stochastic model of an industrial glass furnace; the model is used for supervisory control.*

## SUMMARY

This paper describes the procedure that has been used for the identification and subsequent regulation of an operating float glass furnace at GLAVERBEL S.A., Belgian's largest flat glass manufacturing company. The objective in a glass melting furnace consists in controlling the combustion of fuel above the glass and the batch in order to maintain a "basic temperature" in the molten glass that is as constant as possible. The large time constants, the essentially unstable behaviour of the glass furnace and the presence of feedback are the main difficulties encountered in this problem. In this work a lumped stochastic prediction model has been identified that allows one to predict the "basic temperature" of the melting from the batch quantities, the temperatures measured at various other points and the controls applied at the fuel flows. This model has been implemented on a process control minicomputer and used for supervisory control. A substantial reduction in the standard deviation of the "basic temperature" has been achieved.

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## I. INTRODUCTION AND OUTLINE OF THE PAPER

The purpose of this paper is not to develop some new theories on the problem of identification. Rather this paper describes how existing identification methods have been put together and applied to a real-life and rather complicated identification problem, namely the "identification of an operating manually controlled industrial glass furnace melting". An attempt will be made to "tell the whole story" of the identification procedure, from the analysis of the measured data to the obtention of the final model. With this attempt we will have presented an example where the careful application of a recent identification method for feedback systems has led to a significant improvement in the performances of an industrial process.

The glass furnace and its functioning will be briefly described in section II. The main difficulties associated with the control of a glass furnace will be pointed out as well as the strategy that was selected to cope with these difficulties. The behaviour of the furnace melting was strongly affected by feedback due to the actions of the manual operator. It was therefore necessary to use an identification method that was able to identify the open loop dynamics from feedback affected measurements ; Section III describes the method. In Sections IV to VI the successive steps of the identification procedure are described. Section IV deals with the preliminary treatment of the data: elimination of "bad" data, removal of trends, prefiltering, cross-correlation analysis, selection of the significant variables. In Section V an innovations representation is obtained for the joint stochastic process made up of all the selected variables. In Section VI the open-loop input-output and noise dynamics model is derived from this global innovations representation, and the optimal control is computed from the obtained model. The numerical performances of this regulator are compared with the performances previously obtained by the manual regulation.

## II. STATEMENT OF THE PROBLEM

The glass production line generally consists of batching, melting and fining, delivery and conditioning, forming, annealing, finishing and inspection. Fig.1 is a schematic description of the furnace, with the batching and melting area to the left and the fining area to the right.

The glass furnace behaviour is governed by several physical laws. The major phenomena are:

- radiative heat transfer in semitransparent media
- the melting process (change of state)
- heat and convective mass transfer in fluid media.

These three phenomena are always present in the glass furnace, and their proper control is of paramount importance for the production of high quality glass.

In hot crown melters the energy is transferred to the melter by combustion of fuel above the glass and batch. The radiative heat transfer problem is extremely complex, because the crown and glass cover reflects and absorbs energy from all sources within the medium. The batching, melting and fining process is essentially controlled by acting on the fuel flows at the burners. In doing so, the following goals have to be pursued :

- the required melting rate must be produced ; this can be achieved by controlling the temperatures near the batch material.
- the residence times, and thus the mixing of the melting glass, must be adequate; this requires that the temperature distribution in the glass be controlled. The distributed nature of the energy entering in the melt and the subsequent temperature and density distributions produce the appearance of a convective flow pattern in the glass melt (see Fig. 1). The establishment of adequate convective flow profiles is probably the single most important phenomenon for the production of high quality glass.
- the stability of the melter operation must be maintained; to achieve this it is necessary to maintain the "basic temperature" ($T_1$ to $T_6$ in Fig. 1) at a constant operating point that is relatively insensitive to disturbances in pull, ambiant temperature and composition variations.

Some of the major problems in controlling a furnace melter are the presence of a strong inherent feedback due to the convective flow patterns (see Fig.1), the very long response times that range between 5 and 24 hours, and the fact that the melter has to be maintained at a near stable regime. About 80% of the glass melt that flows to the fining end comes back to the melting area; the mass of energy that is thereby transferred produces a strong and delayed feedback effect on the basic temperature in the bottom of the melter. Up to the present study, the furnace melter had been regulated by manual operators, working in three 8 hour shifts. Provided with a number of measurements the operator adjusts the fuel valves using logs based on his past experience. Because of the long response times, the effects of the actions of one operator are only felt by the next one, which complicates the regulation even further.

It was hoped that by obtaining a dynamic model of the melter, that would be used to design a feedback regulator, a better regulation would be achieved.

In modelling melters several techniques have been used in the past. Briefly stated, some of them are:

- Describing the melter by a single overall deterministic dynamic model, with time constants and time delays, obtained through the use of tracers.
- Physical modelling of the melter: a viscous substance at a lower temperature than molten glass is used in a scale model of the melting container.
- Analytical model building using conservation laws and constitutive equations to generate partial differential equations for the temperatures and flows.
- Statistical model building using measurements of a small number of significant variables to identify a lumped stochastic model.

The first two techniques are unable to give a global description of the furnace behaviour, and in particular of the evolution of the temperature. The third technique leads to a numerically complex solution which cannot be implemented in real time. It was therefore decided to try to identify a very simple lumped stochastic linear model relating several variables for which measurements were available, namely the load L, the consumption Q of fuel at the burners, the "basic" temperatures $T_1$ to $T_8$ at 8 different points in the bottom of the melter, and the external temperature $T_E$ (see Fig.1). About 1000 sets of measurements of these variables were available with a sampling interval of 1 hour. These measurements had been made on the operating furnace. Therefore an identification method had to be used that could identify the open loop transfer function and noise dynamics from measurements contaminated by feedback; this method is briefly presented in the next section.

## III. IDENTIFICATION OF A FEEDBACK PROCESS : THE JOINT PROCESS METHOD.

The identification of linear systems operating under feedback control has been the subject of intensive investigation in the last three years. In this paper we shall not review the most important results in this field, nor shall we justify the use of any particular method, leaving this subject to other papers (see e.g. [1] ). Rather we shall briefly describe the feedback identification method first proposed by Phadke [2] , [3] and, independently, by Caines and Chan [4] , [5] , that we have used in this particular application, and which we shall call the "joint process method".

This method is applicable to time invariant linear systems with a linear feedback; the equations of the system are :

$$\begin{cases} y(k) = A(z)\, u(k) + B(z)\, e(k) & \text{(1a)} \\ u(k) = C(z)\, y(k) + D(z)\, w(k) & \text{(1b)} \end{cases}$$

where $y(k)$ and $u(k)$ are, respectively, the $p$-vector of outputs and the $m$-vector of inputs of the system; $e(k)$ and $w(k)$ are unobservable zero mean stationary white noise sources of dimensions $p$ and $q$ respectively, which are possibly correlated; A, B, C, D are transfer function matrices of appropriate dimensions. Equation (1a) is interpreted as describing the behaviour of the open loop system; equation (1b) describes the behaviour of the feedback system. We recall that the synthesis of an optimal regulator requires that the open loop dynamics (i.e. $A(z)$ and $B(z)$) be identified despite the presence of the feedback loop (see Fig. 2).

The "joint process method" is based on the idea that the true inputs to the system are the external disturbances $e(k)$ and $w(k)$. A joint vector stochastic process $Z(k)$ of dimension $r = p + m$ is formed, made up of the input and output processes.

$$Z(k) = \begin{bmatrix} y(k) \\ u(k) \end{bmatrix} \qquad (2)$$

The process $Z(k)$ can be modelled as the output of a white noise driven innovations representation

$$Z(k) = L(z)\ \varepsilon(k) \qquad (3)$$

where $\varepsilon(k)$ is a r-component white noise process of zero mean and - assuming that $Z(k)$ is full rank - with positive definite covariance matrix :

$$E\{\varepsilon(k)\ \varepsilon'(j)\} = \delta_{kj} \cdot R_\varepsilon \qquad , R_\varepsilon > 0 \qquad (4)$$

It can be shown [6] that under certain conditions on the structure of the system, the transfer function matrices A, B, C, D can be uniquely derived from the joint process representation (3). One sufficient condition is that there exists a delay in both the open loop and the feedback loop, which is the case with the glass-furnace.

The matrix transfer function $L(z)$ can be decomposed as follows :

$$\begin{bmatrix} y(k) \\ u(k) \end{bmatrix} = \begin{bmatrix} L_{11}(z) & L_{12}(z) \\ L_{21}(z) & L_{22}(z) \end{bmatrix} \begin{bmatrix} \varepsilon_1(k) \\ \varepsilon_2(k) \end{bmatrix} \qquad (5)$$

It is then easy to express A, B, C, D in terms of the $L_{ij}$ :

$$\begin{aligned} A &= L_{12}\, L_{22}^{-1} \\ B &= L_{11} - L_{12}\, L_{22}^{-1}\, L_{21} \\ C &= L_{21}\, L_{11}^{-1} \\ D &= L_{22} - L_{21}\, L_{11}^{-1}\, L_{12} \end{aligned} \qquad (6)$$

The existence of $L_{11}^{-1}$ and $L_{22}^{-1}$ is guaranteed by the invertibility of the innovations representation.

In the glass furnace problem, the innovations representation for $Z(k)$ has been identified using covariance factorization and the stochastic realization theory, as described in Section V. However, prior to identifying a model for the vector process $Z(k)$, a number of preliminary operations have to be performed on the raw data. These will now be described.

# IV. PRELIMINARY TREATMENT OF DATA.

We recall that 11 time series of measurements were available, each made up of 1000 data points with a time interval of 1 hour: the load L, the fuel flow Q, 8 different temperatures $T_1$ to $T_8$ in the bottom of the melter and the external temperature $T_E$.

## a. Elimination of "bad" data

The data had been collected without interruption over a period of about 40 days. Over such a long time span it is likely that a number of incidents will have occurred, such as a sticking valve or a failing measurement device. Insofar as the data collected at the time of these incidents do not reflect the dynamics of the system, they have to be eliminated. The data analysis therefore must begin with a careful (and tedious) visual examination of the data.

Only those time series of measurements that had been collected during periods where no important incidents disturbed the functioning of the furnace wre retained for the identification. In spite of that the series showed a number of anomalies, located in time, that were due to the deficiencies of the sensors. When a sampled value Z(k) fell outside the interval $(\overline{Z} \pm 2\sigma)$, it was replaced by a smoothed value obtained from the six neighbouring values.

## b. Removal of trends

The observed time series were of course not zero mean; in addition, because of the progressive degradation of the physical characteristics of the process, they were not stationary. Therefore each of the time series was decomposed into the sum of a deterministic plynomial trend f(k) and a residual zero mean random sequence v(k):

$$Z(k) = f(k) + v(k) \qquad (7)$$

The trends were computed using orthogonal polynomials (see[7]). Polynomials of successively higher order were computed; a polynomial of degree n was used when the highest degree coefficient in the polynomial of degree n + 1 was less than $10^{-5}$. It wsa found that the trends of all 11 series could well be approximated by first and second degree polynomials.

Fig. 3 shows the time series $T_4$ before and after elimination of the trend. From this point on, only the residual time series are used.

c. Prefiltering

It is well known that the error in the estimates of cross-covariances between two processes are greatly increased as a result of large autocovariances within each process (see e.g.[8]). Therefore a filtering operation was applied to each of the 11 detrended series to convert them to white noise or almost white noise processes. For each stationary series $v_i(k)$ a low-order autoregressive moving-average (ARMA) model was obtained using correlation methods:

$$A_i\,(z^{-1})\;v_i\;(k) = B_i\;(z^{-1})\;w_i\;(k) \qquad i = 1, \ldots, 11 \qquad (8)$$

where $A_i\;(z^{-1})$ and $B_i\;(z^{-1})$ are polynomials of degree p and q respectively, and $w_i\;(k)$ is white noise. For each of the time series, models of increasing complexity were successively attempted, in the following order: AR (1), AR (2), ARMA(1,1), ... . This choice was based on the visualization of the autocorrelation functions of the individual time series. A test on the whiteness of the residuals was used to validate the models: a model was accepted only if less than 5% of the autocorrelation coefficients $\rho(k)$, for $k \neq 0$, exceeded the 95% confidence interval around zero. The time series could all be modelled with either autoregressive models of order 1 or 2, or ARMA(1,1) models. Table 1 shows the first few autocorrelation coefficients and the models obtained for the detrended time series corresponding to $T_4$, Q and L.
Notice that the autocorrelation function of L was smoothed before identifying the ARMA(1,1) model.

After identification of low order models for each of the series $v_i(k)$, the residual "white" noise series $\tilde{Z}_1(k)$, $\tilde{Z}_2(k)$, ... , $\tilde{Z}_{11}(k)$ were formed through inverse filtering

$$\tilde{Z}_i(k) = \frac{A_i(z^{-1})}{B_i(z^{-1})}\;v_i(k), \qquad i = 1, \ldots, 11 \qquad (9)$$

In the sequel the filtered series $\tilde{Z}_i(k)$ are used.

d. Computation and analysis of auto- and crosscorrelations

The autocorrelation functions $r_{\tilde{Z}_i}(k)$, $k = 0, 1, \ldots$ , and the crosscorrelation functions $r_{\tilde{Z}_i \tilde{Z}_j}(k)$, $k = \ldots, -1, 0, 1, \ldots$ , between each two residual time series were estimated and plotted. Typical curves are shown in Fig. 4b.The corresponding auto- and crosscorrelation functions obtained from the time series data before whitening (i.e. obtained from the $v_i(k)$ rather than the $\tilde{Z}_i(k)$ ) are shown in Fig. 4a for comparison. By comparing the correlation functions of Figs. 4a and 4b, it may appear at first hand that most of the existing crosscorrelation between, say, Q and $T_4$ has been blurred out by the prefiltering operation. However it must not be forgotten, as stated above, that much of the apparent crosscorrelation information contained in the curves of Fig. 4a is probably erroneous, because of the large autocorrelation of each of the individual time series.

To decide whether any two variables were correlated, confidence intervals were drawn. It was concluded that there was no significant correlation between the ambiant temperature $T_E$ and the other variables; the variable $T_E$ was therefore eliminated. In addition it was decided that, of the 8 "basic temperature" measurements, only $T_4$ would be retained in the model, because it showed the largest correlation with Q and the smallest lag. The subsequent identification was therefore performed on a "joint vector process" $\tilde{Z}(k)$ made up of three variables: the residual processes (detrended and filtered) obtained from the basic temperature $T_4$, the fuel consumption Q and the load L:

$$\tilde{Z}(k) = \left[\tilde{T}_4(k) \quad \tilde{Q}(k) \quad \tilde{L}(k)\right]^T$$

## V. IDENTIFICATION OF THE MATRIX TRANSFER FUNCTION.

Since nothing was known about the structure of the model for $\tilde{Z}(k)$, it was decided to use an identification method that does not require any a priori knowledge on the structure. Covariance factorization methods havethis property, as opposed to maximum likelihood methods that require an a priori parametrization. A state-variable innovations model was sought for the Z(k) process in the following form

$$\begin{cases} x(k+1) = Fx(k) + G\varepsilon(k+1) & (10a) \\ \tilde{Z}(k) = Hx(k) & (10b) \end{cases}$$

where $\varepsilon(k)$ is a vector white noise process with the same dimension as $\tilde{Z}(k)$. The innovations model was obtained via the following steps.

a) First a Hankel matrix $\mathcal{H}(\hat{R}_{\tilde{Z}}(k))$ was formed using the estimated 3 X 3 autocovariance functions

$$\hat{R}_{\tilde{Z}}(k) = \frac{1}{N} \sum_{j=k}^{N} \tilde{Z}(j)\, \tilde{Z}'(j-k), \quad k = 0, 1, 2, \ldots \qquad (11)$$

A covariance factorization algorithm of Rissanen(see [7]) was used to factor the Hankel matrix and thereby determine the order of the model and the factors H, F and N such that

$$\hat{R}_{\tilde{Z}}(k) = HF^{k} N \qquad k = 0, 1, 2, \ldots \qquad (12)$$

A numerical test was designed to decide on a stopping rule for Rissanen's algorithm. A fifth order model was found to lead to a satisfactory factorization of $\hat{R}_{\tilde{Z}}(k)$, i.e. H, F and N have dimensions 3 X 5, 5 X 5 and 5 X 3 respectively.

b) From the factors H, F and N, the input matrix G and the innovations variance matrix $R_{\varepsilon}$ are obtained using the stochastic realization theory [10]. This requires the solution of the following matrix Riccati equation to its steady-state

$$\begin{cases} \Sigma_{i+1} = F\Sigma_i F' + (N - F\Sigma_i F'H')(HN - HF\Sigma_i F'H')^{-1}(N - F\Sigma_i F'H') & (13a) \\ \Sigma_0 = 0 & (13b) \end{cases}$$

$$\Sigma = \lim_{i\to\infty} \Sigma_i \qquad (14)$$

It was found that this equation converges very fast. G and R, of dimensions 5 X 3 and 3 X 3, are given by

$$\begin{cases} G = (N - F\Sigma F'H')(HN - HF\Sigma F'H')^{-1} & (15a) \\ R_\varepsilon = HN - HF\Sigma F'H' & (15b) \end{cases}$$

The following estimates were obtained for the matrices H, F, G and $R_\varepsilon$ that define the model (10) :

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ .01 & 1 & 0 & 0 & 0 \\ -.02 & -.10 & 1 & 0 & 0 \end{bmatrix} \qquad G = \begin{bmatrix} 1 & 0 & 0 \\ -.01 & 1 & 0 \\ .02 & .09 & 1 \\ -.01 & .05 & -.02 \\ 0 & -.10 & -.01 \end{bmatrix}$$

$$F = \begin{bmatrix} .06 & 0 & -1.20 & 1 & 0 \\ 0 & -.18 & -.04 & .11 & 1 \\ 0 & -.06 & -.04 & -.04 & .23 \\ .13 & .60 & -.32 & -.20 & -.43 \\ 0 & -.21 & -.07 & .03 & .36 \end{bmatrix} \qquad R_\varepsilon = \begin{bmatrix} .68 & .52 & -1.10 \\ .52 & .35 & -.05 \\ -1.10 & -.05 & .93 \end{bmatrix}$$

c) The transfer function matrix L(z) is then computed from the state-variable model using the classical formula

$$L(z) = H(zI - F)^{-1}\, zG \qquad (16)$$

To perform the inversion of (zI - F) in a numerically efficient way, Rissanen's Padé approximation algorithm [9] was used. The matrix transfer function for $\tilde{Z}(k)$ was found to be

$$L(Z) = \frac{1}{\chi_F(z)} \begin{bmatrix} .27z + .03z^2 + 1.25z^3 - .22z^4 + z^5 & -.05z + .05z^2 + .06z^3 - .19z^4 & .01z - .01z^2 - .22z^3 \\ -.15z + .20z^2 - .06z^3 - .03z^4 & .07z + .18z^2 + .06z^3 - .16z^4 + z^5 & .04z^2 - .11z^3 + .99z^4 \\ -.01z - .15z^2 + .19z^3 - .06z^4 & .02z - .34z^2 + .16z^3 - 1.23z^4 & -.03z^2 + .01z^3 + .10z^4 + z^5 \end{bmatrix} \qquad (17)$$

with $\chi_F(z) = -.02 + .36z + .26z^2 + 1.27z^3 - .2z^4 + z^5$

## VI. OPEN LOOP MODEL PREDICTION AND CONTROL STRATEGY

### a. Computation of the open-loop and noise models

The open-loop model is computed from the joint process transfer func- matrix using the relations (6) and the prefilters computed in Section IV. Here $T_4$ is considered the output to be controlled, Q is the control input and L is a known but uncontrolled input. The open loop model has the following form

$$\alpha T_4(k) = \left[L_{12}L_{22}^{-1}\right]\begin{bmatrix} \beta Q(k) \\ \gamma L(k) \end{bmatrix} + \left[L_{11} - L_{12}L_{22}^{-1}L_{21}\right]\varepsilon_1(k) \qquad (18)$$

where the $L_{ij}$ are obtained from the appropriate partitioning of the transfer function matrix (17) and $\alpha$, $\beta$ and $\gamma$ are the filters obtained in Table 1 :

$$\alpha(z^{-1}) = 1 - 1.01\, z^{-1} + .04\, z^{-2}$$

$$\beta(z^{-1}) = 1 - 1.03\, z^{-1} + .06\, z^{-2}$$

$$\gamma(z^{-1}) = \frac{1 - .9\, z^{-1}}{1 - .7\, z^{-1}}$$

The white noise process $\varepsilon_1(k)$ is the first component of the vector process $\varepsilon(k)$, with variance $\sigma^2_{\varepsilon_1} = .68$. Notice that $T_4$, Q and L in equation (18) are the detrended zero mean components of the "basic temperature", the fuel consumption and the load, respectively. The model (18) can be rewritten in the form

$$A(z^{-1})\, T_4(k) = B_1(z^{-1})\, Q(k) + B_2(z^{-1})\, L(k) + C(z^{-1})\, \varepsilon_1(k) \qquad (19)$$

where A, $B_1$, $B_2$ and C are polynomials in $z^{-1}$. They are

$$A(z^{-1}) = 1 - 3.3\, z^{-1} + 9.3\, z^{-2} - 18.5\, z^{-3} + 29.8\, z^{-4} - 41.7\, z^{-5} + 48.6\, z^{-6} - 49\, z^{-7} + 44\, z^{-8} - 30\, z^{-9} + 19\, z^{-10} + 8.5\, z^{-11} + 2.4\, z^{-12} - 1.6\, z^{-13}$$

$$B_1(z^{-1}) = 1.9\, z^{-5} - 2.6\, z^{-6} + 3.1\, z^{-7} - 2.9\, z^{-8} + 2.4\, z^{-9} + 1.6\, z^{-10}$$

$$B_2(z^{-1}) = 1.9\, z^{-4} - 2.3\, z^{-5} + 2.6\, z^{-6} - 2.2\, z^{-7}$$

$$C(z^{-1}) = 1 - 2.3\, z^{-1} + 6.8\, z^{-2} - 11.3\, z^{-3} + 14.7\, z^{-4} - 22.9\, z^{-5} + 24.9\, z^{-6} - 22.7\, z^{-7} + 19.4\, z^{-8} - 6.9\, z^{-9} + 7\, z^{-10}$$

It is interesting to observe that there exists a five hour delay before any variation in the fuel flow at the burners starts having an effect on the basic temperature $T_4$ in the bottom of the melter. A variation in the load starts affecting the basic temperature after four hours. While the presence of a delay has enabled one to uniquely identify a model despite the presence of feedback, the length of this delay is a serious drawback when it comes to regulating the temperature in the melter.

b. Prediction

The minimum variance i-step predictor for $\hat{T}_4(k + i/k)$ was computed for i = 1 up to 5 hour. It is given by (see [12])

$$C(z^{-1})\hat{T}_4(k + i/k) = G_i(z^{-1})T_4(k) + B_1'(z^{-1})F_i(z^{-1})Q(k + i - 5) + B_2'(z^{-1})F_i(z^{-1})L(k + i - 4)\ ,\ i = 1, \ldots, 5 \qquad (20)$$

where $B_1'(z^{-1}) = z^5 B_1(z^{-1})$, $B_2'(z^{-1}) = z^4 B_2(z^{-1})$ and $F_i$ and $G_i$ are computed from

$$C(z^{-1}) = A(z^{-1})F_i(z^{-1}) + z^{-i}G_i(z^{-1})\ ,\quad i = 1, \ldots, 5 \qquad (21)$$

Notice that the prediction of $T_4(k + 5)$ at time k requires the knowledge of $L(k + 1)$; this future value of the load is known because it depends on the production planning which is determined several hours ahead.

c. Control strategy

The control can only be exerted through the fuel flow Q, the load L being a predetermined that depends mainly on the amount and thickness of glass to be produced. We recall that several goals have to be pursued when regulating a glass melter ; they have been described in Section II. It was felt that these objectives could best be summarized by maintaining the temperature $T_4$ as constant as possible around a predeterminedd set point. The control Q(k) was computed so as to minimize the variance of $T_4(k + 5)$, assuming knowledge of $T_4(j)$ and $Q(j)$, $j \leq k$, and $L(l)$, $l \leq k + 1$. With this objective the control law is

$$B_1'(z^{-1})F_5(z^{-1})Q(k) = - G_5(z^{-1})T_4(k) - B_2'(z^{-1})F(z^{-1})L(k + 1) \qquad (22)$$

where $F_5$ and $G_5$ are defined through (21). Notice that the control law is such that the predicted "basic temperature" coincides with the desired temperature. The following control law was obtained

$$\left[1.9 - .7\ z^{-1} + 2.0\ z^{-2} - .9\ z^{-3} + 5.0\ z^{-4} - 2.3\ z^{-5} + 8.7\ z^{-6} - 3.8\ z^{-7} + 6.2\ z^{-8} + 3.5\ z^{-9}\right] Q(k) =$$

$$\left[8.7 - 23.6\ z^{-1} + 45.8\ z^{-2} - 71.5\ z^{-3} + 101.5\ z^{-4} - 115.6\ z^{-5} + 135.2\ z^{-6} - 106.4\ z^{-7} + 83.7\ z^{-8} + 46.6\ z^{-9} - 18.7\ z^{-10} - 6.2\ z^{-11} + 3.5\ z^{-12}\right] T_4(k)$$
$$+ \left[-1.9 - .4\ z^{-1} - 1.8\ z^{-2} + .4\ z^{-3} + 6.1\ z^{-4} - 4.7\ z^{-5} + 6.9\ z^{-6} - 4.8\ z^{-7}\right] L(k + 1)$$

B. Performances

The predictor has been implemented on a process control computer in which the measurements are fed in real time. In the first few months of operation the controls were still adjusted manually by the furnace operators and the role of the model was limited to predicting the temperatures that would be attained with the manually applied controls. The reason for this is that it is difficult to convince production engineers that models can achieve any better than they can. It is only after they became impressed with the accuracy of the predictions that the automatic controls were plugged in. At present the minimum variance feedback control is automatically computed every hour, and applied to the fuel valves.

The implementation of the minimum variance computer control has enabled one to obtain a substantial reduction in the variations of the temperature in the melter. The standard deviation of the basic temperature, which was at 5.5 °C under manual control, has been lowered to 2.2°C with the computer control, a reduction of about 60%.

## VII. CONCLUSION

An industrial flat glass furnace melter is essentially a distributed parameter system governed by complicated partial differential equations relating the temperature and velocity distributions in the melt. Our study has shown that a very simple lumped linear model relating a few selected variables can give excellent results, for both prediction and control purposes.

The procedure that has been followed for the identification of the melter has been described step by step. A recently developed feedback identification method has shown to work very well. The identified model is now used on a process control computer for temperature prediction and automatic control of a glass melter that produces up to 600 tons of flat glass per day. The standard deviation of the basic temperature in the melter has been reduced up to 60%, thereby substantially increasing the productivity of the furnace. The parameters of the model have to be periodically adjusted to take into account the wear of the furnace.

To the authors' knowledge this is the first implementation of a computer controlled industrial flat glass furnace, in which the fuel valves are feedback controlled by the temperature of the melter.

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Table 1

| | $\rho(k)$ | Type of model | Model |
|---|---|---|---|
| $T_4$ | $\rho(1) = .979$<br>$\rho(2) = .957$ | AR(2) | $T_4(k) - 1.01\ T_4(k-1) + .04\ T_4(k-2) = w_1(k)$ |
| Q | $\rho(1) = .978$<br>$\rho(2) = .957$ | AR(2) | $Q(k) - 1.03\ Q(k-1) + .06\ Q(k-2) = w_2(k)$ |
| L | $\rho(1) = .431$<br>$\rho(2) = .474$<br>$\rho(3) = .449$<br>$\rho(4) = .418$ | ARMA(1,1) | $L(k) - .9\ L(k-1) = w_3(k) - .7\ w_3(k-1)$ |

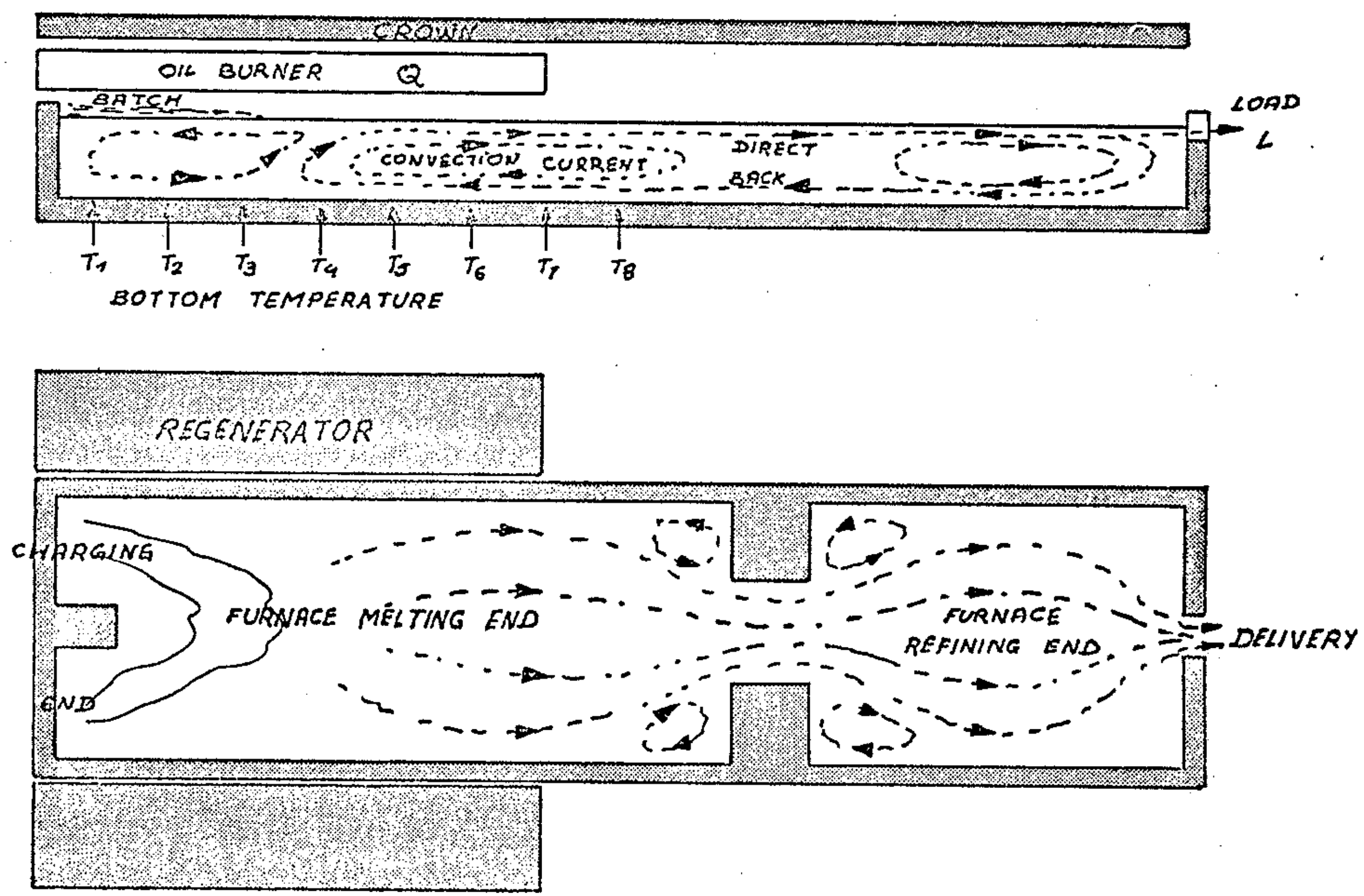

CROWN
OIL BURNER
Q
BATCH
LOAD
L
CONVECTION CURRENT
DIRECT
BACK
T1
T2
T3
T4
T5
T6
T7
T8
BOTTOM TEMPERATURE
REGENERATOR
CHARGING
END
FURNACE MELTING END
FURNACE
REFINING END
DELIVERY

Fig. 1

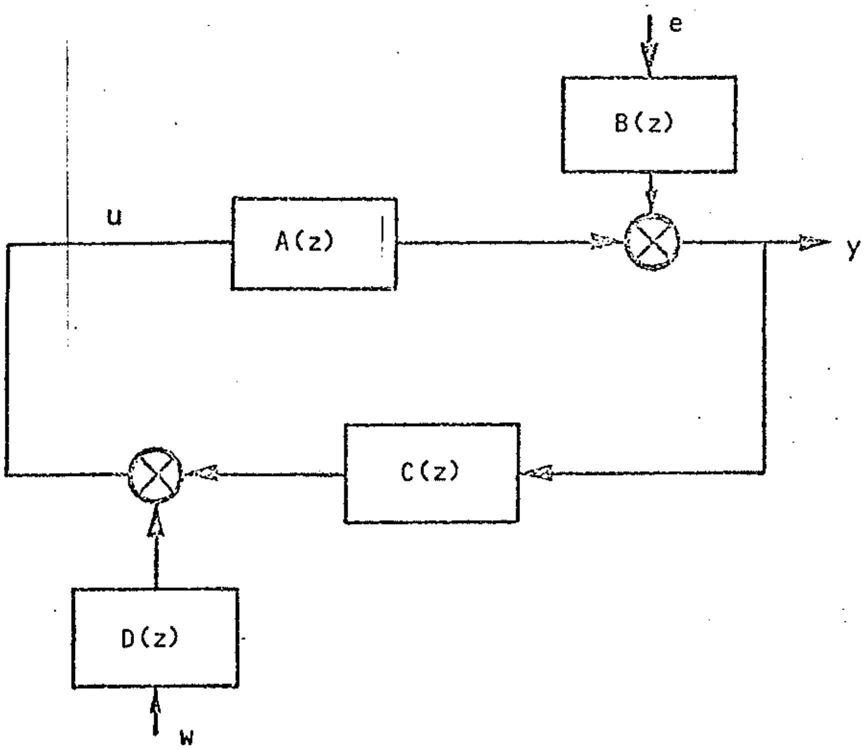



Fig. 2.

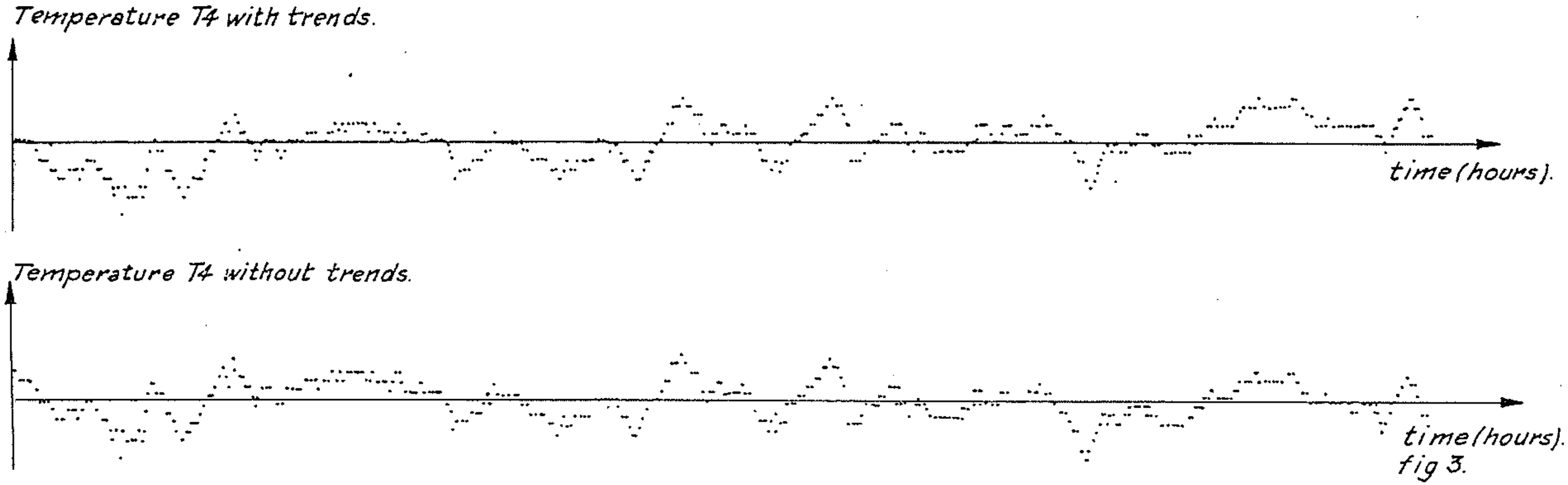
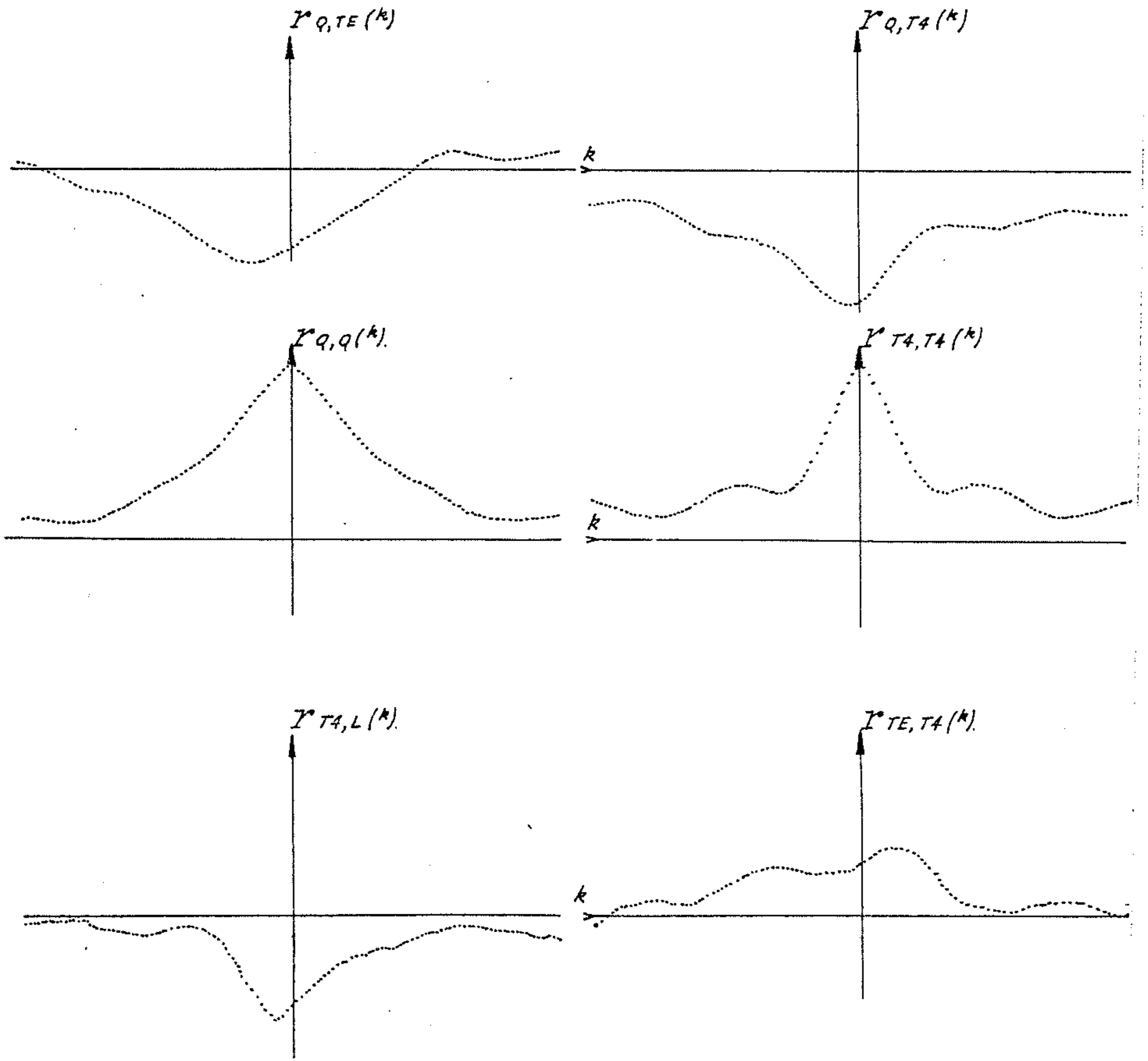
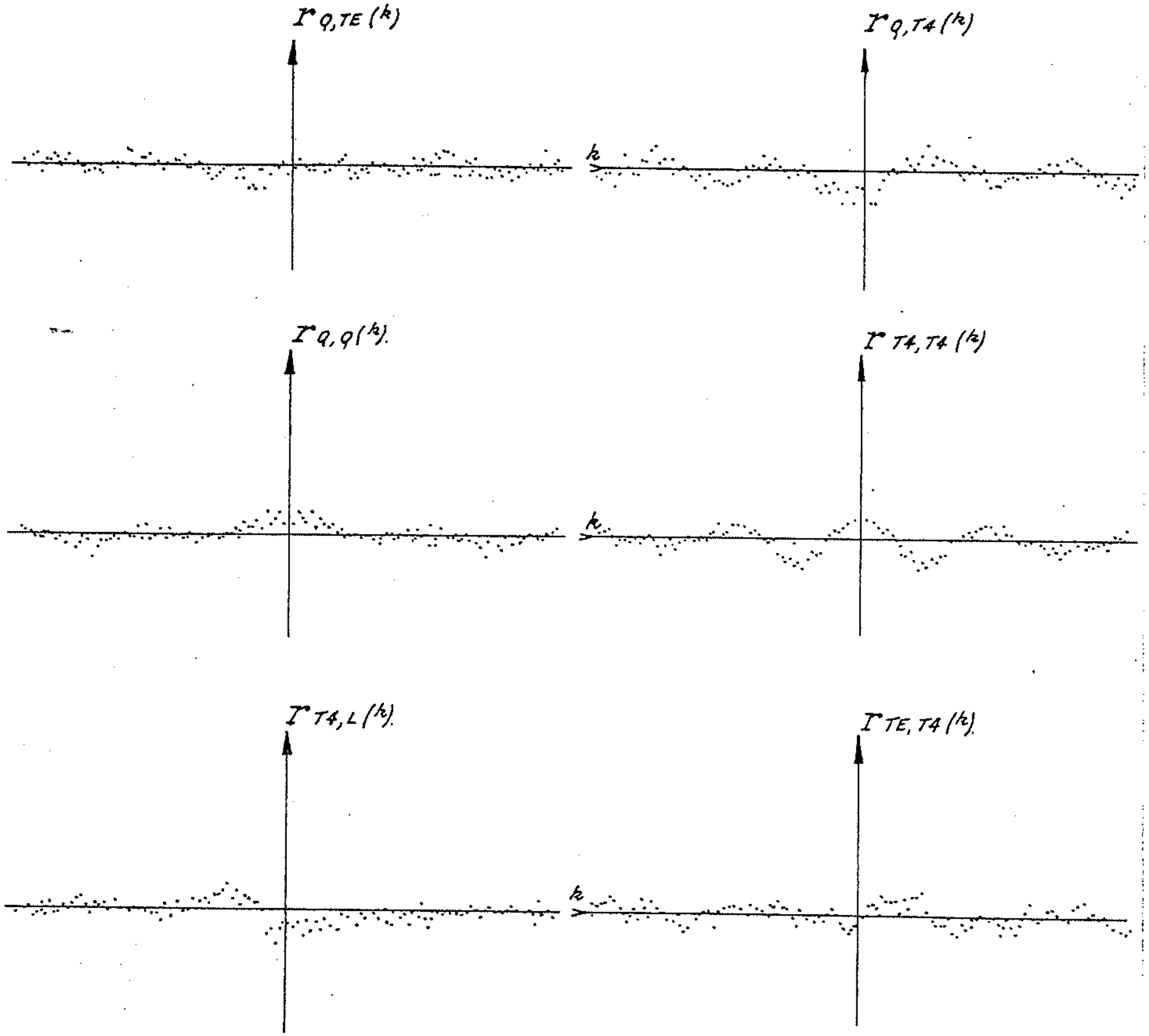

Temperature T4 with trends.
time (hours).
Temperature T4 without trends.
time (hours).

fig 3.




Auto-and cross-correlations before prefiltering   fig 4a.




Auto-and cross-correlations after prefiltering    fig 4b.