FORECASTING WHEN PATTERN CHANGES OCCUR BEYOND THE HISTORICAL DATA*

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N° 85 / 08

Director of Publication :

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Printed by INSEAD,
Fontainebleau, France

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April 1985

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*The research reported in this paper has been partly funded by a grant from Le Fonds F.C.A.C. of the Province of Quebec.

ABSTRACT

Forecasting methods currently available assume that established patterns or relationships will not change during the post-sample forecasting phase. This, however, is not a realistic assumption for business and economic series. This paper describes a new approach to forecasting which takes into account possible pattern changes beyond the historical data. This approach is based on the development of two models : one short the other long term. These models are then reconciled to produce the final forecasts by setting certain parameters as a function of the number, extent, and duration of pattern changes that have occurred in the past. The proposed method has been applied to the 111 series used in the M-Competition. Post-sample forecasting accuracy comparisons show the superiority of the proposed approach over the most accurate methods in the M-Competition.

KEYWORDS

Forecasting; Time Series Forecasting; Short and Long Term Forecasting Models; Post-Sample Forecasting; Post-Sample Forecasting Accuracy; Forecasting Pattern Changes.

INTRODUCTION

Table 1(a) and 1(b) list the percentage errors produced by eight forecasting methods for two quarterly series (310 and 301) used in the M-Competition (See Makridakis et al., 1982, 1984). The errors were found by comparing the actual values (unknown at the time the models were developed) to the forecasts made by an expert for each of the eight methods.

Table 1(a) reveals that apart from deseasonalized single exponential smoothing, the remaining methods provide fairly precise forecasts for up to eight periods ahead. Furthermore, their errors are independent of the length of the forecasting horizon. The two most accurate methods in Table 1(a) (i.e., Box-Jenkins and Parzen) are also the most statistically sophisticated ones. Their MAPE (Mean Absolute Percentage Error) is a little more than 1%.

INSERT TABLE 1 ABOUT HERE

A completely different picture arises, however, when looking at Table 1(b). The seven most accurate methods of Table 1(a) become the least precise ones. Moreover, forecasting accuracy rapidly deteriorates as the forecasting horizon increases. A "technique breakdown" is observed as most methods produce large, unacceptable errors. Interestingly enough, the MAPE of deseasonalized single exponential smoothing is considerably smaller than that of all other methods.

What caused the large forecasting errors observed in Table 1(b)? Before the end of the historical data, a drastic change in the data pattern occurred and prevailed throughout the post-sample forecasting phase. The methods, not recognizing that such change had taken place, extrapolated the established historical pattern and produced large errors. Deseasonalized single exponential smoothing did relatively well, not because it could identify and predict the change in pattern, but because it tracked the changing mean of the process. This made its forecasts closer to the actual values than the remaining methods which extrapolated a monotonic increase of the previously established pattern.

INSERT FIGURE 1 ABOUT HERE

The type of data shown in Figure 1(b) is not unusual, especially in the business and economic fields. Methods must be found, therefore, to quantitatively forecast data series similar to that of Figure 1(b).

This paper is organized as follows. In Section 1, the reasons necessitating a new forecasting approach capable of handling data as those of Figure 1(b) are discussed. Section II provides the foundations and reasoning of the proposed approach. In Section III, a structured, operational framework for applying the proposed approach is outlined. In Section IV, this framework is illustrated with the two time series shown in Figure 1. In order to validate the new approach the sub-sample of 111 series, used by all methods in the M-Competition, is utilized in Section V. The results show improvements in forecasting accuracy ranging from 9% to 25% as compared to the most accurate method of the M-Competition. Finally, Section VI discusses guidelines of forecasting assuming possible pattern changes during the forecasting phase. A concluding section indicates possible directions for future research.

I. EMPIRICAL EVIDENCE ABOUT FORECASTING METHODS

In the last two decades a considerable body of empirical evidence, comparing the forecasting accuracies of various methods, has been accumulated. This evidence has shown that complex and/or statistically sophisticated methods are not necessarily more accurate than simple approaches. This proves true when empirical comparisons are made between complex and simpler econometric models (see Armstrong, 1978; Leser, 1968; McNees, 1979, 1982), between econometric models (usually more complex) and univariate time series methods (Armstrong, 1978; Nelson, 1972) or between sophisticated and simple time series techniques (Groff, 1973; Makridakis and Hibon, 1979; Makridakis et al., 1982). It is important to understand why sophisticated methods do not forecast more accurately than simple approaches in order to find ways to correct the problem.

Forecasting economic and business data involves two distinct phases: The first phase requires fitting a model to available historical data. The second involves forecasting for future values which are not yet known. Available forecasting methods are concerned with optimizing the accuracy of

model fitting rather than of minimizing post-sample forecasting errors. Although future values cannot be known in advance, a great deal can be inferred by utilizing all information contained on historical data. Current forecasting methods, however, use only a small part of the existing historical information.

All forecasting methods are by necessity extrapolative in nature. Their differences lie in the way established patterns and/or relationships are identified and extrapolated in order to forecast. Least square methods identify the "average" patterns or relationship. Assuming that short-term fluctuations are of no interest, they weigh all observations equally, regardless of their time position. In effect, their forecasts are extrapolations of the average pattern or relationship and they are, thus, oriented towards the long-term.

Discounted least squares and the great majority of time series methods produce short-term oriented forecasts. (This is particularly true of adaptive methods). They assume that changes in data are possible and that recently established patterns will heavily determine post-sample forecasts. Forecasts are, consequently, found by assigning greater weight to more recent observations. In effect, these methods ignore the early past as their memory is exponentially decaying.

Empirical evidence shows that methods geared towards the short-term outperform least square methods aimed at the long-term (Makridakis and Hibon, 1979; Makridakis et al., 1982). In addition, the two most successful methods in the M-Competition Lewandowski's FORSYS (Lewandowski, 1979, 1982) and Parzen's ARARMA models (Parzen, 1982) produced superior results because of the way they distinguish and predict the short and long-term.

FORSYS does not directly extrapolate the most recent trend. Instead it dampens it (see Lewandowski, 1982) towards a plateau. The extent of dampening depends upon the randomness of the series (the greater the randomness, the faster the dampening). FORSYS outperformed all other methods in the M-competition by a large margin for longer forecasting horizons.

ARARMA models distinguish two types of data (see Parzen, 1982), those that contain long-term patterns and those that do not. In the former case, a

long-term autoregressive model is applied; in the latter, a short or random walk model is used. In some instances, the two models are combined.

Although FORSYS and ARARMA models are a step ahead of the remaining forecasting methods, they still cannot deal with major pattern changes in data. As is evident in Table 1(b), they both miss the pattern change that occurred and, therefore, overshoot their forecasts.

II. STABILITY OF DATA PATTERNS AND FORECASTING

The accuracy of forecasting methods is greatly influenced by the stability of data patterns and the length of the forecasting horizon. The more abrupt the changes during the forecasting phase, the higher the likelihood of "technique breakdown" as the forecasting horizon becomes longer.

Economic and business data are characterized by trend, cycle, seasonality and randomness (see Shiskin, 1958, 1965). Forecasting methods generate their forecasts by 'filtering' the randomness out of the data. The majority of available methods identify and extrapolate by combining the trend, cycle and seasonality patterns of the historical data. The combined forecast of the three patterns may suffice, for extrapolative purposes, when no changes occur. If this is not the case, however, it becomes important to know the origin of such change, for it may be caused by shifts in the trend, cycle, or seasonality patterns.

Figure 2(a) is a graph of the actual data of paper orders. Figure 2(b) shows the same data without randomness and seasonality (i.e., the trend cycle), Figure 2(c) shows the seasonal pattern, while Figure 2(d) presents the randomness. In Figure 2(a), the various patterns are intermixed in a way that makes them difficult to observe individually and know whether any of them have changed. In Figure 2(b), the trend and/or cycle can be readily identified. The trend is stable in almost twenty-eight years of historical data. There are recurring cycles around the trend, their duration and depth vary from cycle to cycle, at times considerably. In Figure 2(c), the seasonality is recurring and both its duration (i.e., one year) and depth are constant. In Figure 2(d) randomness, as expected, does not show any stable or repetitive pattern.

INSERT FIGURE 2 ABOUT HERE

Figure 3 shows the trend-cycle pattern of another series. The cycles of this series are insignificant while the trend is not constant. A discontinuity occurred at the end of 1973, then several smaller changes took place. Obviously, if the same model was used to forecast the series displayed in Figures 2 and 3, post sample forecasting accuracy would be different. In Figure 3, for instance it makes little sense to predict the long-term by extrapolating an exponential curve that has been fitted to all data. On the other hand, this would be the best strategy for the data shown in Figure 2.

III. FORMALIZING THE PROPOSED FORECASTING APPROACH

The forecasting approach advocated in this paper differentiates between two models (strategies): a short and long-term. The former employs models that can readily adapt to changes in the data pattern as they occur. Since its objective is the short-term, it is not concerned with whether the changes are temporary or permanent. The long-term strategy recognizes that not all pattern changes are permanent; therefore, the most recent pattern does not necessarily provide the best basis for extrapolating into the distant future. Instead, a long-term model that captures the long-term trend is needed. The two models usually produce different predictions which must be reconciled to produce final forecasts. It is the utilization and reconciliation of the two models that differentiates the proposed approach from techniques such as Bayesian Forecasting (Harrison and Stevens, 1976), those that attempt to predict the various components of a time series (Gersch and Kitagawu, 1983), or those that combine the forecasts of more than one model (Makridakis and Winkler, 1983).

The general model formulation which encompasses both strategies can be written as:

$$x(t) = \left[\sum_{j=0}^{q} b_j(t)t^j\right] \prod_{i=1}^{L} I_i(t)^{z_i(t)} + e(t) \qquad (1)$$

where t indicates time period, thus t=1,2,3,..., T, and T is the number of historical data periods.

$x(t)$ represents the observations of the time series at time t,

$z_i(t)$ equals 1 if the t-th observations is of season i otherwise it is 0,

L is the length of the seasonality,

q is the degree of a polynominal in time,

$I_i(t)$ is the value, at time t, of the seasonal coefficient assigned to the i-th season.

The b's are the time-varying values assigned to the various specified terms (mean, trend, quadratio, etc.) of the polynominal function,

and $e(t)$ is a random noise term with a mean of zero and a constant variance.

Forecasting strategies are determined within the context of (1) by specifying a value for q -- the higher tha value of q, <u>the more short-term the forecasting strategy</u>. If q is set to two, this results in a quadratic model which for all practical purposes is adequate for adapting and capturing short-term pattern changes. The model when q=2 is as follows:

$$x(t) = \left[b_o(t) + b_1(t)t + b_2(t)t^2 \right] \prod_{i=1}^{L} I_i^{z_i(t)} + e(t). \tag{2}$$

The long-term model can be best expressed, when q=o, as:

$$x(t) = b_o(t) \prod_{i=1}^{L} I_i(t)^{z_i(t)} + e(t) . \tag{3}$$

Expression (3) is used to obtain values for b_o which are in effect the seasonally adjusted smoothed values of $x(t)$. Forecasts are then generated by extrapolating the time regression fitted on the estimated values of b_o. They are found by:

$$x(T+m) = (C_o + C_1 (T+m)) \prod_{i=1}^{L} I_i(T+m)^{z_i(T+m)} \tag{4}$$

where m=1,2,..., K, and K is the number of desired forecasts;
C_o and C_1 are the intercept and slope parameters obtained from the time regression.

$$b_o(t) = C_o + C_1(t) + u(t) \tag{5}$$

and I's are the values of the seasonal indices estimated from the historical data.

Forecasts established by expression (4) reflect the long-term trend pattern since transient fluctuations are filtered through expression (5). The parameters of (2) and (3) can be estimated using a number of forecasting methods. In our case, the AEP forecasting procedure (see Carbone and Longini, 1977; Makridakis et al., 1984) which updates all parameters of (2) as a function of the noise level is employed.

The short and long-term forecasts are reconciled as follows:

$$F(h) = \begin{cases} F_s(h) & \text{if } h < h_o \\ F_\ell(h) + \alpha^{h-h_o}(F_s(h) - F_\ell(h)) & \text{if } h \geq h_o \end{cases} \tag{6}$$

where $F(h)$, $F_s(h)$ and $F_\ell(h)$ are the final short, and long-term forecasts respectively.

The parameters h_o and α determine the timing and speed of reconciliation. If K is the maximum forecasting horizon their limits are:

$$h_o \leq K$$
$$0 < \alpha < 1$$

In expression (6) it can be seen that the short-term model is exclusively used until period h_o. After period h_o both the short and the long-term models are utilized and their differences $(F_s(h) - F_\ell(h))$ reconciled. The reconciliation depends upon the value of α and is done in an exponential fashion. It is not necessary that the reconciliation of the short and the long-term models be exponential, or that it follows (6). Alternative approaches could work as well and need to be explored.

IV. APPLYING THE PROPOSED APPROACH TO TWO TIME SERIES

The short and long-term models for the two quarterly time series of Figure 1 are the following:

Series 310 (Figure 1(a)):

(a) The short-term forecasting model is:

$$x(T+m) = \left[2889.9 + 23.3\ (T+m) + .87\ (T+m)^2\right] I \qquad (7)$$

where T is the latest period of available data, I is unity since the series is non-seasonal, and m is the number of periods to be forecasted.

(b) The long-term forecasting model is:

$$x(T+m) = (2467 + 59(T+m))\ I \qquad (8)$$

The value of h_o should be set to eight, the number of desired forecasts, since no pattern changes can be seen in Figure 1(a). Doing so results in a MAPE for the post sample errors of 1.02 which is comparable to that of the two best methods of Table 1(a).

Alternatively, a value of $h_o = 4$ and a value of $= .9$ can be used to illustrate their effect. In this case, two sets of eight forecasts will result by applying the short-term model (7), and the long-term one (8). These forecasts must be reconciled using (6) in order to come up with final forecasts. The post sample MAPE of such forecasts is 2.16%.

Series 301 (Figure 1(b):

(a) Short-term strategy (model):

$$x(T+m) = (54.8 + 1.37\ (T+m) - .005\ (T+m)^2)\ I \qquad (9)$$

where I as before is unity, since the series is non-seasonal

(b) Long-term strategy (model):

$$x(T+m) = \left[57 + 0.95\ (T+m)\right] I \tag{10}$$

Since a substantial change in the data pattern can be observed towards the end of the historical data (see Figure 1(b)) a small value of h_0 should be used as well as a value of α close to zero. If $h_0 = 4$ and $\alpha = .1$, the MAPE of the reconciled forecasts (using expression (6)) is 6.76%. This MAPE is better than that of deseasonalized single exponential smoothing (see Table 1(b)). It should be pointed out that the values of h_0 and α for series 310 and 301 were determined exclusively by looking at a plot of the historical data of these two series.

The patterns of series 310 and 301 are simple enough to allow an easy determination of h_0 and α. For more complex series (as in Figure 3) more analysis may be required to specify their values. Moreover the user can incorporate his/her own judgmental inputs about possible pattern change during the forecasting phase and their duration. There is a shift, therefore, from using judgmental inputs to model a time series to predicting possible pattern changes during the post-sample forecasting phase.

V. APPLICATION TO THE 111 SERIES

To validate the proposed approach, equations (2), (3), (4), (5), and (6) were applied to the sub-sample of the 111 time series used by all methods in the M-Competition. Final forecasts were obtained, using (6), by reconciling the short and the long-term models.

The short and long-term models were established for each of the 111 series using the AEP filtering program (under an automatic execution mode). No effort was made to establish the best reconciliation parameters h_0 and α. Instead, three sets of values for h_0 (labelled I, II, III) and three sets of values for α (labelled A, B, C) were arbitrarily chosen. In all, nine cases were examined. They are shown in Table 2 with the corresponding overall performance for over 1300 forecasts. Performance is expressed in terms of the post-sample MAPEs of the final (reconciled) forecasts.

INSERT TABLE 2 ABOUT HERE

The value of α for set A assumes that all series have relatively stable patterns. B reflects a "middle" strategy as if no knowledge about the behavior of the data pattern exists. Strongly changing patterns are assumed under C. The turning point indicator (h_0) under I assumes that the short-term model is exlusively used for many periods. The number of periods exclusively covered by the short-term model are successively reduced with II and III.

Detailed values of specific MAPEs are displayed in Table 3 for the best, average, and worst of the nine cases. These MAPEs are shown together with those of the most performant methods. The MAPEs of the proposed approach show a marked improvement in forecasting accuracy across all data and the seasonal/ non-seasonal classification. Furthermore, the improvement extends into both the short and long-term forecasting horizons. Finally, the difference in forecasting accuracy from the best to the worst case seems small. This is encouraging as it reveals that even when no attempt is made to optimally define h_0 and α a considerable improvement in accuracy can result. For all data and forecasting horizons, the improvement over the best method is about 9% (i.e., a MAPE of 15.4% for Parzen versus 14.0% for the proposed approach). Finally, Figure 4 shows a graphical comparison of the proposed approach (CM) with those of the most accurate methods in the M-Competition. The comparison involves both the mean absolute percentage errors and the median of absolute percentage errors.

It is expected that forecasting accuracy would further improve if the values of h_0 and α were chosen in a more optimal way. This would have required establishing the maximum horizon for using the short-term model (h_0), and deciding on the extent and character of change(s) in the data pattern. This can be done by looking at a graph of each series and utilizing whatever additional information was available (inside knowledge, proposed promotions, price changes etc.). Guidelines of how h_0 and α can be specified are discussed in the next section.

INSERT TABLE 3 ABOUT HERE

VI. PATTERN CHANGES AND THEIR IMPLICATIONS ON FORECASTING

The data graphed in Figures 1, 2, and 3 are illustrations of a range of real-life series. For a series with a stable pattern, like that shown in Figure 1(a), traditional forecasting methods are adequate. In terms of the proposed approach, the short-term model should be used exclusively by setting $h_o = K$. Series 1(b), 2 and 3 exhibit pattern changes in the historical data which must be dealt with by specifying appropriate values for h_o and α.

The specific values of h_o depend upon the existence and character of change (i.e., temporary vs. permanent). The value of α is a function of the extent and duration of change. In general, the smaller the pattern change and the further away from the end of the historical data, the closer should the value of h_o be to K. Moreover, as the change becomes more pronounced, the smaller should become the value of α.

Table 4 shows the behavior of various patterns. Table 5 lists possible pattern changes in trend, seasonality, and cycle and outlines possible reconciliation strategies. Classifying pattern changes according to Tables 4 and 5 is not difficult once a graph of the data has been consulted. On the other hand, knowing whether a change is temporary or permanent is not possible unless inside knowledge is available (e.g., those forecasting cigarette consumption may want to decide that the declining trend they are experiencing is of permanent duration). Although it might be difficult to predict the character (temporary versus permanent) of a change it is important to make forecasting users aware of such distinction. The fact that available forecasting methodologies do not consider temporary versus permanent pattern changes, is an omission that ought to be corrected.

There may be series, like that of Figure 1(a), which exhibit no change(s) in the historical data, but which undergo a change in pattern during the forecasting phase. Similarly, what may initially be considered a temporary cyclical change may, in fact, turn out to be a permanent change in trend. Such events, however, are rare. On the average, if many series are involved, one can play the odds and minimize post-sample forecasting errors.

VII. DIRECTIONS FOR FUTURE RESEARCH

Future research should identify and test various reconciliation strategies. The advantages and drawbacks of setting h_0 and α must be better understood, and their implications on post-sample forecasting errors, under a variety of conditions, explored. For instance, it might be desirable to identify the stage of the business cycle before forecasting and then predict assuming an "average" cycle (see McLaughin, 1982) as a medium term model. Reconciliation would then involve three models and it would aim at finding an optimal path from the short to the medium to the long-term. Furthermore, research work is required to experiment with other forecasting methods, in addition to AEP, to generate short and long-term models. Finally, different types of data (i.e., yearly, monthly, quarterly) might require different values for h_0 and α or different methods. From the 111 series, it appears that yearly data are best forecasted when h_0 is close to K. This is because changes in the trend of yearly data are usually of a more permanent duration than cyclical pattern changes that characterize monthly data which, therefore, require a smaller value of α .

This paper has discussed pattern changes. Relationships can also be stable or changing. As with patterns, the position (timing) of a change relationships is important. A change that shifted a relationship many years ago is not as critical as one that happened two months or two quarters ago. Different strategies concerning the effect of changes in relationships need, therefore, to be contemplated. The problem of dealing with changes in relationships is complicated by the fact that time must enter as a factor. This would require a three dimensional graph even when a simple two variable relationship (e.g., sales and advertising) is being studied. When multiple relationships are involved, things can become more complicated since one of the variables may explain what may have otherwise been considered to be a change in relationship(s).

This paper has been concerned with pattern changes during the post-sample forecasting phase. First, it showed that available forecasting methods ignore the problem, and then it presented an approach for dealing with such changes. This approach involved a short and a long-term model and the specification of certain parameters so that the two models may be reconciled to produce final forecasts. The proposed framework has been illustrated by applying it to the 111 series used in the M-Competition.

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Table 1: Percentage errors of various methods for two different quarterly time series

(a) Series 310

Forecasting Horizons (in quarters)	FORECASTING METHODS							
	Deseas. Single Expon. Smoothing	Deseas. Holt	Winters	Bayesian	AEP	Lewandowski	Parzen	Box-Jenkins
1	1.14	-1.08	-1.08	-0.44	-0.94	-2.87	-0.82	-0.71
2	2.86	-1.50	-1.50	-1.50	-0.82	-1.74	-0.33	0.23
3	4.86	-1.55	-1.55	-1.33	-1.09	-0.73	-0.20	0.84
4	5.81	-2.66	-2.66	-2.72	-2.19	-0.88	-1.12	0.19
5	5.48	-5.14	-5.14	-5.54	-4.39	-3.42	-2.95	-1.41
6	7.61	-4.85	-4.85	-5.62	-4.01	-1.76	-2.20	-0.30
7	11.36	-2.58	-2.58	-3.75	-1.90	1.54	0.00	2.02
8	13.38	-2.19	-2.19	-3.81	-1.31	3.16	0.61	2.55
MAPE	6.56	2.69	2.69	3.03	2.08	2.01	1.03	1.03

(b) Series 301

Forecasting Horizons (in quarters)	FORECASTING METHODS							
	Deseas. Single Expon. Smoothing	Deseas. Holt	Winters	Bayesian	AEP	Lewandowski	Parzen	Box-Jenkins
1	-2.24	-3.36	-3.85	-7.62	-2.49	-5.64	-2.74	-3.50
2	-1.46	-3.66	-4.17	-8.61	-1.37	-5.58	-1.97	-4.35
3	-0.16	-3.41	-4.00	-9.44	-1.39	-5.21	-2.89	-5.08
4	-5.26	-9.81	-10.18	-15.16	-6.45	-11.93	-9.03	-11.32
5	-13.93	-20.07	-20.90	-30.93	-15.18	-22.48	-19.37	-22.40
6	-14.86	-22.28	-23.16	-34.23	-14.94	-24.43	-20.52	-25.64
7	-10.36	-18.68	-19.61	-31.66	-11.92	-20.46	-19.11	-23.34
8	-8.11	-17.42	-18.07	-29.13	-9.54	-19.28	-17.97	-21.95
MAPE	7.05	12.34	12.99	20.85	7.91	14.38	11.70	14.70

Table 2: Overall MAPEs on the 111 series of the M-Competition

Speed of reconciliation (α)	CASES	Turning Point Indicator (h_o)								
		I			II			III		
		Type of Data			Type of Data			Type of Data		
		Yearly	Quarterly	Monthly	Yearly	Quarterly	Monthly	Yearly	Quarterly	Monthly
		6	4	8	5	3	7	4	2	6
$\alpha = 0.9$	A	14.3			14.1			14.0		
$\alpha = 0.5$	B	14.1			14.2			14.4		
$\alpha = 0.1$	C	14.3			14.5			14.7		

Table 3: Comparison of MAPEs for Selected Methods (All, Seasonal, Non-Seasonal data)

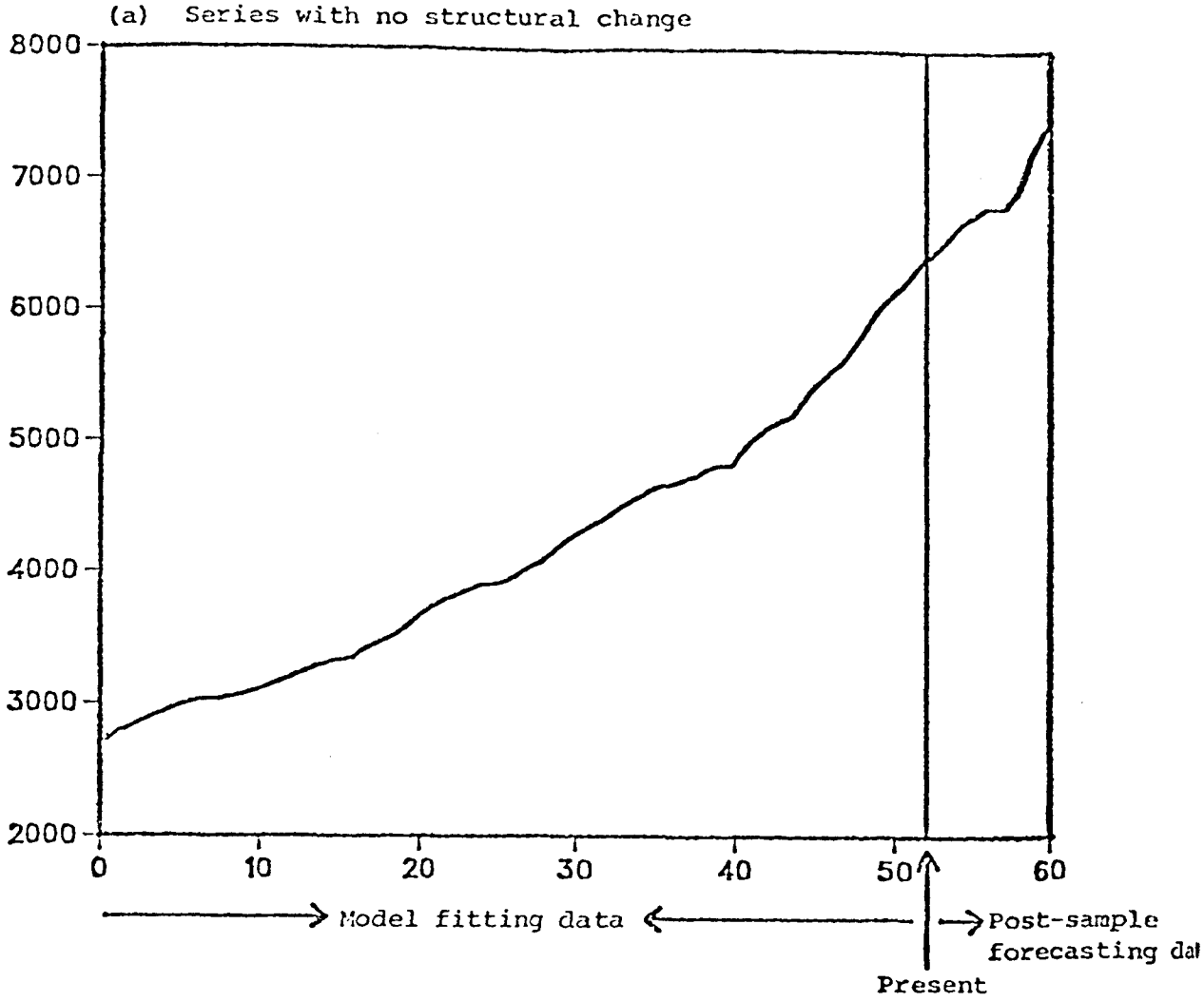
SEASONAL DATA (60 series)	1	2	3	4	5	6	8	12	15	18	1-4	1-6	1-8	1-12	1-15	1-18
D. SINGLE	6.1	9.7	9.8	12.0	10.6	13.2	16.9	12.3	27.8	25.5	9.4	10.2	11.8	12.3	13.8	14.9
D. HOLT	6.6	9.8	10.2	13.0	11.2	15.1	19.7	15.7	37.0	33.6	9.9	11.0	13.1	14.2	16.5	18.4
PARZEN	11.0	10.0	10.1	12.8	12.2	13.7	16.1	13.9	19.2	24.8	11.0	11.6	12.7	12.9	13.8	14.9
BAYESIAN	8.1	10.8	9.5	11.3	10.0	13.1	18.1	14.2	22.7	22.9	9.9	10.5	11.9	12.4	13.5	14.4
BOX-JENKINS	10.5	10.1	10.0	13.5	13.7	15.9	20.6	15.1	23.3	30.6	11.0	12.3	14.3	14.8	15.8	17.2
WINTERS	8.9	9.8	10.5	13.6	11.5	14.7	19.9	14.9	34.0	32.7	10.7	11.5	13.5	14.2	16.0	18.1
LEWANDOSKI	10.8	12.9	12.6	14.3	12.9	17.3	19.8	16.6	33.7	23.8	12.7	13.5	14.7	14.9	16.9	17.6
AUTOM-AEP	10.3	11.6	13.6	15.0	15.3	20.2	26.0	14.6	27.7	29.0	12.6	14.3	17.0	16.4	17.4	18.6
CARBONE-MAKRIDAKIS (Best)	8.0	9.9	10.3	13.1	10.1	13.3	15.1	11.4	22.5	21.7	10.3	10.8	12.0	11.9	12.9	13.7
CARBONE-MAKRIDAKIS (Average)	8.0	9.9	9.8	12.0	9.0	11.9	13.2	12.7	21.5	21.2	9.9	10.1	10.9	11.3	12.4	13.3
CARBONE-MAKRIDAKIS (Worse)	8.0	9.9	10.1	11.9	8.9	11.9	13.7	12.8	21.5	21.2	10.0	11.0	11.0	11.4	12.5	13.3
NON-SEASONAL DATA (51 series)																
D. SINGLE	9.9	12.1	16.9	17.4	21.8	21.9	15.7	17.6	33.7	43.8	14.1	16.7	17.2	16.8	18.0	20.2
D. HOLT	9.5	11.3	16.7	17.6	24.5	23.5	29.8	19.0	31.6	40.1	13.8	17.2	19.9	19.8	20.7	22.2
PARZEN	10.1	11.5	11.4	14.3	16.9	15.9	12.8	12.8	32.4	31.6	11.8	13.3	14.1	14.1	15.0	16.3
BAYESIAN	12.8	15.0	18.4	18.1	23.5	21.8	21.3	22.1	42.0	53.6	16.1	18.3	19.5	19.1	20.6	23.5
BOX-JENKINS	10.0	11.3	13.0	15.7	19.5	18.4	15.5	20.4	35.1	45.0	12.5	14.7	15.3	15.6	17.1	19.5
WINTERS	9.5	11.3	16.7	17.6	24.5	23.5	29.8	19.0	31.6	40.1	13.8	17.2	19.9	19.8	20.7	22.2
LEWANDOSKI	12.6	12.7	16.8	16.4	21.0	18.0	17.2	18.1	31.0	42.9	14.6	16.2	16.6	16.8	17.8	20.5
AUTOM-AEP	9.3	10.8	13.9	15.2	18.8	17.2	18.0	20.9	38.0	48.7	12.3	14.2	15.4	15.9	17.4	19.9
CARBONE-MAKRIDAKIS (Best)	8.6	7.4	11.4	13.9	18.5	16.8	16.7	13.2	18.6	22.0	10.3	12.8	13.9	14.0	14.2	14.7
CARBONE-MAKRIDAKIS (Average)	8.6	7.4	11.7	15.8	20.7	20.3	20.1	16.2	19.8	22.5	11.2	14.3	15.6	15.9	16.2	16.4
CARBONE-MAKRIDAKIS (Worse)	8.6	7.4	14.6	17.0	23.1	21.9	21.3	16.4	19.9	22.5	11.9	15.5	16.9	17.0	17.2	17.3
ALL DATA (111 series)																
D. SINGLE	7.8	10.8	13.1	14.5	15.7	17.2	16.5	13.6	29.3	30.1	11.6	13.2	14.1	14.0	15.3	16.8
D. HOLT	7.9	10.5	13.2	15.1	17.3	19.0	23.1	16.5	35.6	35.2	11.7	13.8	16.1	16.4	18.0	19.7
PARZEN	10.6	10.7	10.7	13.5	14.3	14.7	16.0	13.7	22.5	26.5	11.4	12.4	13.3	13.4	14.3	15.4
BAYESIAN	10.3	12.8	13.6	14.4	16.2	17.1	19.2	16.1	27.5	30.6	12.8	14.1	15.2	15.0	16.1	17.6
BOX-JENKINS	10.3	10.7	11.4	14.5	16.4	17.1	18.9	16.4	26.2	34.2	11.7	13.4	14.8	15.1	16.3	18.0
WINTERS	9.2	10.5	13.4	15.5	17.5	18.7	23.3	15.9	33.4	34.5	12.1	14.1	16.3	16.4	17.8	19.5
LEWANDOSKI	11.6	12.8	14.5	15.3	16.6	17.6	18.9	17.0	33.0	28.6	13.5	14.7	15.5	15.6	17.2	18.6
AUTOM-AEP	9.8	11.3	13.7	15.1	16.9	18.8	23.3	16.2	30.2	33.9	12.5	14.3	16.3	16.2	17.4	19.0
CARBONE-MAKRIDAKIS (Best)	8.3	8.8	10.8	13.5	13.9	14.9	15.6	12.2	21.5	21.8	10.3	11.7	12.8	12.7	13.4	14.0
CARBONE-MAKRIDAKIS (Average)	8.3	8.8	11.1	13.8	14.3	15.7	15.5	13.5	21.1	21.5	10.5	12.0	12.9	13.0	13.4	14.4
CARBONE-MAKRIDAKIS (Worse)	8.3	8.8	12.1	14.2	15.4	16.4	16.2	13.6	21.1	21.5	10.9	12.5	13.5	13.5	14.2	14.7

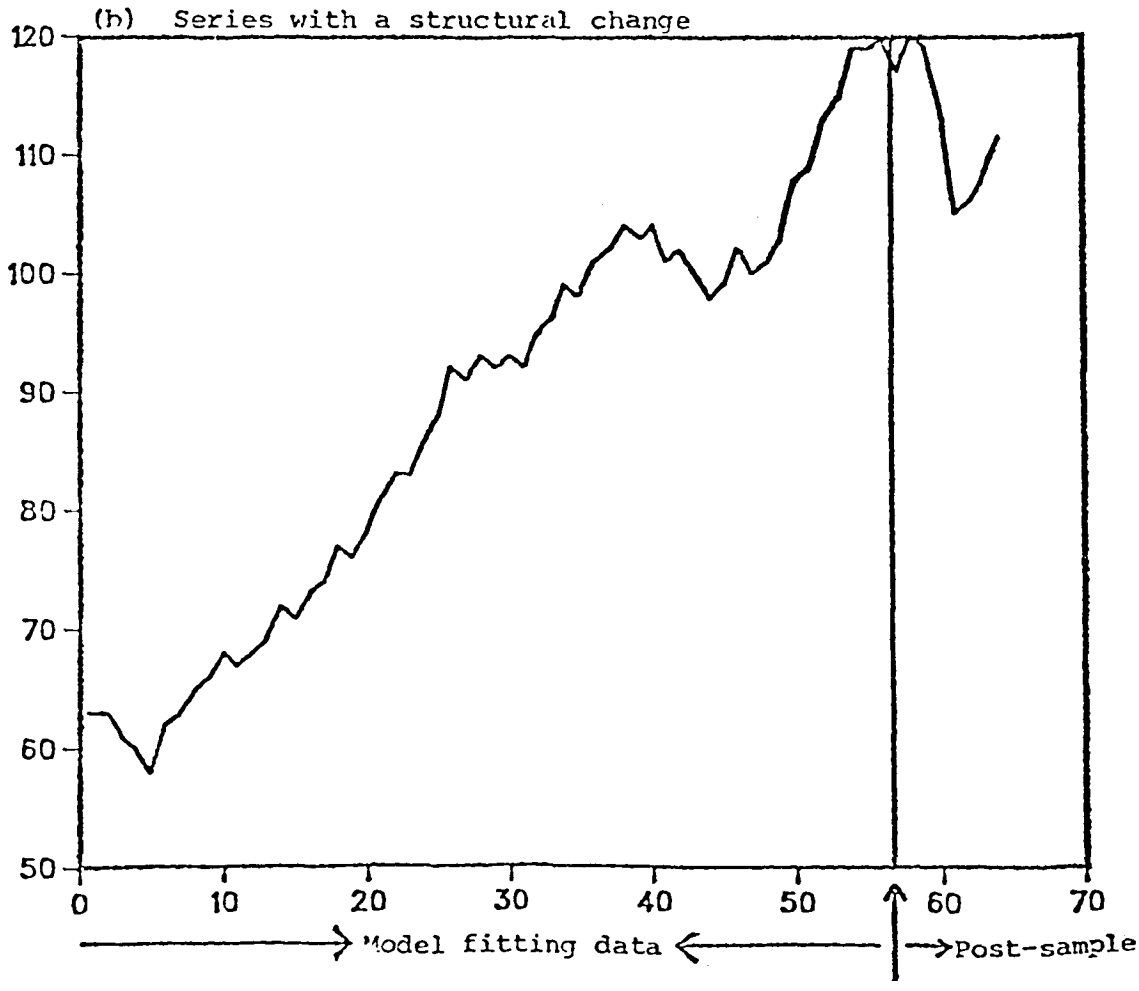
Table 4 : Time series patterns and their bahaviour

type of pattern	Behaviour of Pattern			
	Stable Data Pattern $h_0 = K$		Changing Data Patterns $h_0 < K$	
	Constant	Recurring	Varying	Discontinuous
TREND	Uninterrupted Continuation of an existing secular trend (see Figures 1(a) or 2(b))		Changes in trend (see Figures 3 after 1974)	Abrupt interruptions in level and / or trend (see Figures 3 at end of 1973)
SEASONALITY		Fluctuations around an average pattern of similar depth recurring at regular (equal length) time intervals (see Figure 2 (c))		
CYCLE		Recurring pattern whose length and depth can vary considerably (see Figure 2 (b) cycles around the long term trend)		Huge cyclical changes (e.g. depressions)

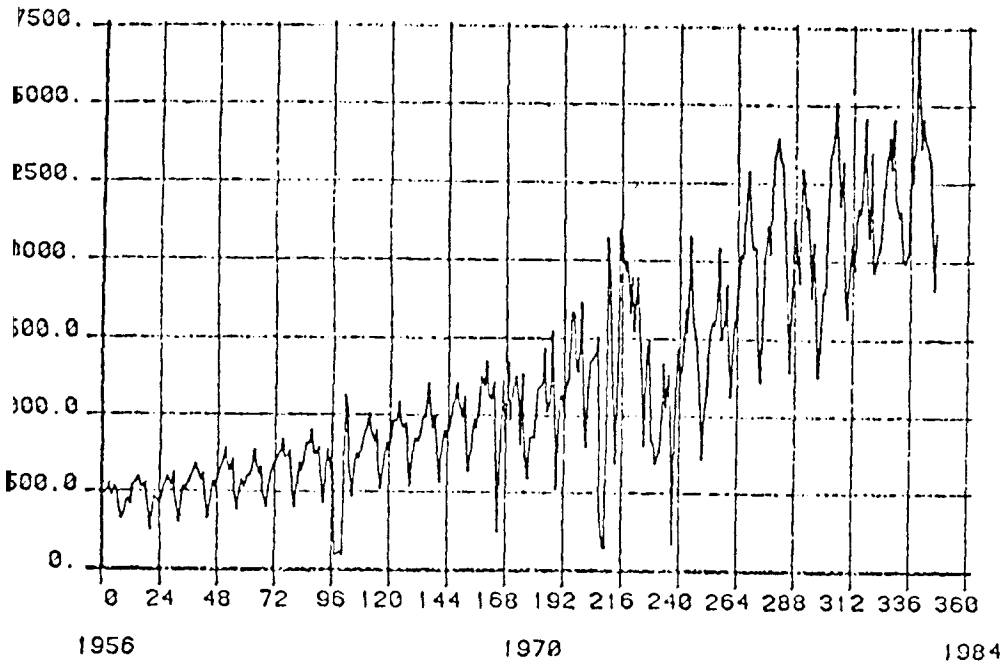
Table 5: Pattern changes and reconciliation strategies

Type of Changing Patterns	Varying Patterns			Discontinuous Pattern		
	Well before end of series	Throughout series	Close to end of series	Well before end of series	Throughout series	Close to end of series
TREND	Mostly ignore change as its effect seems to be fading. Set α around 0.9.	A very unusual case. Set α close to 0 unless a repetitive pattern can be identified in the way the trend is changing.	Value of α depends upon extent of change. The bigger the change the closer α should be to 0. Important to know if the change in pattern is temporary or permanent in order to set the value of h_0 appropriately.	Mostly ignore change as its effect seems to be fading. Set α around 1.	Extremely unlikely case. Forecasting is very difficult. Use α=0.	Value of α depends upon the extent of change. The bigger the change, the closer α should be to 0. Important to know if the discontinuity in pattern is temporary or permanent in order to set h_0 appropriately.
CYCLE	Unlikely case Cycles by definition are recurring. Mostly ignore change, put α close to 0.9.	The most usual case. Give α middle values (ie. 0.5). Very important to determine h_0. It should be specified as a function of how much the latest trend-cycle values are above or below the long trend. The more they are, the smaller should be the value of h_0	Unlikely case. Cycles by definition are recurring. Difficult to establish that change is cyclical and not due to α modification of trend. The bigger the change, the closer α should be to 0. Important to establish that change is indeed cyclical (ie. temporary).	Mostly ignore change as its effects seem to be fading. Set α around 0.9 Large cyclical changes (ie. depressions) do not occur often.	Extremely unlikely case. Forecasting is very difficult. Use α =0.	The value of α depends upon extent of change. The bigger the change, the closer α should be to 0. If it is known that discontinuity is cyclical (ie. temporary) h_0 should be set to the length of the change)

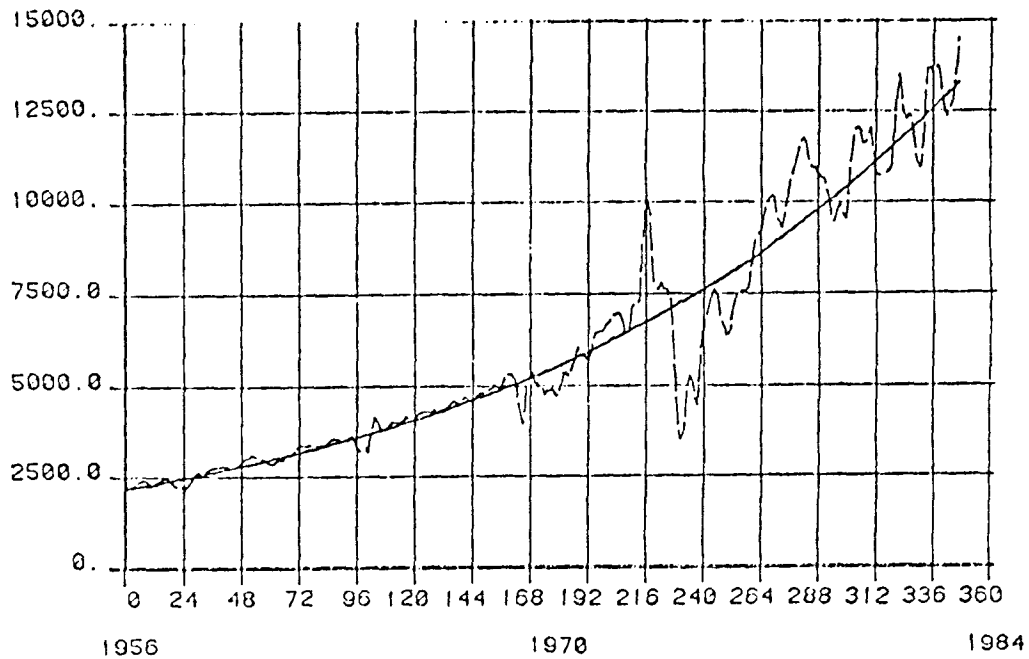

(a) Series with no structural change
8000
7000
6000
5000
4000
3000
2000
0
10
20
30
40
50
60
Model fitting data
Post-sample
forecasting dat
Present


(b) Series with a structural change
120
110
100
90
80
70
60
50
0
10
20
30
40
50
60
70
Model fitting data
Post-sample

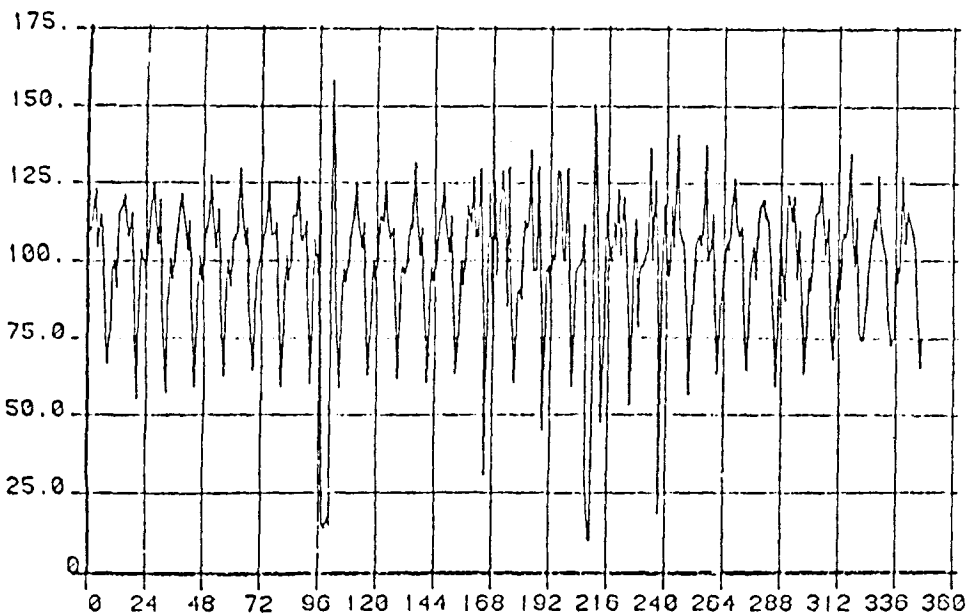
(a) Original Data



(b) Trend-Cycles and long term trend



(c) Seasonal Factors and Randomness



(d) Residual Randomness

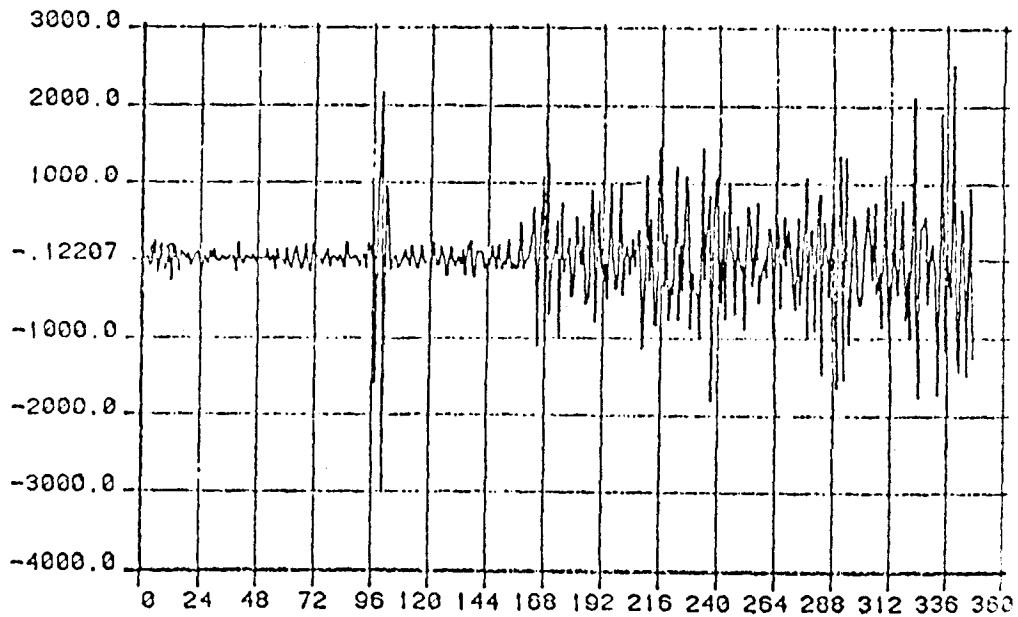


FIGURE 3: GASOLINE CONSUMPTION IN FRANCE

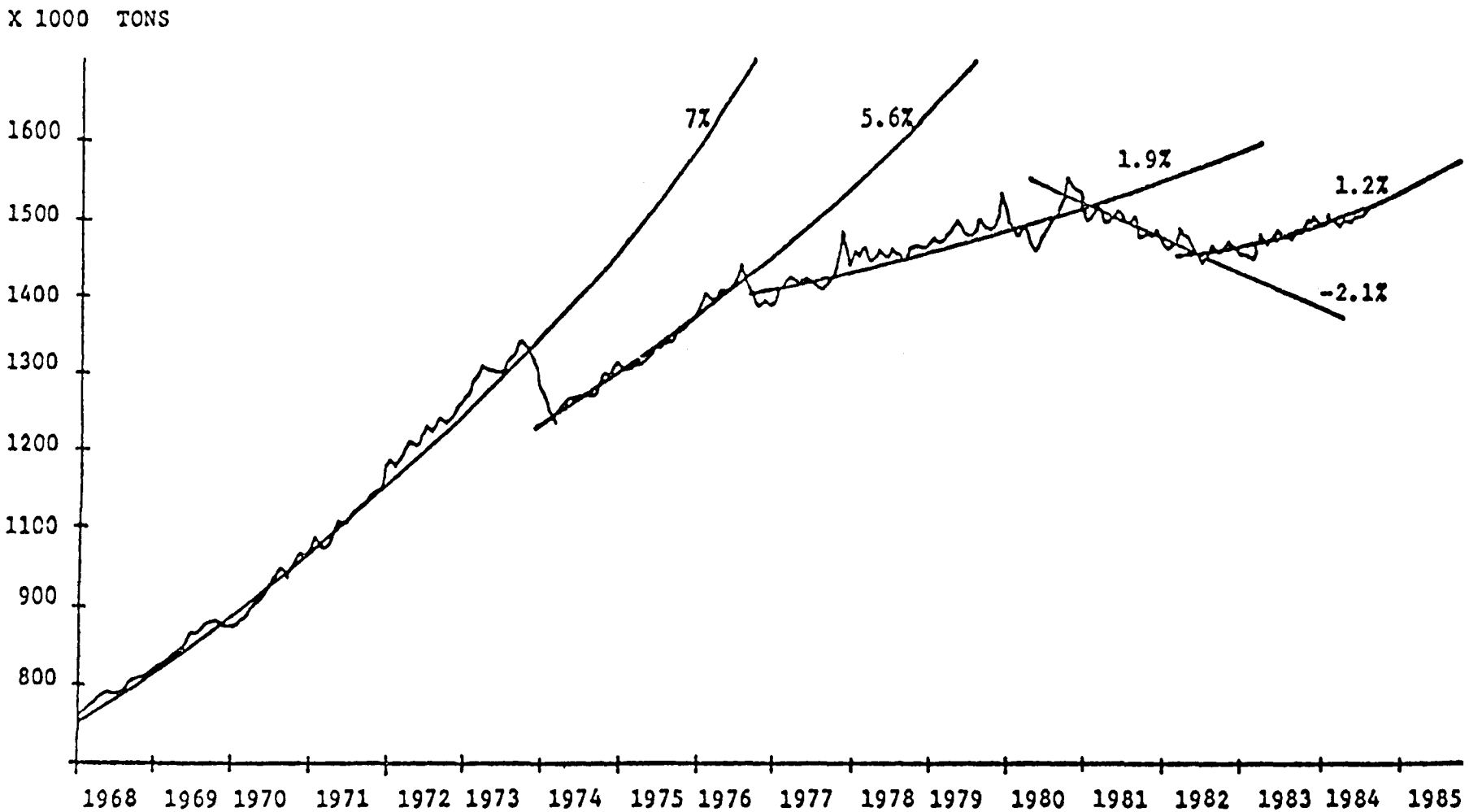
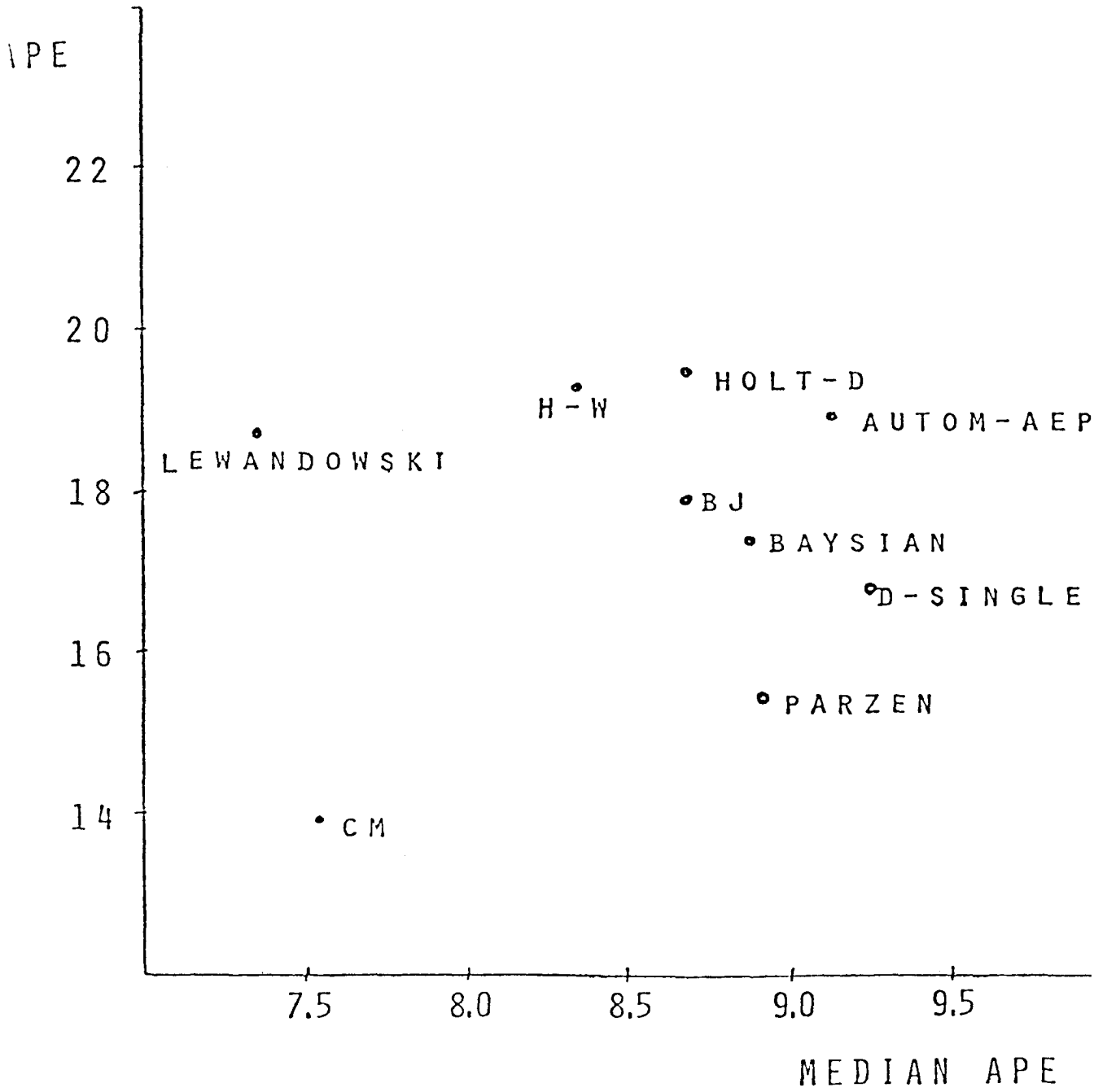


FIGURE 4: MEAN ABSOLUTE PERCENTAGE ERRORS (MAPE) VERSUS MEDIAN ABSOLUTE PERCENTAGE ERRORS (APE) FOR THE 111 SERIES OF THE M-COMPETITION



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