SHORT TERM FORECASTING WITH THE SURVEY OF BUSINESS INTENTIONS OF THE SPANISH MINISTRY OF INDUSTRY*

C. HERNANDEZ M.B. ZARROP R.G. BECKER

This gives an account of an study conducted by the authors to empirically - asses the predictive value and causal relationships of the Monthly Survey - of Business Intentions of the Spanish Ministry of Industry.

The approach implies some extensions of the Box-Jenkins procedures for -- time series modelling and forecasting. After giving some economic and intuitive justification for our model parametrization, models for the individual series were estimated. Then two forecasts were obtained for each series: a model based one (off-line) and an automatic forecast (without series model) 'self-tuning' predictor. The 'self-tuning' predictor provides additional -- evidence on the 'optimality' of Box-Jenkins forecasting methods. Finally a cross-correlation analysis, with the innovations of pairs of series was -- used, to establish the relationships between series. When that was of a -- feedback free nature, input-output models were estimated, and a third forecast with these models were obtained. The three forecasts were compared in performance.

The main conclusions are: the suitability of the methods used for the study; the predictive value of the Survey was confirmed, and the 'consistency' of the empresarios answeres, allowing for further econometric analysis. -- In addition we verified the need for specification analysis from the raw data, and the lack of efficiency of 'long AR' models.

1. INTRODUCTION

The purpose of this paper is to illustrate, by means of a "case study" the application of time series methods, as understood in the control literature, to the analysis of the predictive value and consistancy of the Survey of Business Intentions of the Spanish - Ministry of Industry.

Our main intention is to motivate the reader and here we keep theoretical discussions to a minimum. The reader may find it useful to refer to S.E.E.M.A. /33/ and Hernández - et al. /19/ for a compact survey of the relevant theory. It is nevertheless our aim - to review, in future numbers of this Journal, some selected topics of the methods, - as they have been actually implemented in - the S.E.E.M.A. package /36/ used to conduct the study. Appendix A contains a sample of the results which have been fully reported in S.E.E.M.A. /34/.

The paper is organised as follows:

A Brief Description of the Monthly Survey - as it is actually conducted by the Spanish Ministry of Industry.

Modelling and Forecasting with a Single Time Series. Following a justification of the Box and Jenkins /7/ parametrisation, a general multiplicative polynomial representation is proposed to be fitted to the raw data, to obtain its associated innovation sequence. The fitting procedure maximises the approximate likelihood using a conjugate -- gradient search algorithm. The residuals -- and relevant gradients are calculated in a recursive and economical way by using a state space representation of the model to be

* This paper is a reduced and partial version of ref. /19/, presented at the 2^{nd} International Conference On Dynamic Modelling And Control of National Economies. January, 1977. Vienna.

- C. Hernández is with the Department of Statistics, Univ. Politécnica de Barcelona, Spain. Formerly with the Department of Computing & Còntrol, Imperial College, London.
- M.B. Zarrop & R.G. Becker are with the Department of Computing & Control, Imperial College.

- Paper received on October.

estimated, as in Astrom and Bohlin /5/ but recast to allow for the nonlinear parametrisation.

A theoretically equivalent long AR representation is also estimated and results noted. We point out the importance of treating the raw data and not the deseasonalised series.

A predictor based on the fitted model follows easily; it is itself a linear system for the above two representations.

Self-tuning predictor. If the ultimate goal is forecasting from given observations it may be proved that it is possible to model directly the predictor system, Wittenmark /39/. The self-tuning predictor may track slowly time varying parameters and allows for the incorporation of subjective judgment on the reliability of the data by using an appropriate "forgetting factor". It seems to cope well with nonstationarities and gives insight into why well-known forecasting procedures, such as "exponential smoothing" may occasionally work well.

Detection and Assessment of Relationships; Forecasting with Leading Indicators. Before trying a possible model relating two series of the Survey, we test for feedback. Econometricians by and large fail to do this and this has very serious consequences for regression analysis. Not only are crosscorrelation methods for transfer function estimation (Box and Jenkins, /7/) rendered invalid when feedback is present, Akaike /1/, but even diagnostic checks have to be used with care.

Our detection for "causality" was suggested vaguely by Granger /14/ and we drew heavily from Haugh and Box /17/ for our implementation. If feedback is absent, a transfer function model of interseries relationships may be consistently estimated by a variant of two-stage least squares. Because all pertinent information is obtained through the interresidual model, the estimates have desirable properties and this is true even if the series have seasonalities.

Forecasting when an estimated model is available follows in a straight-forward way. Results are reported and commented upon.

Conclusions and Limitations of the Method Used. The main conclusions are gathered together in this section. The judgment on the internal and external consistency of the Survey is positive. The relevance of our approach is discussed and related work considered.

2. THE MONTHLY SURVEY OF THE SPANISH MINISTRY OF INDUSTRY

Surveys of anticipatory data are conducted and regularly published in the U.S.A. and in most European countries. A sizeable amount of evidence exists on their importance in a variety of individual studies, particularly those referring to industrial investment forecasting. Some of the series from Business Intention Surveys (from now on B.I.S.) are today used as proxies in econometric model building.

The observation by Okun /28/ is well known: "The investment anticipations reported annually by the Commerce SEC Survey have an impressive record of predictive accurary...." "I know of no naive model and "causal" explanation resting on predetermined variables which rivals the anticipatory data in accuracy". This emphasises the importance of anticipated investment in forecasting actual expenditure. Jorgenson et al. /21/ studied the relevance of anticipations in the performance of their model for investment behaviour which has been proved superior to any econometric model.

A comparative evaluation of B.I.S. in O.E.C.D. countries was reported by Granzer /16/. For alternative applications we refer the reader to the reports of the C.I.R.E.T. Conference[1].

Several Spanish agencies publish B.I.S. but the most widely used is the one elaborated by the Spanish Ministry of Industry. It consists of two monthly sets of data: The "Encuesta de la Coyuntura Industrial" on the Manufacturing and Mining Industries and the other refers to the Building Industry. On the other hand there are two quarterly surveys: Capacity Utilisation and Investment Expectations for the Manufacturing Industry. The latter started in the second quarter of 1972 so that the record length - is still too short for any meaningful sta-- tistical study.

The present study deals with the Monthly -- Survey for the Manufacturing and Mining Industries which we describe very briefly. -- (See Table 1.).

Items i) to v) are "ex-post" questions and vi) and vii) "ex-ante".

The Survey includes some other questions, - e.g. on the number of employess. It was initiated in 1963 following the recommendations of the I.F.O. and covers 3500 firms that -- are grouped into 19 activity sectors. The - aggregation at the lower levels (subsectors) is based on the number of employees in the firm At higher levels it is based upon -- their contribution to the Industrial Gross Product (P.I.B.) which is calculated year-- ly by the Ministry of Industry. The aggre-- gated data (18 series) are published for industry as a whole and for the main three -- sectors (Investment, Consumption and Intermediate Goods). At this the highest level - the weights for aggregation, based upon -- their estimated contribution to the Gross - Industrial Product, are 43.95, 20.33 and -- 35.72 respectively. To obtain a time series from the answers to a particular question - the difference $X_1 - X_3$ is taken, where X_1, X_2, X_3 is the vector of relative frequencies for the three possible answers (say, "high", "normal" and "low"). Unfortunately, there - is no normalisation of the data with respect to some measure of dispersion such as a "disconformity" index $d(x) = (X_1X_3)^{1/2}$.

Appendix A displays a typical series for -- the Total of the Industry. Full details on the Survey can be found in Ministerio de - Industria /24/ and J. Rodriguez /30/ gives an account of the uses so far made of these anticipatory data.

3. MODELLING AND FORECASTING WITH A SINGLE TIME SERIES

There are at least four main reasons why we want to analyse time series:

a) To try to summarise its characteristics in an efficient way by a description of its statistical structure.

b) From this description we might try to -- gather information on how the series was generated. Theoretical knowledge of the mechanism which produced the series is - often indicated by the revealed structure.

c) Either from its past structure or from - the insights and information gahtered into its causal mechanism we might then -- try to forecast future values of the series.

d) If the forecast values are not to our -- liking we may be tempted to take some -- control action to modify them.

The importance of the aims increases from - a) to d) and so does the difficulty of - achieving them. The main aim of the B.I.S. under the non-interventionist attitude of - the Spanish Ministry of Industry is to provide the managers with suitable data and -- perhaps recommendations for an appropriate

Table 1.

The main questions	Possible answers		
i) Unfilled orders	High	Normal	Low
ii) Unfilled orders: tendency	Increase	Unchanged	Decrease
iii) Foreign unfilled orders	High	Normal	Low/Null
iv) Level of stocks of finished goods	Normal	Normal	Normal
v) Stocks level tendency	Increase	Unchanged	Decrease
vi) Expected tendency of production for the next 3 months	Increase	Stable	Decrease
vii) Prices: Expected trend for the next two-three months	Increase	Stable	Decrease

methodology to achieve a) to c). Indeed it it is arguable if the "revealed", "rational" "natural-rate", Sargent, /31/ or wahtever - of the firms' expectations would remain unchanged, if managers stopped being cooperative on finding out that their answers were used to manipulate their own expectations.

2.1 The Box-Jenkins Methods

The Box and Jenkins /7/ methods are well -- adapted to fulfil these aims. In fact the - model called by B-J "autoregressive-integated-moving average" (ARIMA) has been accepted as an almost universal model conception which covers almost all previous conceptions (in particular, decomposition into trend plus seasonal plus stationary fluctuations). This statement is particularly true for our B.I.S. series where any guidance -- that econometricians are likely to receive from standard economic theory is very slight. The so-called ARIMA model is of the form:

$$g(z^{-1})\ (1 - z^{-1})^d\ Y_t = h(z^{-1})\ \varepsilon_t \qquad (1)$$

where z is the unit forward shift operator, i.e.

$$z^i\ Y_t = Y_{t+i},$$

$$(1 - z^{-1})$$

is a differencing operation to induce stationary of Y_t, g and h are polynomial operators of degrees p and q respectively, Y_t is the datum a t time t and ε_t is a "white noise sequence".

The theoretical basis for this representation is well established since Wold (see e. g. Wiener and Masani, /38/).

Let

$$Y_t = (Y_{1t} \dots Y_{rt})$$

denote the observed variates, and assume -- that a transformation T exists, such that -

$$y_t = (y_{1t} \dots y_{rt})' = T^* Y_t$$

is a covariance stationary time series -- r-vector. Then Wold showed that there exists a canonical one-sided moving-average representation of the form

$$y_t = \sum_{j=0}^{\infty} \psi_j\ \varepsilon_{t-j} \qquad (2)$$

where ε is an r-component independent identically distributed orthonormal process -- with ψ_0 invertible. Although it is a fact - of limited relevance for us, it is true -- that this representation can be made unique by taking ψ_0 upper triangular with positive elements on the diagonal. If we further -- assume y_t to be a finitely generated stationary process (that is to say, a sub-class - of regular full rank stationary process) - there exist two sets of real matrices

$$H = \left[H_1 \dots H_n\right]$$

and

$$G = \left[G_0 G_1 \dots\ G_n\right]$$

such that

$$y_t + H_1 y_{t-1} + \dots + H_n y_{t-n} = G_0 \varepsilon_t + \dots + G_n \varepsilon_{t-n} \qquad (3)$$

The convolution of the two operations: transformation to stationary and the white noise transfer function expansion, leads to the - above representation (1).

2.2 On the motivations for and interpretations of B-J methods

These facts are familiar to today's econometricians but they have received them with a great deal of scepticism through looking only at their "black-box" interpretation. A - typical question the applied research worker may ask is how could such a model have - arisen in practice. Granger and Morris /15/ have devoted a paper to answering this type of question. Here are some of the generic - situations where and ARMA model can arise - from simpler models:

A) Aggregation and Observational Error Models

Virtually all macroeconomic series are aggregates of other series and contain observational errors. As examples we quote some special cases from the main theorem of Granger et al. /15/, p. 248:

i) AR(p) + white noise = ARMA(p,p)

This corresponds to and AR(p) signal - as true process plus a simple white -- noise observation error;

ii) AR(p) + AR(q) = ARMA(p+q, max(p,q))

This case corresponds to a series which is aggregated from two independent AR series;

iii) MA(p) + MA(q) = MA(max(p,q))

That is, if a true process follows an MA model then the addition of a white noise observation error will not alter the class of model, although the parameter values will change;

iv) AR(p) + MA(n) = ARMA(p,p+n)

This corresponds to the aggregation case or noisy observations with correlated errors.

If we agree that time series in economics - obey either AR or MA models as far as the - behaviour of the basic agent is concerned - (a reasonable assumption that we will briefly consider further on in D), then the above special cases will imply almost always - and ARMA model for "rational expectations" behaviour.

B) Time aggregation, Non integer lags and - Feedback models

i) As proved by Amemiya and Wu /3/, a variable which is an AR sampling at K units of time, but which is actually observed at an interval of M units will follow - an ARMA model. This is certainly the case of "stocks", one of the relevant variables of B.I.S.

ii) If X , Y are a pair of variables generated by a bivariate autoregressive -- scheme with feedback

$$a(z^{-1})\ X_t + b(z^{-1})\ Y_t = \varepsilon_t$$

$$c(z^{-1})\ X_t + d(z^{-1})\ Y_t = \eta_t$$

where ε_t and η_t are uncorrelated white noise series, then the model obeyed by X_t alone is found by eliminating Y_t in the above equations to be an ARMA model:

$$\left[a(z^{-1})\ d(z^{-1}) - c(z^{-1})\ b(z^{-1})\right] X_t =$$

$$d(z^{-1})\varepsilon_t + b(z^{-1})\eta_t$$

In view of the previous considerations we - may conclude that the model most likely to be found in practice is a mixed-autoregressive moving average model.

C) Information and Rational Expectations

Following Hicks /20/ we may consider three types of information upon which expectations (e.g. in our price series) could be formed: i) non-economic events such as the wather, politics, wars and psychological variables; ii) structural economic events such as monetary and fiscal policy and iii) "experien--ce" of the variable involved.

It would be rather unthinkable to try to model anticipations with elements of the first information set. Such events are typically regarded by economists as stochastic shocks which do not produce a predictable systematic effect, although they can be considered in 'correcting' past data.

Elements from the second set would be relevant to an agent forming rational expecta--tions in the sense of Muth, since these "expectations" "are essentially the same as -- the predictions of the relevant economic -- theory" (Muth, /26/ p. 316). Economic theory is particularly sparse regarding the -- B.I.S. variables.

The third information set contains the past history of actual variation rates. Practi--cally all the empirical work dealing with - the effects of inflationary anticipations - has used this information set by way of a - distributed lag model. The general model is of the form:

$$p_t^e(\ell) = \sum_{i=0}^{n} w_{i\ell}\ P_{t-i}$$

where $p_t^e(\ell)$ = expected inflation rate, say, for time t+ℓ formed at time t and P_{t-i} = actual inflation rate at time t-i. The familiar adaptive expectations model of Koyck /23/ and Cagan /10/ treats $p_t^e(\ell)$ as equal for all ℓ, i.e. the agent forecasts a single variation rate for all future time periods. As shown by Muth /26/ this type of forecast is optimal if the process generating the variation rate is given by

$$P_t - P_{t-1} = \varepsilon_t - \Theta_1 \varepsilon_{t-1}$$

$$E(\varepsilon_t) = 0$$

$$E(\varepsilon_t \varepsilon_s) = \sigma_\varepsilon^2 \qquad t = s$$

$$E(\varepsilon_t \varepsilon_s) = 0 \qquad t \neq s$$

i.e. an ARMA model.

Walters, Sargent and Wallace /32/ also worked with models in which expectations are based only on the variation rate experience (inflation rate). They conclude that such expectations are rational or "consistent" (Walters) if the underlying structural model of the inflation process can be collapsed into a reduced form equation with past variation rates as the pre-etermined variables. Further motivation for past variation rates to conform to "rational" expectations have been proposed by Feige and Pearce /13/ arguing in terms of "economically rational" expectations.

D) A final argument that forms the core of this paper in favour of a B-J model for time series modelling is based on the following argument:

Intuitively, X causes Y only if after explaining whatever of Y_t can be explained on the basis of its own past history $\underline{Y}_t$ some more remains to be explained by X_s, s<t i.e. by $\underline{X}_t$. This suggests relating X to that part of Y_t which cannot be explained by $\underline{Y}_t$. But this is the "innovation" ε_{y_t} in the univariate time series model

$$g(z^{-1})\ y_t = h(z^{-1})\varepsilon_{y_t}$$

Thus we want to get at $\{\varepsilon_{y_t}\}$ i.e. to "whiten" $\{y_t\}$. Similarly to assess "causality" between y and x (in the sense to be explained in section 4) we "whiten" X according to a univariate model:

$$M(z^{-1})\ X_t = N(z^{-1})\ \varepsilon_{x_t}$$

There are several ways to achieve this, all of which are equivalent to estimating g,h and M,N after prior stationarity-inducing transformations.

2.3 Transformations to Achieve Stationarity and the Problem of Deseasonalised Data

By a judicious choice of transformation the stationarity assumption can be made less restrictive than it may at first appear. Part of this transformation may include ordinary of seasonal differencing, lags or more generally the power transformation of Box and Cox /6/. The differencing transformations allow for homogeneous stochastic non-stationarities in Y_t, i.e. roots equal to unity in the autoregressive representation of Y_t. The same applies to seasonal differencing to achieve stationarity for both stochastic and deterministic seasonal nonstationarity in Y_t.

The Bureau of the Census has developed X-11, a computer program for seasonal adjustment which is widely used in econometric building and in all the studies so far carried out on the Spanish B.I.S. series. The basic feature of the program is that it uses a sequence of moving average filters to descompose a series into a seasonal component plus a trend plus an irregular component (claimed to be white noise). The program is robust but the fact that it uses the same set of filters for most series sometimes causes trouble by introducing spurious effects. Moreover, when the interrelationships of several series are being investigated, one evidently risks throwing away valuable information by working with the deseasonalised series (see section 4).

Cleveland /11/ has in fact shown that the X-11 program's seasonal adjustment can be approximated by

4a: $y_t = P_t + S_t + e_t$

4b: $(1-z^{-1})^2\ P_t = (1 - \psi_{11}z^{-1} - \psi_{12}z^{-2})b_{1t}$

$$4c: \quad (1-z^{-12})S_t = (1-\psi_{21}z^{-12}-\psi_{22}z^{-24})b_{2t}$$

$$\psi_{11} = -.49 \quad \psi_{12} = .49 \quad \psi_{21} = -.64 \qquad (4)$$

$$\psi_{22} = -.83$$

$$\sigma^2_{b_2}/\sigma^2_{b_1} = 1.3 \qquad \sigma^2_e/\sigma^2_{b_1} = 14.4$$

y_t is the observed series; P_t is the trend component; S_t is the seasonal component, -- and e_t is the noise, with very similar -- weighting functions to those of the moving average filters of the X-11 additive version. This model in turn implies an overall model:

$$(1-z^{-1})\ (1-z^{-12})y = (1 - .337z^{-1} + .144z^{-2}$$

$$+ .141z^{-3} + .139z^{-4} + .136z^{-5} + .131z^{-6}$$

$$+ .125z^{-7} + .117z^{-8} + .106z^{-9} + .093z^{-10}$$

$$+ 0.077z^{-11} - .417z^{-12} + .232z^{-13} \qquad (5)$$

$$- .001z^{-20} - 0.003z^{-21} - 0.004z^{-22}$$

$$- .006z^{-23} + .035z^{-24} - 0.021z^{-25})\varepsilon_t$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

Models (4) and (5) explain why the Census - X-11 program fits economic series well. A - nonstationary seasonal pattern is presumed and the model allows for a trend P of -- changing slope. On the other hand they show us the risks of a blind use of the program, mainly:

The additive decomposition (4a) is non unique; different additive models can lead to the same overall model.

If the actual series have a different structure to that implied by the X-11 program, - its use is not justified.

For these reasons and given the very apparent seasonality of the series of the B.I.S., we adopted general differencing to tackle - the nonstationarity problems and thus followed Box-Jenkins.

2.4 Parsimonious Models versus Long AR Models

The object of the analysis is not to obtain the "best" possible fit to the historical - data. A sufficiently complicated model can always be postulated which will exactly 'explain' any series of finite length. That -- this is pointless is clear. The object is - to pick out the "real" patterns as far as - possible. This implies aiming always for -- the simplest model compatible with the data. That is the principle of "parsimonious" fitting. For our monthly data, both quarterly (τ_1=3) and annual (τ_2=12) "periods" may be present, and a valid fitting but meaningless model would be of the form:

$$(1 + \alpha(3)\ z^{-3} + \ldots + \alpha(15)\ z^{-15})\ Y_t = \varepsilon_t$$

When one encounters parametrisations of the above kind as often occurs, one should check whether it can be recast as

$$(1 + \alpha(3)\ z^{-3})\ (1 + \alpha(12)\ z^{-12})\ Y_t =$$

$$\varepsilon_t = (1 + \alpha_t\ z^{-\tau}1)\ (1 + \alpha_2\ z^{-\tau}2)\ Y_t$$

In our B.I.S. data this is typically the case.

Kendall /22/ states that "we might as well be content with autoregressive series..... taking (the order) as far as is necessary - to give approximate independence in the residuals....". We disagree. This statement - misses the basic points we have already made in 2.2. Let us consider the simple MA model

$$Y_t = (1 - 0.8\ z^{-1})\ \varepsilon_t \qquad (7)$$

This is equivalent to an infinite autoregressive model

$$(1 + .8\ z^{-1} + .64\ z^{-2} + .51\ z^{-3} + .41\ z^{-4} \qquad (8)$$

$$+ .332\ z^{-5} + .26\ z^{-6} + .21\ z^{-7} + \ldots)Y_t = \varepsilon_t$$

We would like to think that the policy-maker prefers to use model (7) to (8). If, on the other hand, the argument in favour of long AR models is that: "If the ultimate aim is forecasting all we need are good innovations", we may refer the reader to section

3 where it is shown that forecasting can be carried out without a model at . l. However, as a long AR provides a valid data fit, it may be used in several ways to improve the estimates of a parsimonious model. We have used the long AR device whenever we needed a provisional "innovation" sequence, e.g. - in generating initial parameter values in - the estimation program. We have, neverthe-- less, fitted long AR models to the B.I.S. - series to check and illustrate some of the points already made.

2.5 Parametrisation and Modelling: Some Results

For the above reasons, we adopted the following parametric form:

$$(1-z^{-1})^d \prod_{j=1}^{\ell_1}(1-\phi_j\ z^{-\tau_j})\ A(z^{-1})\ (Y_t-\overline{Y}) = \tag{9}$$

$$\prod_{i=1}^{\ell_2}(1-\psi_i\ z^{-\tau_i})\ C(z^{-1})\ \varepsilon_t$$

$$\varepsilon_t \sim N(0,\ \sigma^2)$$

We then followed the three stages of the -- Box-Jenkins modelling method: tentative -- identification (model candidates selection), parameter estimation and model validation.

Fig. 1 of Appendix A shows a typical B.I.S. series (Unfilled Orders, Total Manufactur-- ing Industry) with relevant statistics and Fig. 2 of Appendix A shows the accepted model with final "innovations" (residuals) -- statistics.

Let us make some brief comments:

a) In the Identification stage it is essential to have meaningful graphic displays. Nonstationarity is frequently assessed - by inspection if the series are displayed with their a.c.f. and p.a.c.f. In our B.I.S. series this was very helpful. It could be easily "guessed" that most se-- ries had a seasonal component of either 12, 6 or 4 months and a fairly constant cycle of about two years. It was clearly shown that prices have no cyclic compo-- nent as previously stated in some of the Spanish studies.

b) When estimating a candidate model an option has been included to automatically initialise the optimisation algorithm by providing initial parameter estimates -- and related "provisional" residuals. It was done by fitting an auxiliary "true" long AR model, as indicated in Section -- 2.4. The actual optimisation algorithm maximises the approximate likelihood using a conjugate gradient search. The residuals and gradients are calculated in an economical and recursive way by using a state space representation of the model as in - Astrom-Bohlin /5/ but modified to allow - for the nonlinear parametrisation.

c) Model validation was achieved through a - white noise "innovation" test. This may - perhaps be a bit restrictive but was found to be a robust check in a variety of si-- tuations including when looking for cau-- sal relations Durbin /12/.

   The ranking of validated models was via a minimum cost criterion. To induce "parsimony" we have normalised the cost func-- tion by considering the "marginal de-- crease" in cost induced by adding extra - parameters.

d) Some of the results obtained. We found -- that in general the final model structure was almost always that suggested at the - identification stage. Models are listed - in Appendix A.

Except for prices and unfilled foreign orders, there is a very clear cycle of about - two years that we modelled through and ARMA (2,2) that coped very well with the "local" irregular components.

A seasonality of 12 months was common to -- most series, although a periodicity of 14 -- months was found in Series 007 (expected tendency in stocks) possibly spurious.

No cycles were found in foreign unfilled orders which is rather surprising. Prices did not present any cyclical pattern and follow very simple ARMA models with some 2 or 4 -- month periodicity for the sectoral series. - This is against current opinion in Spanish --

studies.

The difference between sectoral price models may explain why we found it difficul to model the price series for the whole of industry, except by using an "envolving" trend. This indicates that removing "homogeneous" nonstationarities by fixed filters was not enough. It seems that a proper model for this series needs a time-varying parameter model. This fact was reinforced by the behaviour of the parameters of the self-tuner predictor for this series.

For purposes of comparison we modelled the series by long AR fittings. It is remarkable the size of the models needed to get white residuals, e.g. stocks (a well behaved series) needs an AR(24) model and for total industrial prices it was virtually impossible - within reasonable orders - to get white noise residuals.

We used the long AR fit to check roughly if the stationarity-inducing transformation introduced spurious structure. For no single series did the cost (or the order) of the long AR fall below that of the parsimonious model.

A final point is that in some series and for the first two years, the building sector was included. It seems that this does not modify the above findings.

2.6 Forecasting: Procedure and Results

Once a model is available, forecasting is an easy task and the standard procedures are well summarised wlsewhere (Anderson /4/, Nelson /27/). We will make a few points.

It is still frequently argued that simpler forecasting methods may perform as well as, if not better than, B-J forecasting. Kendall /22/ says that we must each decide for ourselves if the methods are in advance of traditional approaches in the light of experience in our own particular field. We have to agree with him in as much as there is no panacea for forecasting problems. However, we disagree in as much as the traditional methods are particular applications of the B-J approach. If the criterion of forecasting performance is to minimise the mean square prediction error, i.e.

$$\hat{y}_k(\ell) \triangleq \{E\; y_{k+\ell} | y_k, y_{k-1}, \ldots\} =$$

$$\arg\min E\{y_{k+\ell} - \hat{y}_k(\ell)\}^2$$

then exponential smoothing yields the optimal forecast if the series is an IMA(1,1) process:

$$(1 - z^{-1})\, y_t = (1 - \theta z^{-1})\varepsilon_t \qquad (10)$$

as can be seen by considering that (10) has a "random-shock" expansion

$$y_t = \varepsilon_t + \sum_{i=1}^{\infty} \psi_i \varepsilon_{t-1} \text{ with } \psi_i = 1-\theta \text{ for all i.}$$

It is clear, however, that if the true underlying model is ARIMA(p,d,q), then the descomposition of y_t into current disturbance and an exponentially weighted MA of past observations provide non-optimal forecasts.

<u>The infinite expansion</u> approach to B-J forecasting methods obscures the point that the predictor is itself a linear model. In reference /19/ it is shown that the best ℓ step ahead forecast

$$\hat{y}_k(\ell) = E\{y_{k+\ell} | y_k, y_{k-1}, \ldots\}$$

for the ARMA model:

$$A(z^{-1})y_k = C(z^{-1})\varepsilon_k \qquad \varepsilon_k \sim N(0, \sigma^2)$$

satisfies the ARMA-type relationship:

$$C(z^{-1})\hat{y}_k(\ell) = G(z^{-1})y_k \qquad (11)$$

When we write the predictor in this canonical form, it becomes clear to what extent other procedures are particular cases.

One is also interested in prediction as a key concept in time series modelling. The minimum information about the past of a time series needed to form all future predictors $\hat{Y}_k(\ell)$ gives an intrinsic characterisation of a time series model. Developments of this idea lead to the concept of the self-tuner. The details of our forecasting procedure are described in reference /19/. It differs from the B-J procedure in that the parsimonious -

predictor description (11) is used. This is obtained through a polynomial partition algorithm and the variance of the forecast error is obtained without difficulty. It shows the relationship between the dimensions of the series model and the predictor model.

A typical forecast is shown in Fig. 3 of Appendix A with the forecast error variance boundaries. The cyclical "turning points" are not always well predicted.

Compared to the corresponding prediction using long AR models, it is much more sensitive to local movements. The long AR predictor practically reproduces the cyclical component somewhat smoothed.

3. THE SELF-TUNING PREDICTOR

If the ultimate goal is forecasting using given observations, then it is desirable to model the predictor system directly. The idea, first implemented by Wittenmark /39/ is a consequence of Akaike's formulation of the "predictor space" Akaike /2/. He proved that in the predictor space associated with the data, there exists a unique canonical realisation.

The self-tuning predictor is a kind of Kalman filter, and avoids the need of a series model for forecasting. While Box-Jenkins' so-called "adaptive" forecasting only updates the forecasts, for a fixed model, the self-tuner also updates the predictor parameters recursively and the forecasts are obtained in an automatic way (on-line). The details are given in Hernández et al. /19/.

We have used the tuner to check (visually) how stable the structural parameters are as a rough test for the stationarity of the series. If the underlying parameters are sloly time-varying a 'forgetting factor' can be used to discount past data. One weakness is that we have been unable to find proper forecasting error boundaries.

Some results from the self-tuner are shown in Fig. 5 and 6 of Appendix A.

4. DETECTION AND ASSESSMENT OF RELATIONSHIPS. FORECASTING USING LEADING INDICATORS.

Econometric modelling, on the whole, has consisted of efficiently estimating parameters in a model structure that was already specified from current economic theory. For econometric studies with B.I.S. data, not much reliable economic theory has been available and the empirical studies are very much a "blind" selection of models using "goodness of fit" criteria.

In the work we are reporting here, we try to empirically specify the kind of relationships that exist between the Spanish B.I.S. variables. The approach taken follows the ideas of Granger /14/ and reproduced in intuitive terms in (2.2D). There are several possible approaches but the one taken here is heavily based on Haugh & Box /17/. The main feature is that the relevant information is obtained from the "innovation" cross correlations, thus allowing us to relate the raw data containing homogeneous nonstationarities. On the other hand, if feedback is detected, then even for the bivariate case, the actual interseries model would be really multivariable and not collapsible into a structural equation. In reference /19/ we detail our implementation of Haugh's method.

4.1 A general Scheme for the Analysis of the Relationships between Variables

Let us assume that our vector of variables is stationary (after a suitable transformation) and we want to analyse the relationship between two subvectors y and u of dimensions p an q respectively.

Definition: We say that the pair of processes (y,u) are feedback-free if and only if, for the matrix:

$$\Phi(z) = H^{-1}(z)\ G(z) = \begin{bmatrix} A(z) & B(z) \\ C(z) & D(z) \end{bmatrix}$$

in (3), we have $C(z)=0$. If $C(z)\neq 0$ we say there is feedback from y to u. With this definition, the following theorem by Caines & Chan /8/ gives a compact description of alternative ways for detection of relationships between variables.

Theorem: The folowing statements about the jointly stationary process $(y^T,u^T)^T$ are equivalent:

(1) The ordered pair of processes (y,u) is feedback free;

(2) Let $\Phi(z)\Phi^T(z^{-1}) = \Psi(z)$ denote the $(p+q)x(p+q)$ spectral density matrix of the stationary stochastic process $(y^T,u^T)^T$. Then there exist matrices of rational functions $A(z)_{pxp}$, $B(z)_{pxq}$, $D(z)_{qxq}$, with A(z) and D(z) of full rank, with the poles of A(z), B(z), D(z), $A^{-1}(z)$ and $D^{-1}(z)$ lying outside the closed unit disc, and with A(0) and D(0) upper triangular with positive elements on their diagonals, such that

$$\Psi(z) = \begin{bmatrix} A(z)A^T(z)+B(z)B^T(z) & B(z)D^T(z) \\ D(z)B^T(z) & D(z)D^T(z) \end{bmatrix}$$

(3) The least squares estimate $\hat{y}_{t|t}$ of y_t given the observations $\{\ldots u_{t-1},u_t\}$ is identical to the estimate $\hat{y}_{t|\infty}$ of y_t given the observations $\{\ldots u_{t-1},u_t,u_{t+1},\ldots\},t\varepsilon Z$; in other words, the anticipative and non-anticipative filters for the estimation of y from u are identical;

(4) There exists a unique representation of y with respect to u of the form

$$y_t = \sum_{i=0}^{\infty} K_i u_{t-i} + \sum_{i=0}^{\infty} L_i v_{t-i}$$

where $K(z) \triangleq \sum_{i=0}^{\infty} K_i z^i$

and $L(z) \triangleq \sum_{i=0}^{\infty} L_i z^i$

are matrices of rational functions such that L(z) has full normal rank, K(z), L(z) and $L^{-1}(z)$ have all their poles outside the closed unit disc, L =L(0) is upper triangular with positive elements on the diagonal, the processes u and v are orthogonal and v is an orthonormal process;

(5) The least squares stimate $u_{t+k}|\underline{U}^t$ of u_{t+k} given the observations $\{\ldots u_{t-1}, u_t,\ldots\}$ is identical to the estimate $u_{t+k}|\underline{U}^t+\underline{Y}^t$ of u_{t+k} given the observations $\{\ldots u_{t-1},u_t,\ldots\}\{\ldots y_{t-1},y_t\ldots\}$ for all $t\varepsilon Z$, $k\geq 1$.

Condition (3) is in the sprit of Sims' /37/ definition of causality; condition (5) is Granger's /14/ definition. Our method uses (4) and (5).

4.2 Our Method for Detection of Relationships and Transfer Function Modelling

The modelling procedure has several steps:

i) Single time series models for each of the series;

ii) Interresidual analysis for causality detection and delay specification;

iii) For specified delay, estimate covariance structure of interresidual model;

iv) Estimate transfer function model between original series by generalised least squares (prefiltering with estimated covariance from (iii)). Model validation.

Step (i) has already been dealt with above.

4.2.1 Problems with correlation between the original series

The procedure used by Sims, regressing y on past, present and future x (or vice versa) and then performing F tests on the set of regression coefficients, would in principle be a valid way to assess causality. Alternatively, one might expect the B-J procedure, using the sample crosscorrelation function for y and x to reveal the basic relations between the two series. In practice, however, both these procedures may be of little use in identifying a feasible model structure. The sample ccf may present a complicated pattern, particularly when feedback is present Akaike /1/, Haugh & Box /17/. It is preferable to take account of the autocorrelation in y and x prior to crosscorrelation analysis.

4.2.2 Joint Analysis of Univariate Residuals (Innovations)

Assume that we have the following bivariate model for stationary y, u:

$$\begin{bmatrix} u_t \\ y_t \end{bmatrix} = \begin{bmatrix} A(z) & B(z) \\ C(z) & D(z) \end{bmatrix} \begin{bmatrix} a_t \\ b_t \end{bmatrix}$$

$$E(a_t b_s) = 0; \quad E(a_t a_s) = 0$$
$$E(b_t b_s) = 0 \text{ for all } t,\ s. \tag{12}$$

and that (y,u) is feedback free in the sense that $B(z) = 0$, so that u 'causes' y but not vice versa. Then

$$u_t = A(z)\, a_t \tag{13}$$

$$y_t = C(z)a_t + D(z)b_t = V(z)u_t + D(z)b_t \tag{14}$$

where $V \triangleq C/A$,

a dynamic regression (structural equations) model.

On the other hand, we have the individual - white noise models:

$$L_y(z) = \varepsilon_y \quad \text{and} \quad L_u(z) = \varepsilon_u \tag{15}$$

If u causes y (but there is no feedback), - we would have a model of the form (14) and then, using (15), we have

$$\varepsilon_y = \{L_y(z)/L_u(z)\}V(z)\varepsilon_u + \{D(z)/L_u(z)\}b_t \tag{16}$$

The lag distribution in (14) in one-sided - if and only if the same holds in (16). These patterns are modelled by regressing ε_y on ε_u (or vice versa) or by crosscorrelating ε_y and ε_u. Since they are innovations sequences, the - crosscorrelation function $\rho_{\varepsilon_y\varepsilon_u}(k)$ (or $\rho(k)$ for brevity) is symmetric and can characterise causality in both directions. The table below (Table 2) lists some possible causality patterns according to the behaviour of $\rho(k)$.

Haugh /17/ has shown that the sample residual crosscorrelations for N data points -- form an independent normally distributed sequence with zero mean and standard deviation $1/\sqrt{N}$, if u and y are not causally related.

4.2.3 The Estimation of the Input-Output Model. Forecasting.

In view of the above arguments, we followed the scheme:

1* Crosscorrelate $\varepsilon_y, \varepsilon_u$ and use $\rho(k)$ to decide on a provisional interinnovation - model with delay, if any. If there is - feedback, stop;

2* Estimate the interinnovation model:

$$A(z)\varepsilon_y(t) = z^{-\lambda}B(z)\varepsilon_u(t) + C(z)e(t) \tag{17}$$

and check for validity (white residuals). Repeat 1 and 2 if the estimated model is not valid; otherwise, go to step 3;

3* If model (17) is valid, an obsious inter series model will be

Table 2.

Relationship	Behaviour of (k)
u causes y	$\rho(k) \neq 0$ for some $k>0$
y causes u	$\rho(k) \neq 0$ for some $k<0$
pure gain	$\rho(k) = 0$ for all $k\neq 0$, $\rho(0)\neq 0$
feedback	$\rho(k) \neq 0$ for some $k>0$ and some $k<0$
y does not cause u	$\rho(k) =$ for all $k<0$
u ——> y	$\rho(k) \neq 0$ for some $k>0$ and $\rho(k)=0$ for all $k<0$
instantaneous causality	$\rho(0) \neq 0$
y ——> u	$\rho(k) \neq 0$ for some $k<0$ and $\rho(k)=0$ for all $k>0$
u,y independent	$\rho(k) = 0$ for all k

$$L_y(z)\ A(z)y_t = z^{-\lambda}L_u(z)B(z)u_t+C(z)e_t \quad (18)$$

To simplify the final model structure, however, we can perform a regression -- fit (after prefiltering by C(z)) and express the final model in the form:

$$\tilde{A}(z)y_t = z^{-\lambda}\tilde{B}(z)u_t + e_t \qquad (19)$$

It is clear that all the relevant information is obtained from the interresidual model and that, even if the original series were nonstationary, the method of detection of relationships through the single time series residuals will still be the same.

Finally, if an interseries model is arrived at, forecasts can easily be generated (see reference /19/).

4.3 Results. Some comments.

Let us illustrate the above procedure using series 001 (Unfilled Orders) and 006 (expected unfilled orders). From the sample crosscorrelations of the innovations (Fig. 7 of Appendix A) we can see that the model will have a pure delay of two months. Expected unfilled orders are a leading indicator for unfilled orders and the 'causality' is undirectional: from 006 to 001.

A final model is estimated by generalised least squares.

Although the interresidual model is very simple, the final model (via (15)) may be very complicated. It would have been preferable to work with a non-linear (and parsimonious) parametrisation as for single time series.

Fig. 8 of Appendix A shows the forecasts of 001 using 006 as the leading indicator. One can see that the turning point is predicted in advance.

Innovations crosscorrelations analysis reveals the inter-series relationships of Tables 1 and 2 in Appendix A:

* It is remarkable that most of the series for the whole of industry are interrelated, thus proving the internal consistency of the survey.

* Checks on external consistency are also positive for series 100, the Industrial Production Index. We found that several of the B.I.S. series are leading indicators for this important variable.

* After deseasonalising series 001, 003 and 004 (unfilled orders, stocks and expected trend in production) we tried to assess causal relationships. The innovations crosscorrelations, however, did not provide a meaningful pattern of behaviour.

5. CONCLUSIONS AND LIMITATIONS OF THE METHODS USED

Parsimonious representations for all but one of the 28 series of the Spanish B.I.S. "Encuesta de Coyuntura" have been obtained and analysed. They indicate that the series have a fairly strong cycle of around two years and a very strong seasonality of about one year. Five parameters are usually sufficient to model each series.

Prices and Unfilled Foreign Orders were either pure trends or very simple ARMA processes. Long AR models were also fitted but the number of terms needed to achieve a valid model was very large indeed, thus showing the relevance of a parsimonious representation. The Intermediate Goods Sector was the most difficult to model; not surprisingly since the components of the sector are difficult to define. In fact they were found to be highly 'feedback related' to the Consumption Sector series. A troublesome problem was that some series included the Building Sector for the first two years. This does not modify the models significantly.

The self-tuning predictor showed that the model parameters (except for prices (total)) settled down well within the period recorded. This indicates that the series do not demand a time-varying parameter model.

Forecasting results using single time series show that the turning points, corresponding to the peaks and valleys of the cycle, were not anticipated well --

using the B-J method. The self-tuner, however, reacts very quickly when one of these points is reached. Forecasts using long AR models tend to ignore local variations in series behaviour and practically reproduce the cyclical component.

When assessing possible relationships between pairs of series, we have found that most exhibited strong interactions. Delays were picked out and leading indicators selected. This strong 'internal consistency' is very encouraging, since similar recent studies (Flige & Pearse /13/, Pierce /29/ among others) have found that many common macroeconomic series were not causally related.

An important criterion for the B.I.S. data is that it should have predictive value for other macroeconomic series. Here we have selected the Industrial Production Index. We have found a strong causal relation with several series of the survey, thus proving its 'internal consistency'.

It is clear that some previous studies of a 'blind regression' type (e.g. J. Rodriguez /30/) are rendered meaningless and empirically unfounded. Deseasonalising raw data, as is at present automatically carried out by the main Spanish governmental agencies, may have very serious consequences. Spurious relationships will frequently emerge that don't actually exist, or relationships will appear stronger than in reality. It is clear that relationships between series should be inferred from the original data.

Once leading indicators have been found, forecasts show that the important turning points are detected. When elaborating a final forecast, judicious evaluation should be made of the various available forecasters: ARIMA model, self-tuner or using a leading indicator

An important part of the work we are reporting was to evaluate to what extent Box-Jenkins-type methods could produce a substantial improvement in government modelling and forecasting. We think that we have provided enough arguments in defence of the methods. They are not difficult to use for the policy maker once a versatile suite of programs of an interactive nature (as SEEMA aims to be) is available. We have seen that a number of real data series can be modelled parsimoniously. The fact that the resulting predictor is itself linear opens up interesting economic interpretations in terms of 'permanent' variables and shows that some commonly used forecasting methods are simple versions of this approach. Hernández, /18/.

The self-tuning predictor is an adaptive predictor and is useful for the detection of nonstationarity and structural change as well as in forecasting.

Since our work was initiated in 1975, several related studies on macroeconomic series, using very similar methods for causal detection, have been published. Some of their arguments and findings are very relevant when evaluating our methods and we refer the reader to the literature.

We consider B-J-type methods very useful. They provide the most versatile modelling and forecasting approach and also a very robust method for specification analysis, a basic step in econometric modelling. There are, of course, limitations. If the series are truly nonstationary then the B-J methods may not be suitable. Secondly, when applying the causality detection method, one has to be careful if stationarity has been achieved through the removal of an additive deterministic component. Any deterministic series is 'caused' by its own past, so there is no room for improvement by forecasting using other variables.

Several extensions to our work are possible (as well as improvements in our computational methods). For example, when trying to model truly multivariate series - the simplest case being a pair of series in feedback - a better procedure would be a recursive approach a la Wold /40/, using the actual individual innovations. For the case of two series this would imply expressing model (15) in the form:

$$L_y(z)\ Y_t = \psi_{11}(z)e_1 \qquad \psi_{11} = 1$$

$$L_x(z)\ X_t = \psi_{21}(z)e_1 \oplus \psi_{22}(z)e_2 \tag{20}$$

where '$\oplus$' implies that the components of the sum are orthogonal. In the absence of specification, the information for a possible multivariable model is embodied in the "predictor space" generated by the innovations. The recursive construction of a model of the form (20) has several advantages, not least of which is the possibility of using simple least squares in its estimation. This advantage is lost, however, if a nonlinear parametrisation is allowed, as seems necessary when dealing with raw data.

Once the consistency of the survey has been demonstrated, this opens up a wide range of econometric applications for further studies. For example, the application of our methods to other surveys from O.E.C.D. countries would be useful for comparison with the Spanish B.I.S. results.

6. ACKNOWLEDGMENTS

The authors wish to express gratitude to the Department of Computing & Control, Imperial College London, for making this research possible and to the Spanish Ministry of Industry for providing financial assistance and understanding throughout the development of the project.

7. REFERENCES

/1/ AKAIKE, H. "Some problems in the application of cross-spectral methods in time series analysis". Advance Seminar on Spectral Analysis of Time Series. Ed. Harris. New York. 1967.

/2/ AKAIKE, H. "Stochastic theory of minimal realization". IEEE Trans. Aut. Control, AC-19, 6. December 1974.

/3/ AMMEMIYA, T. & WU, R.Y. "The effect of aggregation on prediction in the autoregressive model". J. American Stat. Assn, 67, pp. 628-632. 1972.

/4/ ANDERSON, O.D. "Time series analysis and forecasting; the Box-Jenkins approach". Butterworths, London. 1975.

/5/ ASTROM, K.J. & BOHLIN, T. "Numerical identification of linear dynamic systems from operating records". IFAC Symp. Theory of Self-Adaptive Systems, Teddington, England. 1965.

/6/ BOX, G.E.P. & COX, D.R. "An analysis of transformations". J. Roy. Stat. Soc., Series B, 26, N° 2. 1964.

/7/ BOX, G.E.P. & JENKINGS, G.M. "Time Series analysis, forecasting and control" Holden Day, Inc., San Francisco. 1970.

/8/ CAINES, P. & CHAN, C.W. "Estimation, identification and feedback in System Identification: Advances & Case studies" Ed. Lainiotis & Mehra Marcel Dekker, New York. 1975.

/9/ CAINES, P. & LJUNG, L. "Aymptotic normality and accuracy of prediction error estimation". Report 7602, Control Section. Univ. of Toronto. 1976.

/10/ CAGAN, P. "The monetary dynamics of hyperinflation. In Studies in the Quantity Theory of Money". Ed. M. Friedman, Univ. of Chicago Press. 1956.

/11/ CLEVELAND, P. & TIAO, G.C. "Decomposition of seasonal time series: a model for the Census X-11 program". J. Amer. Stat. Assn., 355, September 1976.

/12/ DURBIN, J. "Tests of model specification based on residuals. In A Survey of Statistical Design and Linear Models", Ed. J. N. Srivastava, N. Holland. 1975.

/13/ FEIGE, E. & PEARCE, D.K. "Economically rational expectations: are innovations in the rate of inflation independent of innovations in measures of monetary and fiscal policy?". J. Pol. Econ., 84, 3. 1976.

/14/ GRANGER, C.W.J. Proc. IFAC/IFORS Conf. on Dynamic Modelling & Control of National Economies. Univ. of Warwick, England. 1973.

/15/ GRANGER, C.W.J. & MORRIS, M.J. "Time series modelling and interpretation" J. Roy. Stat. Soc., Series A, Pt.2, p. 246. 1976.

/16/ GRANZER, R. "Comparative evaluation of -

business surveys in O.E.C.D. countries" 11th C.I.R.E.T Conference, London. -- 1973.

/17/ HAUGH, L.D. & BOX, G.P. "Identification of dynamic regression models connecting two time series". Tech. Rpt. - N° 74, Dept. of Statistics, Univ. of Florida. 1974.

/18/ HERNANDEZ-IGLESIAS, C. "Métodos Cuantitativos para la Decisión Económica". - Ph. D. Univ. de Barcelona. Spain. 1975.

/19/ HERNANDEZ, C., ZARROP, M.B. and BECKER, R.G. "Short Term Forecasting with the Survey of Business Intentions of the - Spanish Ministry of Industry". 2^{nd} International Conference On Dynamic Modelling and Control of National Economics. Vienna. 1977.

/20/ HICKS, J.R. "Value and Capital". Oxford Univ. Press. 1946.

/21/ JORGENSON, D.W., HUNTER, J. & NADIRI, I. "A comparison of alternative econometric models of quarterly investment behaviour". Econometrica, 38, 2. 1970.

/22/ KENDALL, M.G. "Review of Box and Jenkins (1970)". J. Roy. Stat. Soc., Series A, 134. 1971.

/23/ KOYCK, L.M. "Distributed lags and investment analysis". North Holland. -- 1954.

/24/ MINISTERIO DE INDUSTRIA. Seminario Iberoamericano sobre "Investigación de la Coyuntura". Ed. Secretaría General Técnica del M. Ind., Madrid. Spain. 1975.

/25/ MUTH, J.F. "Optimal properties of exponentially weighted forecasts". J. Amer. Stat. Assn., 55, pp. 299-306. 1960.

/26/ MUTH, J.F. "Rational expectations and the theory of price movements". Econometrica, 29. 1961.

/27/ NELSON, C.R. "Applied time series analysis for managerial forecasting". Holden Day, Inc., San Francisco. 1975.

/28/ OKUN, A. "The predictive value of surveys of business intentions". Amer. -- Econ. Review, Vol. LII, N° 2. 1962.

/29/ PIERCE, D.A. "Relationships Between -- Economic Time Series with Special Reference to Money and Interest Rates". -- J.A.S.A. March. Vol, 72, n° 357. 1977.

/30/ RODRIGUEZ, J. "Las Encuestas Coyunturales. Su Empleo en España". Banco de España. Servicio de Estudios Económicos, Serie A, 7. Madrid. Spain. 1975.

/31/ SARGENT, T.J. "The observational equivalence of natural and unnatural rate theories of macroeconomics". J. Pol. - Econ., Vol. 84, 31. 1976.

/32/ SARGENT, T.J. & WALLACE, N. "Rational expectations, the optimal monetary instruments and the optimal money supply rule". J. Pol. Econ., 83, 2. 1975.

/33/ S.E.E.M.A. "Fundamentos teóricos para el estudio de la encuesta de coyuntura" Secretaría General Técnica. Min. Industria. Madrid. Spain. 1975.

/34/ S.E.E.M.A. "Análisis de la encuesta de coyuntura a través de la teoría del control:resultados". Sec. Gral. Técnica, - Min. Industria. Madrid. Spain. 1976a.

/35/ S.E.E.M.A. "Diagnóstico y conclusiones. Estudio de la encuesta de coyuntura a - través de la teoría del control". Sec. Gral. Técnica del Ministerio de Industria, Madrid. Spain. 1976b.

/36/ S.E.E.M.A. "Users guide to the SEEMA -- programs". Dept. of Computing & Control, Imperial College. London. 1976c.

/37/ SIMS, C. "Money income and causality". Amer. Econ. Review, 62. 1972.

/38/ WIENER, N. and MASANI, P. "The Prediction Theory of Multivariate Stochastic Processes, I". Acta Mathematica 98. pp. 111-150. 1957.

/39/ WITTERNMARK, B. "A self-tuning predictor". IEEE Trans. Aut. Control, AC-19, 6. December. 1974.

/40/ **WOLD**, H. "A case study of interdepen-- **dent** versus causal chain systems". Re- view **Int**. Stat. Institute, 27. 1958.

8. APPENDIX A

Selected Series. ARIMA Models. Selected Results on Strengths and Directions of Relationships. Some Graphic Displays.

Selected Series

Series 001: Unfilled Orders. Total Manufacturing Industry.
Series 002: Foreign Unfilled Orders. Manufacturing Industry.
Series 003: Stocks of Finished Goods. Manufacturing Industry.
Series 004: Expected Trend in Production. - Manufacturing Industry.
Series 005: Expected Selling Prices. Manufacturing Industry.
Series 006: Expected Unfilled Orders. Manufacturing Industry.
Series 007: Expected Stocks of Finished Goods. Manufacturing Industry.
Serie 100: Industrial Production Index. Time Series "external" to the B.I.S.

Table 1.
Selected Results on Strengths and Directions of Relationships for Series 001 to 007

Series	Series 001	002	003	004	006
002	--->				
003	--->	<---			
004	——> <---	<--- --->	--->		
006	——>	---> <---	---> <——	<---	
007	<—— --->	---> <---	<---	<——	---> <——

Table 2.
Selected Results on Strengths and Directions of Relationships for Series 100 and Series - 001 to 004. External Consistency.

Series	001	003	004
100	<---	<——	<——

Models for Selected Series

Series — Estimated ARIMA Models (with standard desviation).

001. M1: $(1-z^{-12})(1-1.9778z^{-1}+0.9939z^{-2})y(t)=(1-0.5677z^{-12})(1-1.1546z^{-1}+0.3067z^{-2})e(t)$
(0.0241) (0.0241) (0.0736) (0.0843) (0.0835) $\sigma^2=10.7139$
(1.2992)

002. M2: $(1-z^{-1})\ y(t)=(1+0.2062\ z^{-12})\ e(t).$ $\sigma^2=3.6936$
(0.0839) (0.4265)

003. M3: $(1-z^{-12})(1-1.9558z^{-1}+0.9732z^{-2})y(t)=(1-0.5112z^{-12})(1-1.2649z^{-1}+0.3828z^{-2})e(t)$
(0.0323) (0.0317) (0.0787) (0.0849) (0.0831); $\sigma^2=10.3508$
(1.2552)

004. M4: $(1-z^{-12})(1-1.9632z^{-1}+0.9807z^{-2})y(t)=(1-0.4140z^{-12})(1-1.1778z^{-1}+0.2574z^{-2})e(t)$
(0.0300) (0.0292) (0.0832) (0.0887) (0.0872); $\sigma^2=16.1480$
(1.9582)

006. M6: $(1-z^{-1})(1-z^{-12})(1-0.1854z^{-1}+0.2350z^{-2})y(t)=(1-0.6428z^{-12})(1-0.9237z^{-1})e(t)$; $\sigma^2=24.492$
(0.3611) (0.0851) (0.0667) (0.3707) (2.9485)

007. M7: $(1-z^{-14})(1-1.0153z^{-1}+0.1185z^{-2})y(t)=(1-0.5993z^{-14})(1-0.2798z^{-1})e(t)$; $\sigma^2=21.9791$
(0.7014) (0.5919) (0.0705) (0.6871) (2.6556)

100. M10: $(1-z^{-12})^2(1-0.3752z^{-1}-0.5891z^{-2})y(t)=(1-0.8145z^{-12})(1-0.1485z^{-1})e(t)$; $\sigma^2=126.883$
(0.1857) (0.1952) (0.0670) (0.2115) (17.0317)

Code used for Tables 1 and 2.

Independent series +

Instantaneous "causality": ◟ feeble; (moderate; O strong.

Left-margin variable causes top variable: ——> strongly; ---> moderately.

Top variable causes left-margin variable: <—— strongly; <--- moderately.

Feedback: $\underset{<——}{——>}$ strong; $\underset{<---}{--->}$ moderate.

Graphical Material

Fig. 1 and 2: Series 001 and its "innovations" using model M1.

Fig. 5: Time variation for "self-tuner" predictor for Series 001.

Fig. 7: Croxx-correlations between model residuals for Series 001 and 006.

Fig. 3: Forecasting performance of predictor using ARIMA and Long AR models for Series 001.

Fig. 6: Forecasting performance of self-tuning forecasting, for Series 001 and parameters, those of Fig. 5.

Fig. 8: Forecasting performance of predictor using Series 006 as "input" for Series 001, and inter-series model as especified.

9. NOTES

[1]Centre for International Research on Economics Tendency Surveys.

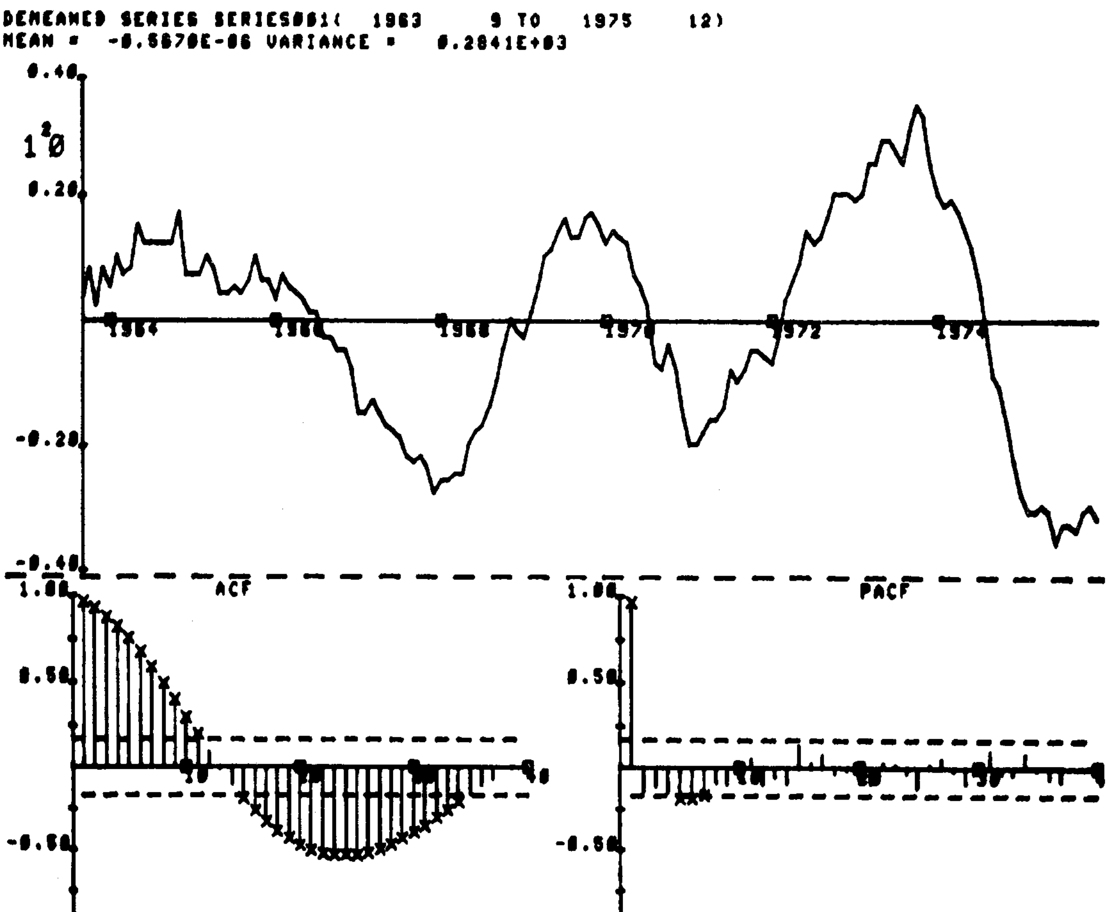


Fig. 1
Unfilled Orders. Manufacturing Industry.
Building Sector Excluded

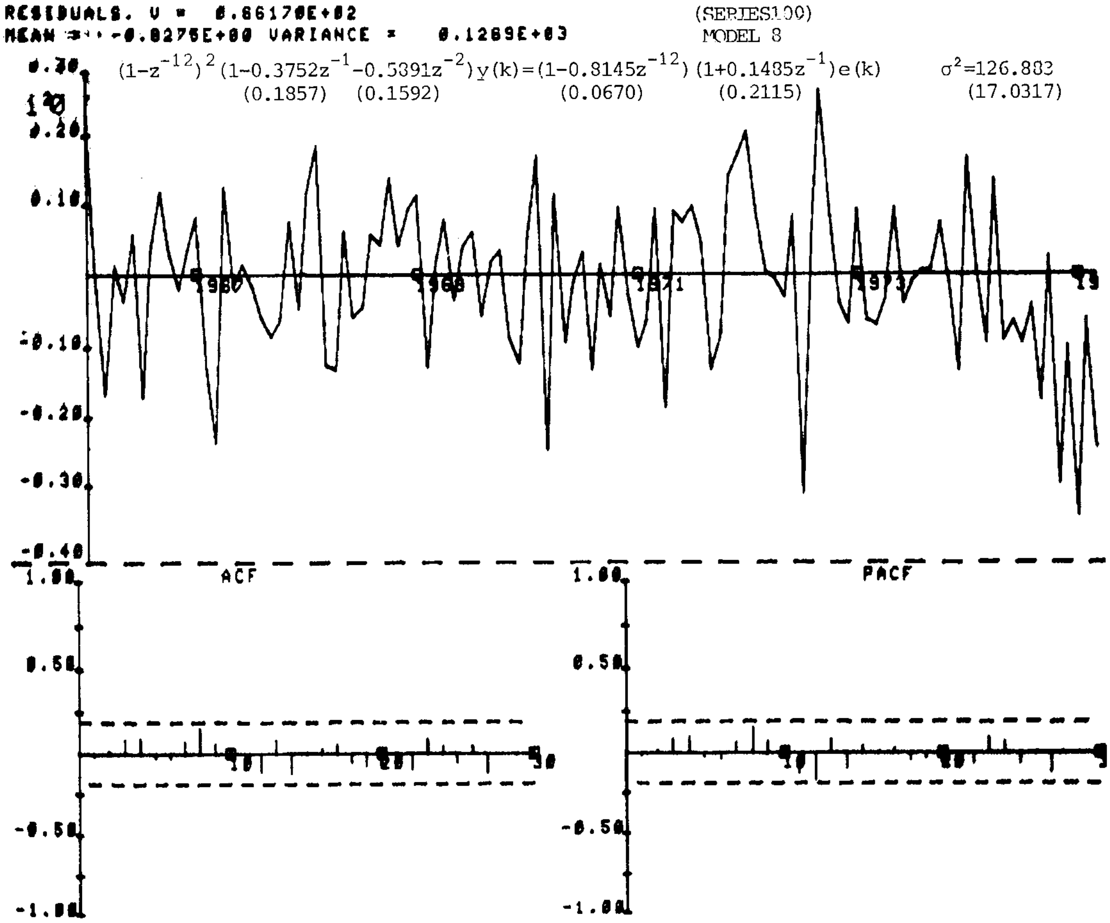


Fig. 2
Residuals innovations for SERIES 001 with model M1

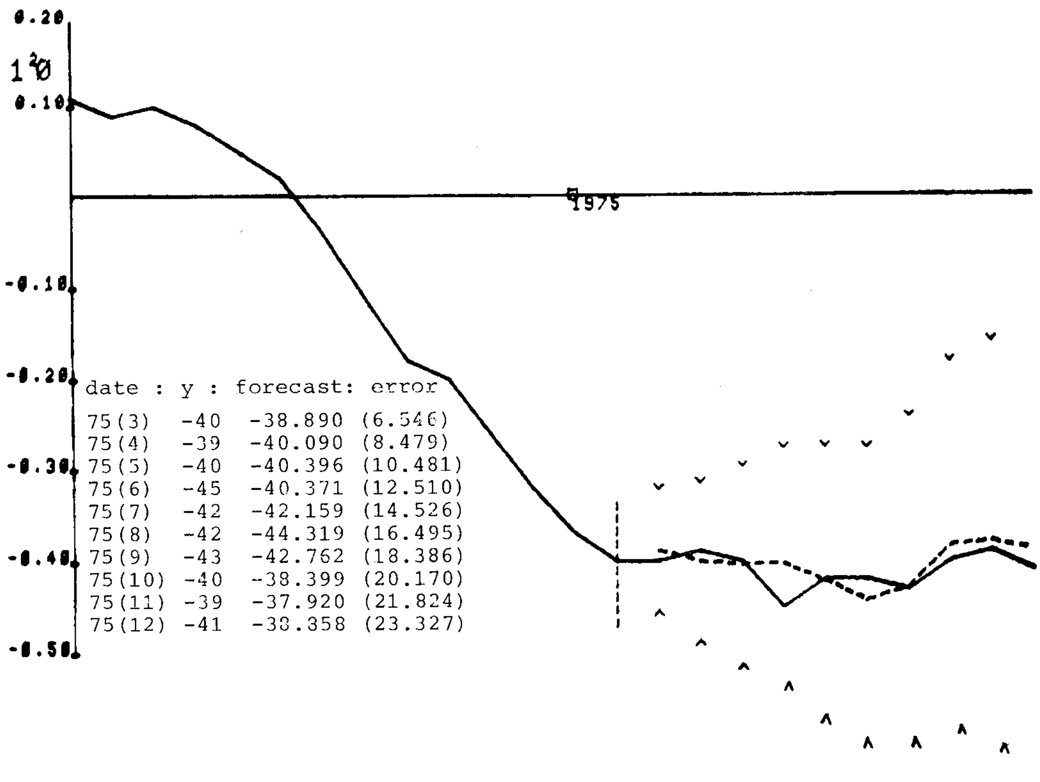
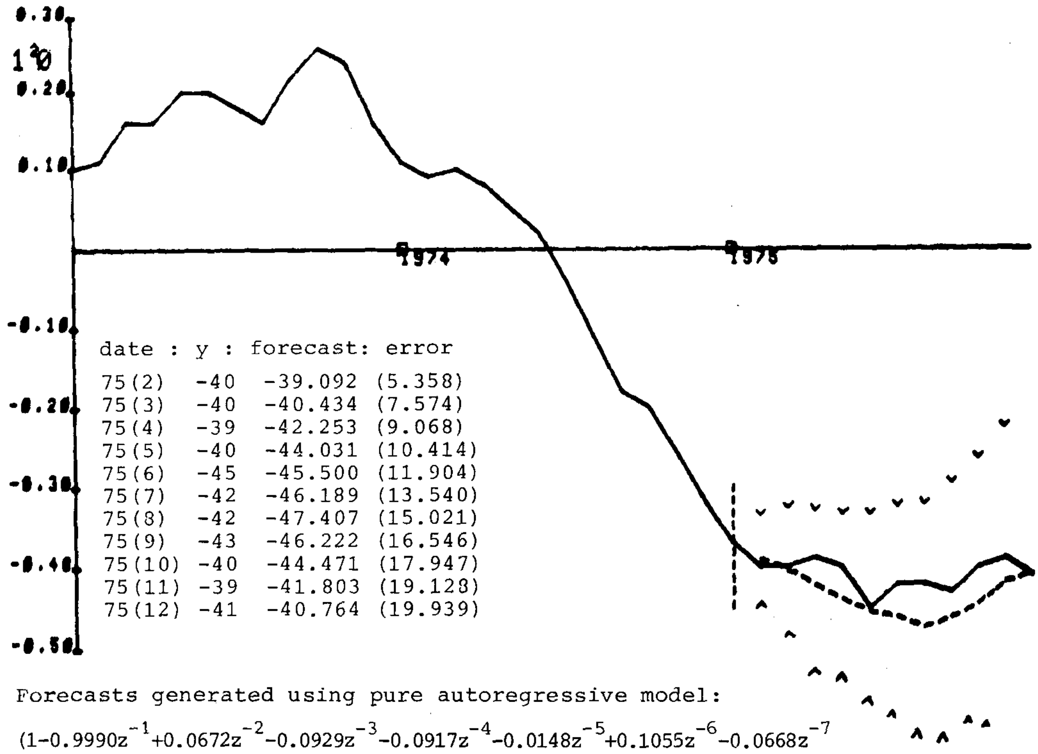


Fig. 3



date	y	forecast	error
75(2)	-40	-39.092	(5.358)
75(3)	-40	-40.434	(7.574)
75(4)	-39	-42.253	(9.068)
75(5)	-40	-44.031	(10.414)
75(6)	-45	-45.500	(11.904)
75(7)	-42	-46.189	(13.540)
75(8)	-42	-47.407	(15.021)
75(9)	-43	-46.222	(16.546)
75(10)	-40	-44.471	(17.947)
75(11)	-39	-41.803	(19.128)
75(12)	-41	-40.764	(19.939)

Forecasts generated using pure autoregressive model:

$$\underset{}{(1}\underset{(0.0823)}{-0.9990z^{-1}}\underset{(0.1163)}{+0.0672z^{-2}}\underset{(0.1128)}{-0.0929z^{-3}}\underset{(0.1129)}{-0.0917z^{-4}}\underset{(0.1128)}{-0.0148z^{-5}}\underset{(0.1104)}{+0.1055z^{-6}}\underset{(0.1115)}{-0.0668z^{-7}}$$

$$\underset{(0.1119)}{+0.1073z^{-8}}\underset{(0.1121)}{+0.0682z^{-9}}\underset{(0.1123)}{+0.1269z^{-10}}\underset{(0.1123)}{-0.3053z^{-11}}\underset{(0.1151)}{+0.1206z^{-12}}\underset{(0.1151)}{-0.1527z^{-13}}\underset{(0.1157)}{+0.3823z^{-14}}$$

$$\underset{(0.1203)}{-0.0835z^{-15}}\underset{(0.0866)}{-0.0781z^{-16}})y(k) = e(k) \qquad \underset{(0.8344)}{\sigma^2=7.1764}$$

Fig. 4

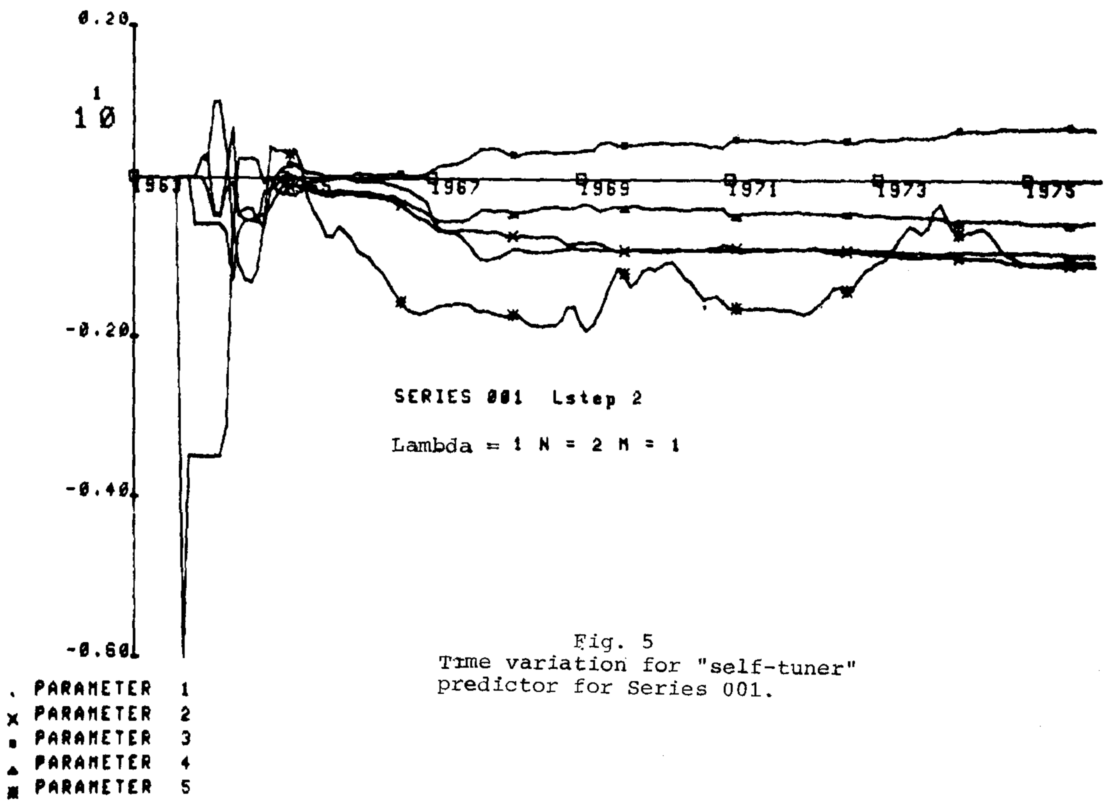


Fig. 5
Time variation for "self-tuner" predictor for Series 001.

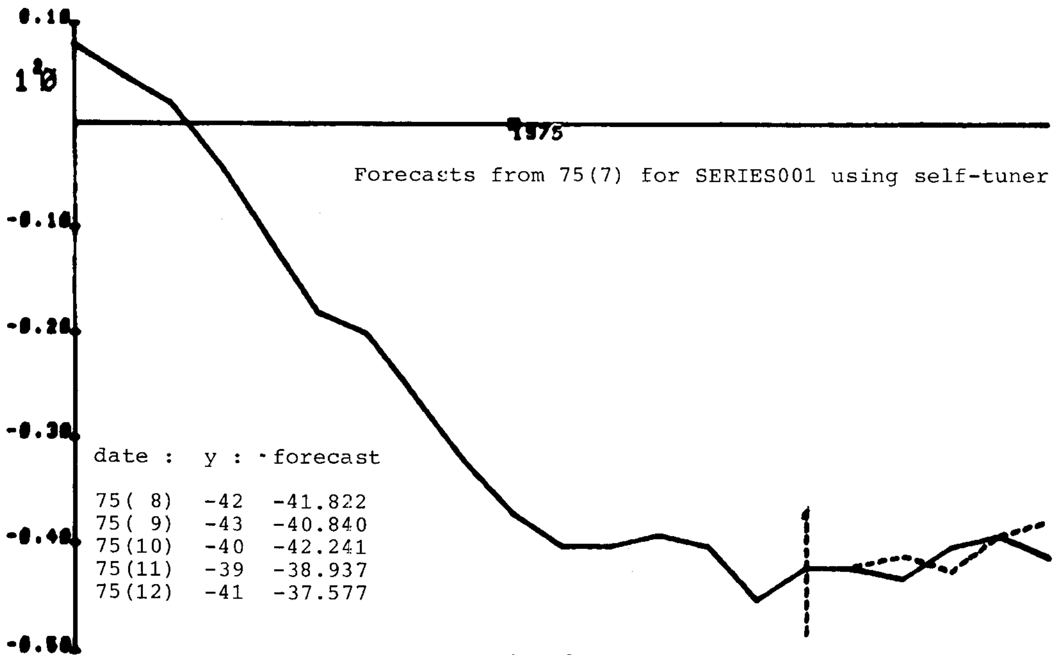


Fig. 6
Forecasting performance of self-tuning forecasting, for Series 001 and parameters

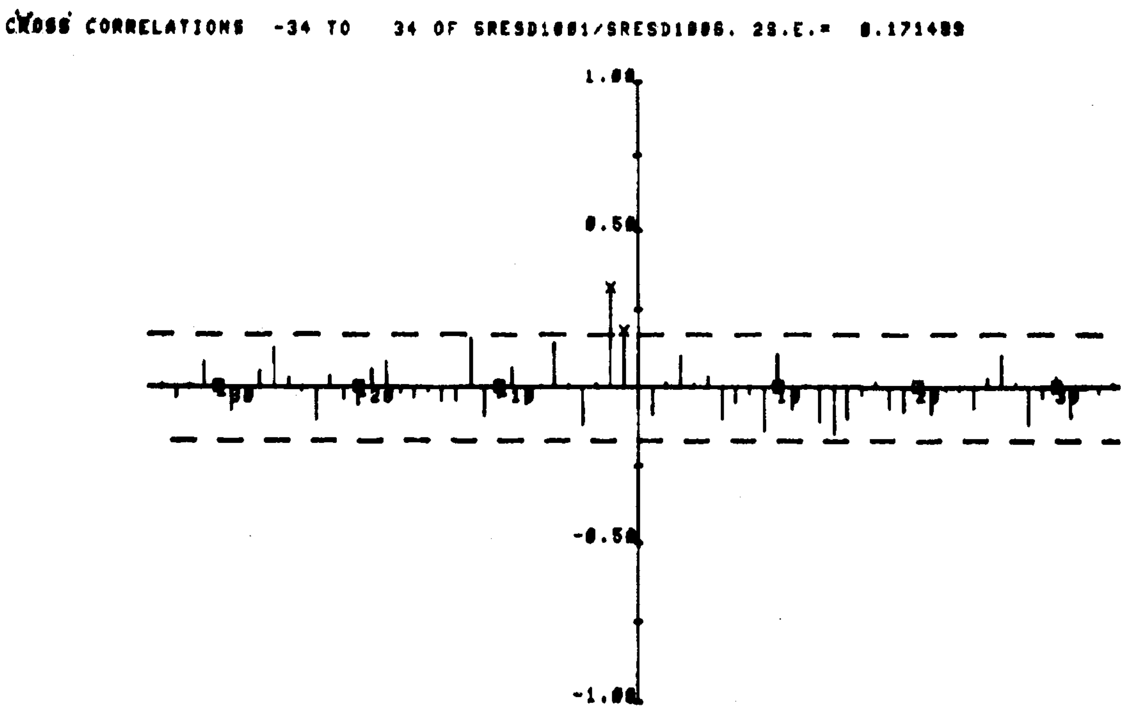
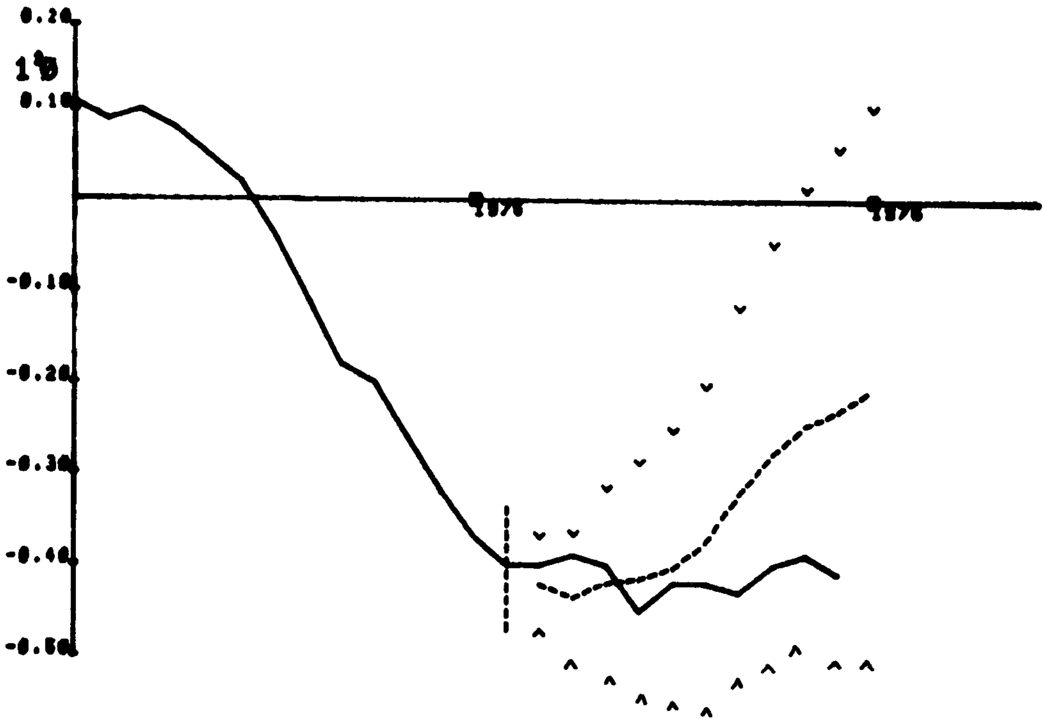


Fig. 7



date	y	forecast	error
75(3)	-40	-42.113	(5.002)
75(4)	-39	-43.495	(6.544)
75(5)	-40	-41.912	(10.011)
75(6)	-45	-41.558	(12.447)
75(7)	-42	-40.297	(14.735)
75(8)	-42	-37.618	(17.098)
75(9)	-43	-32.174	(20.099)
75(10)	-40	-27.805	(22.819)
75(11)	-39	-24.690	(25.691)
75(12)	-41	-23.000	(29.546)
76(1)		-20.501	(30.754)

$$\left(1-\underset{(0.0844)}{0.8436}z^{-1}-\underset{(0.1081)}{0.0992}z^{-2}-\underset{(0.1074)}{0.0249}z^{-3}-\underset{(0.1073)}{0.1459}z^{-4}+\underset{(0.0837)}{0.1730}^{-5}\right)y(k) =$$

$$\left(\underset{(0.0512)}{0.2275}-\underset{(0.0660)}{0.1088}z^{-1}+\underset{(0.0678)}{0.0076}z^{-2}+\underset{(0.0678)}{0.0460}z^{-3}+\underset{(0.0673)}{0.0443}z^{-4}-\underset{(0.0666)}{0.0402}z^{-5}+\underset{(0.0668)}{0.0702}z^{-6}-\underset{(0.0670)}{0.0318}z^{-7}-\underset{(0.0675)}{0.1222}z^{-8}\right.$$

$$\left.+\underset{(0.0681)}{0.0159}z^{-9}+\underset{(0.0682)}{0.1111}z^{-10}-\underset{(0.0679)}{0.0071}z^{-11}-\underset{(0.0521)}{0.1006}z^{-12}\right)u(k-2)+w(k) \qquad \sigma^2=\underset{(0.7642)}{6.2555}$$

Fig. 8