Working Paper 96-31
Statistics and Econometrics Series 10
April 1996

Departamento de Estadística y Econometría
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (341) 624-9849

USING HIGH-FREQUENCY DATA AND TIME SERIES MODELS TO IMPROVE YIELD MANAGEMENT

José Ramón Cancelo and Antoni Espasa*

Abstract

We show the potential contribution of time series models (TSM) to the analysis of high frequency (less than monthly) time series of economic activity. The evolution of the series is induced by stable patterns of behavior of economic agents; but these patterns are so complex that simple smoothing techniques or subjective forecasting can not consider all underlying factors and TSM are needed if a full efficient analysis is to be carried out. The main ideas are illustrated with an apllication to Spanish daily electricity consumption.

Keywords:
Calendar effects, daily data, electricity consumption, forecasting, weekly seasonality.

*Cancelo, J.R. Dpto. Economía Aplicada II, Facultad Ciencias Económicas, Universidad de la Coruña, Campus de La Zapateira, 15071, La Coruña, Spain.
Espasa, A. Dpto. de Estadística y Econometría. Facultad de Ciencias Jurídicas y Sociales, Universidad Carlos III de Madrid.

USING HIGH-FREQUENCY DATA AND TIME SERIES MODELS TO IMPROVE YIELD MANAGEMENT (1)

José Ramón Cancelo (2)

Antoni Espasa (3)

(1) This paper is based upon work supported by the Spanish DGICYT, projects PB93-0236 (both authors) and PB93-0653 (Cancelo).

(2) Dpto. Economía Aplicada II, Facultad Ciencias Económicas, Universidad de La Coruña, Campus de La Zapateira, 15071, La Coruña, Spain. Fax 34 - 81 - 13 29 88.

(3) Dpto. Estadística y Econometría, Facultad de Ciencias Jurídicas y Sociales, Universidad Carlos III de Madrid, c/ Madrid 126, 28903 Madrid, Spain. Fax 34 - 1 - 624 98 49.

ABSTRACT

We show the potential contribution of time series models (TSM) to the analysis of high frequency (less than monthly) time series of economic activity. The evolution of the series is induced by stable patterns of behavior of economic agents; but these patterns are so complex that simple smoothing techniques or subjective forecasting can not consider all underlying factors and TSM are needed if a full efficient analysis is to be carried out. The main ideas are illustrated with an application to Spanish daily electricity consumption.

1. INTRODUCTION

The implementation of time series models (from now on TSM) for efficient analysis of high frequency data on activity variables is one of the most promissing fields in applied economics. There exists a large set of variables (consumption of electricity, water, gas or petrol, withdrawals of funds from financial institutions, commuters using public transports, traffic levels, production levels, sales, lumber and pulp industries, etc.) which are observed weekly, daily or even hourly: time series of thousands of observations, with valuable information on the characteristics of economic phenomena, are available to the analyst; and the problem consists of handling this huge amount of information for efficient decision making.

Forecasting systems development has occurred in response to new capabilities in data accumulation, among other factors (Murdick and Georgoff, 1993). The purpose of this paper is to highlight the usefulness of TSM in analysing high frequency data; we focus on short term forecasting because this is the main concern when dealing with high frequency information, although some other applications are also reviewed. Throughout the paper the expression 'high frequency data' will refer to data observed at least twice per month: the sampling interval may be one week, one day, one hour or any other that meets this condition; and 'short-term forecasting' refers to the specific problem of forecasting this type of data.

The application to yield management and specifically to the optimal sale of perishable products is straightforward: a good model provides an adequate representation of the data generating process, which can be used to reduce the uncertainty of demand forecasts; supply can adjust accordingly, and costs lower.

The paper is organized as follows: general pros and cons of TSM are discussed in section two, and they are compared with some competing procedures; an application to daily electricity consumption is discussed in section three; and the main conclusions are summarized in section four.

2. FORECASTING TECHNIQUES FOR HIGH FREQUENCY DATA

For the purposes of this paper forecasting techniques can be broadly separated into subjective forecasts and model-based methods. Although the former are usually referred to as judgmental forecasting, we think that judgment plays a central role in the forecasting and planning process, no matter the specific forecasting technique involved: as Hogarth and Makridakis (1981) point out, decisions on the specification of goals, choices concerning data sources, forecasting methodologies, adjustments to basic forecasts and the assessment of implementation strategies make the forecasting task, taken in the broad sense, a matter of judgment.

2.1 SUBJECTIVE FORECASTS

In most organizations short-term forecasting is charged to qualified experts that produce reliable forecasts because of their experience (Goodwin and Wright, 1994). Moreover, sometimes non-systematic, heterogeneous information is available: it is hard to introduce this type of information into a quantitative model, but it may be processed and incorporated by an expert into the final forecasts (Brown, 1988).

However, purely subjective forecasting is not the best choice for setting up a forecasting system for high frequency data, because:

1) It is very difficult to transmit to other people the way information is processed to produce forecasts; as a consequence, the whole planning process is highly dependent on the permanence of particular persons in the organization.

2) It is an expensive forecast, as it takes a significant part of the working hours of qualified personnel. Detailed analysis by an expert is justified in specific moments where complex conditions prevail, but not in normal days.

3) Socioeconomic conditions change, so that the variables we are interested in react to changes in the explanatory variables in a more sophisticated way; subjective learning becomes more difficult and new types of tools must be considered.

4) Recent research has focused on the inconsistencies of human judgment, even for very qualified experts: see Goodwin and Wright (1993, 1994) and references therein; see also Ashouri (1993).

2.2 QUANTITATIVE METHODS

Weekly, daily or hourly activity series display the same characteristics than monthly or quarterly series, even though their short term components (seasonal, irregular, calendar effects, outliers, etc) are much more complex; most components are induced by stable patterns of behavior of the economic agents, so that a model -i.e., an explicit representation of the data generation process (DGP)- may be built and used to get informative forecasts. However, because of this complexity simple smoothing techniques do not provide an adequate approximation to the DGP: true TSM are needed if data are to be processed in an efficient way to produce optimal forecasts.

The main purposes of a TSM are:

1) To generate reliable forecasts with no need of suplementary evaluation by an expert.

2) To become an operative tool within the organization: management support, user involvement, personal stake and the implementation strategy are as relevant to forecast success as accuracy (Schultz, 1992).

3) To produce an adequate anchor in the presence of very complex conditions. Goodwin and Wright (1994) point out that it seems that a process of anchoring and adjustment is used in judgmental extrapolation: although the joint ocurrence of anomalous events may require the forecast of the model being adjusted by an expert, this forecast is still the best starting point for the subjctive adjustment.

4) To help the organizations become better learning systems: organizational learning is defined as the capacity within an organization to maintain or improve performance based on experience (Nevis et al, 1995). A TSM is not just a tool for acquisition of knowledge, it has to do with its transfer: knowledge becomes institutionally available, as opposed to being the property of selected individuals.

5) To quantify the influence of explanatory variables with a double purpose: a) better forecasts may be produced if good predictions for explanatory variables are available; and b)

simulation exercises may be carried out.

6) To extract a more reliable signal by eliminating from the observed series the effect of added noise, in order to use it in the decision making process.

The biggest objection to TSM is the amount of resources needed to build and maintain them. Makridakis et al (1983) consider four elements of cost in a forecasting method: development costs, data storage costs, maintenance costs and the costs of repeated applications. Speaking in relative terms with respect to the total amount, development costs are by far the most important. Maintenance costs are important too, as they include adjusting the model whenever changes in the basic pattern are detected. On the contrary, once a TSM is implemented storage and repeated applications costs are almost negligible.

In any case, to build a model for a typical high frequency series is a hard job, and a detailed analysis has to be carried out to decide which variables will have their own TSM. Although each case deserves specific consideration, a good rule is to determine the monetary loss as a function of the prediction error for all variables; next the loss functions are compared to the actual total cost of a TSM, so that a model is built only when a substantial saving is expected (but this is not so simple as it seems: see for instance Remus (1991) on the consequences of the criterion being a nonlinear function of the variable).

3. AN APPLICATION TO DAILY CONSUMPTION OF ELECTRICITY

3.1 THE PROBLEM

Electricity consumption is a typical example of the problem we are considering in this paper: long series of hourly and daily data are available; it is a perishable good, because overproduction (the difference between total production and instantaneous consumption) is wasted, so a very accurate forecast of the demand is needed. Short-term electricity consumption forecasting deserves a remarkable place in the literature of high frequency data analysis: see, inter alia, Bogard et al (1982), Bunn and Farmer (1985), Gross and Galiana (1987), Adams et al (1991) or Engle et al (1992). References on very related problems also provide valuable guidance: see for instance Ashouri (1993) on gas demand.

When we were charged to build a forecasting system for spanish daily consumption, which could also help in setting weekly and hourly production schedules, we approached the job in the following way:

1) To begin with, a several year, homogeneous series of daily data was collected. We had to define consumption in an operative way, in order to separate actual demand from final destination of overproduction. Homogeneous time series for the explanatory variables were also prepared.

2) The second step consisted of determining the main characteristics of the resulting series.

3) Next we built a complex nonlinear transfer function model to explain these characteristics.

4) From this model daily forecasts are obtained automatically. Weekly forecasts result from aggregating daily ones; hourly forecasts can be produced by identifying typical load curves and distributing daily forecasts accordingly.

5) The model is also used to improve our knowledge on the influence of explanatory variables, and to extract a more reliable signal of electricity consumption.

These five stages are related to what Murdick and Georgoff (1993) call the central components of a forecasting system: the input data (point 1), the output we would like (points 4 and 5) the assumptions about the behavior of the variables (point 2 and the extrasample information used in point 3) and the process relating dependent to independent variables (the model that results from point 3).

In the next sections a more detailed description is given. However, in doing so our purpose is just to use this application as an example of the potential use of TSM; as a consequence some relevant results concerning the specific problem of modelling electricity consumption will be ommitted. A complete exposition can be found in Cancelo and Espasa (1991a), available from the authors upon request.

3.2 THE DATA

The variable to model is the net demand for electrical energy, defined as total production from all sources plus international interchanges balance less intermediate autoconsumption and pumping consumption. The only available data referred to the peninsular part of the spanish territory taken as a whole, almost half a million squared kilometers with more than 36 million inhabitants.

The original model was built for the sample 1983-1989. The series displays: a growing trend; annual and weekly seasonal oscillations; complex calendar effects, related to changes in the usual pattern of working conditions (holidays, vacation periods, Easter); some anomalous values, caused by strikes, elections, and the like. Moreover, weather conditions are known to have a significant influence.

3.3 OVERVIEW OF THE MODEL

From section 3.2 it follows that observed consumption in day t (C_t) can be expressed as

$$C_t = TC_t * SC_t * CE_t * IA_t * CMV_t * IC_t$$

where:

* TC_t: trend consumption, related to socioeconomic factors;
* SC_t: seasonal consumption;
* CE_t: calendar effect;
* IA_t: intervention analysis to treat anomalous observations which deserve specific consideration;
* CMV_t: contribution of meteorological variables;
* IC_t: irregular consumption, which captures all transitory disturbances which are not included in previous components.

The model is completely multiplicative, so that all components are assumed to increase in size in direct proportion to the trend level: it seems to be the general rule in activity series, no matter the frequency of observation of the data (Bogard et al, 1982). Taking logarithms

$$\ln C_t = \ln TC_t + \ln SC_t + \ln CE_t + \ln IA_t + \ln CMV_t + \ln IC_t \qquad (1)$$

From (1) a basic consumption (BC_t) can be defined

$$\ln BC_t = \ln C_t - \ln CE_t - \ln IA_t - \ln CMV_t = \ln TC_t + \ln SC_t + \ln IC_t \qquad (2)$$

Basic consumption displays a smooth evolution and may be explained in a satisfactory way from its past values:

$$\ln BC_t = b_1 \ln BC_{t-1} + \ldots + b_p \ln BC_{t-p} + \text{residual}_t \qquad (3)$$

Calendar effects and intervention analysis can be expressed as

$$\ln CE_t + \ln IA_t = F_1 \ DV_{1,t} + F_2 \ DV_{2,t} + \ldots + F_m \ DV_{m,t} \qquad (4)$$

where $DV_{i,t}$ denotes a dummy variable that indicates whether a specific calendar effect or an anomaly happens in t; F_i denotes its dynamic filter, that simplifies into a single coefficient if $DV_{i,t}$ has no dynamic effect.

As for the contribution of meteorological variables,

$$\ln CMV_t = G_1 \ MV_{1,t} + G_2 \ MV_{2,t} + \ldots + G_n \ MV_{n,t} \qquad (5)$$

where $MV_{i,t}$ stands for a meteorological variable and G_i for its dynamic filter, which need not be a linear one.

By combining (2), (3), (4) and (5) it follows that:

$$\ln C_t = b_1 \ln BC_{t-1} + \ldots + b_p \ln BC_{t-p} + F_1 \ DV_{1,t} + F_2 \ DV_{2,t} + \ldots +$$
$$+ F_m \ DV_{m,t} + G_1 \ MV_{1,t} + G_2 \ MV_{2,t} + \ldots + G_n \ MV_{n,t} + \text{residual}_t \qquad (6)$$

In order to express the model solely in terms of observable variables, from (2), (4) and (5)

$$\ln BC_{t-i} = \ln C_{t-i} - \ln CE_{t-i} - \ln IA_{t-i} - \ln CMV_{t-i} =$$
$$= \ln C_{t-i} - F_1 \ DV_{1,t-i} - F_2 \ DV_{2,t-i} - \ldots - F_m \ DV_{m,t-i} -$$
$$- G_1 \ MV_{1,t-i} - G_2 \ MV_{2,t-i} - \ldots - G_n \ MV_{n,t-i} \qquad (7)$$

and by substituting in (6) the final form of the model results

$$\ln C_t = b_1 \ln C_{t-1} + \ldots + b_p \ln C_{t-p} + F_1^* \ DV_{1,t} + F_2^* \ DV_{2,t} + \ldots +$$
$$+ F_m^* \ DV_{m,t} + G_1^* \ MV_{1,t} + G_2^* \ MV_{2,t} + \ldots + G_n^* \ MV_{n,t} + \text{residual}_t \qquad (8)$$

In (8) all observations are handled in a single, general model, which captures all potential changes in electricity consumption due to changes in the explanatory variables. Database management is heavily simplified and forecasts are easily obtained in an automatic way, two major conditions for the system being really useful.

3.4 ON MODELLING THE COMPONENTS

3.4.1 Basic consumption

Trying to model trend and seasonality by including explanatory variables is unfeasible in most cases, because good data observed with the required sampling interval is seldom available. However, their contribution to the present observed value can be approximated quite well by using previous values of electricity consumption, due to the fact that the underlying factors change slowly. Relating trend and seasonal to the past history of the variable allows the resulting estimates to adapt to recent observations (Box et al 1987, Mills 1990), this flexibility being one of the main determinants of the success of modern time series analysis.

3.4.2 Calendar effects

Although the literature has focused mainly on calendar effects in monthly series, they also exist in higher frequency series (Cleveland and Grupe, 1982). In fact, the smaller the sampling interval the more important the influence of the calendar.

Take for instance a holiday. In most cases it will have a minor influence in monthly data; but in a daily series its presence distorts the whole usual weekly pattern. As a consequence, if its effect is not specifically considered then bad forecasts for the day of the holiday and for the following days will result. The trouble is more serious in latin countries like Spain than in the U.S.: in America a given holiday usually falls on the same day of the week, but in latin countries the general rule is to fix the day of the month, so that it may fall on any of the seven days of the week; and this mobility increases the distorting effect.

A TSM makes possible to analyze in full detail the influence of the calendar: a large sample is carefully screened, stable patterns of behavior for each type of effect are detected and general rules for forecasting are stated.

As an example, table 1 summarizes the estimated effects of holidays on spanish electricity consumption: an estimated coefficient of 30, for instance, means that observed consumption would be 30% higher if the holiday did not exist. From table 1 it can be seen that in our series: a) the distortion varies according to the day of the week on which the holiday falls; and b) there is a dynamic effect, so that a holiday falling on t alters the consumption of two or more days.

3.4.3 Meteorological Variables

Among meteorological variables temperature is the most important. Our measure of temperature is a weighted mean of maximum daily temperatures registered in ten selected observatories throughout the whole territory. To model the relationship between this indicator and electricity consumption the following extrasample information must be taken into account:

1) The relationship is U-shaped: there are two bounds of temperature, T^* and T^{**}, that define a neutral zone so that temperatures within this interval do not influence consumption. Below T^* we enter into the cold zone, and above T^{**} in the hot zone. In both zones the response function is also expected to be nonlinear. We have estimated that in our series $T^* = 20C$ (68F) and $T^{**} = 24C$ (75.2F).

2) In daily data a dynamic response is expected, as consumption in day t depends on observed temperatures in t, t-1, ..., t-h.

3) Exhaustion effects may exist: when temperature is so low (high) that every heating (cooling) system is operating at full capacity, then additional decreases (increases) of temperature will have no effect on observed consumption.

4) The influence of a given temperature may be different for a working day than for a non-working day, or vary according to the season of the year, etc.

5) If the sample is several years long, the stock of appliances may increase and shifts in the response function along the sample are to be looked for.

All these effects have been tested and modelled in our application, so that we got a deep knowledge of the relationship between consumption and temperature in our problem.

The effect of other meteorological phenomena of lesser importance (which Ashouri (1993) calls misery factors) are harder to model: homogeneous series for the whole sample are not available, and the forecasts provided by the weather center are not good enough. As a consequence the model does not take them into account, although the experts may adjust the forecasts of the model for their influence in the presence of very extreme conditions.

3.5 ON USING THE MODEL

3.5.1 Forecasting

The final model has a residual standard error equal to 0.0130, which entails a 90% confidence interval for the one period forecast equal to plus/minus 2.13% times the point forecast. It represents a major improvement with respect to previous holistic forecasts. In fact, the actual improvement was greater: the model explains sudden changes in consumption caused by unexpected changes in weather conditions, and large errors are much more uncommon; for this series the extracost caused by a bad forecast is a convex function of the prediction error, so that a remarkable saving is achieved by eliminating big errors.

The model can also be used to obtain provisional forecasts of the consumption with a higher level of time aggregation, and these forecasts may enter as inputs in models explaining other variables. Bodo et al (1991) use daily data on electricity consumption to forecast monthly consumption, and the latter to forecast the monthly industrial production index: while the official figure of the production index for month M is available by the end of M+2, with their proposal a quite reliable forecast can be advanced once the first fortnight electricity consumption of M is known.

3.5.2 Simulation

Given that calendar effects and weather variables are explicitly introduced in the model, the behavior of electricity consumption under different scenarios may be simulated. As an example, assume maximum daily temperature has been constant in 16C (60.8F) during the whole month of January. On Monday, February 1, it suddenly falls to 11C (51.8F), remaining there for a week; then on Monday, February 8, it returns to 16C and keeps unchanged onwards. Assume also that on Wednesday, February 3, a successful 24-hour general strike takes place.

For the purposes of our analysis we may consider that on January 31 we were in equilibrium; the sudden fall in temperature and the general strike are exogenous transitory distrubances, and on the long run consumption will return to equilibrium. However, it is interesting to know how consumption reacts in the short run: figure 1 displays the estimated effects from Saturday, January 30, to Tuesday, February 16.

Equilibrium is characterized by a temperature in the cold zone, so there is overconsumption with respect to the situation where temperature has no influence. The solid line shows overconsumption in equilibrium expressed as the relative increase with respect to normal consumption with no temperature effects. Notice the peaks at weekends, due to the fact that in our series the effect of a given temperature is higher on non-working days.

The dashed line refers to the proposed scenario: overconsumption (removing the influence of the strike) is higher than in equilibrium, because temperature is lower. The dynamic effect of temperature is easy to see: the distortion caused by the cold wave lasts until February 14, although temperature has returned to equilibrium on February 8. The contribution of the strike is also very clear: in order to estimate its effect we treated it as if it were a holiday falling on Wednesday.

The gap between both lines measures the influence of transitory disturbances, and the total effect of the cold wave plus the strike results from aggregating daily gaps.

3.5.3 Signal Extraction

The previous example has shown that our variable is heavily influenced by disturbances that distort time comparisons, up to the point of making them uninformative. With a TSM this type of effects can be eliminated, so that a more informative signal results: see Cancelo and Espasa (1991b), whose main results are summarized in figure 2.

The dashed line displays the relative change in the observed series with respect to the same month of the previous year. The solid line is computed from a daily series of corrected consumption: we first eliminate from the observed series the effect of every type of disturbance that may distort time comparisons (see the original paper for details); then daily data are aggregated to form a monthly series, and relative growth is computed.

It can be seen in figure 2 that the corrected series of growth displays a smoother evolution, so that most of the peaks and troughs of the observed series of growth are caused by short term disturbances. As a consequence, it seems rather inaccurate to base decision making on original growths.

4. CONCLUSIONS

In this paper we tried to show the potential contribution of time series models to the analysis of high frequency data of economic activity. Although most people consider them just a forecasting tool, we remark their central role in the acquisition, sharing and utilization of knowledge within an organization. This view agrees with recent developments in management science, which favour organizational memory and a publicly documented body of knowledge as opposed to personal knowledge that is lost when a long-time employee leaves the organization

(Nevis et al, 1995).

We have argued that forecasting is not the only application of TSM. There are other by-products that may become as important as direct extrapolation from the observed history. Simulations and signal extraction provide valuable information for the planning process: the former goes one step further in analysing the environment, as new scenarios can be defined and their influence quantified; the latter, because high frequency (daily, weekly), free-from-noise signals may be aggregated into lower frequency signals (monthly, quarterly, yearly), providing managers a much better perception of the underlying trends in the observed data.

REFERENCES

- Adams, G., P.G. Allen and B.J. Morzuch (1991): "Probability distributions of short-term electricity peak load forecasts", International Journal of Forecasting, 7, 283-297.

- Ashouri, F. (1993): "An expert system for predicting gas demand: a case study", Omega, 21, 307-317.

- Bodo, G., A. Cividini and L.F. Signorini (1991): "Forecasting the italian industrial production index in real time", Journal of Forecasting, 10, 285-299.

- Bogard, C., G. George, G.M. Jenkins and G. McLeod (1982): "Analysing a large number of energy time series for a utility company", chapter 5 in G.M. Jenkins and G. McLeod (eds., 1982), Case studies in time series analysis, Gwilim Jenkins & Partners Ltd., Lancaster.

- Box, G.E.P., D.A. Pierce and P. Newbold (1987): "Estimating trend and growth rates in seasonal time series", Journal of the American Statistical Association, 82, 276-282.

- Brown, L.D. (1988): "Editorial: comparing judgmental to extrapolative forecasts: it's time to ask why and when", International Journal of Forecasting, 4, 171-173.

- Bunn, D.W. and E.D. Farmer (eds., 1985): Comparative models for electrical load forecasting, John Wiley & Sons, New York.

- Cancelo, J.R. and A. Espasa (1991a): "Forecasting daily demand for electricity with multiple-input nonlinear transfer function models: a case study", Working Paper 9121, Economics Department, University Carlos III of Madrid.

- Cancelo, J.R. and A. Espasa (1991b): "New weekly and monthly indicators of activity based on electricity consumption" (in spanish), Documento de Trabajo 9106, Economics Department, University Carlos III of Madrid.

- Cleveland, W.P. and M.R. Grupe (1982): "Modelling time series when calendar effects are present (with discussion)", in A. Zellner (ed., 1982), Applied time series analysis of economic data, Bureau of the Census, Washington.

- Engle, R.F., C. Mustafa and J. Rice (1992): "Modelling peak electricity demand", Journal of Forecasting, 11, 241-251.

- Goodwin, P. and G. Wright (1993): "Improving judgmental series forecasting: a review of the guidance provided by research", International Journal of Forecasting, 9, 147-161.

- Goodwin, P. and G. Wright (1994): "Heuristics, biases and improvement strategies in judgmental time series forecasting", Omega, 22, 553-568.

- Gross, G., and F.D. Galiana (1987): "Short-term load forecasting", Proceedings of the IEEE, 75, 1558-1573.

- Hogarth, R.M. and S. Makridakis (1981): "Forecasting and planning: an evaluation", Management Science, 27, 115-138.

- Makridakis, S., S.C. Wheelwright and V.E. McGee (1983): Forecasting: methods and applications, John Wiley & Sons, New York.

- Mills, T.C. (1990): Time series techniques for economists, Cambridge University Press, Cambridge.

- Murdick, R.C. and D.M. Georgoff (1993): "Forecasting: a systems approach", Technological Forecasting and Social Change, 44, 1-16.

- Nevis, E.C., A.J. DiBella and J.M. Gould (1995): "Understanding organizations as learning systems", Sloan Management Review, 36, 73-85.

- Remus, W.E. (1991): "Criterion-referenced judgmental forecasting models", Journal of Forecasting, 10, 415-423.

- Schultz, R.L. (1992): "Fundamental aspects of forecasting in organizations", International Journal of Forecasting, 7, 409-411.

TABLE 1.- ESTIMATED EFFECTS OF HOLIDAYS ON SPANISH DAILY ELECTRICITY CONSUMPTION

Day of the holiday	Effect on					
	MON	TUE	WED	THU	FRI	SAT
MON	30.9	4.1				
TUE	10.7	35.1	3.2			
WED			30.4	3.8		
THU				29.3	11.6	2.6
FRI					28.8	9.1
SAT						8.2

FIGURE 1.- SIMULATING THE INFLUENCE OF CALENDAR EFFECTS AND TEMPERATURE ON THE CONSUMPTION OF ELECTRICITY: AN EXAMPLE

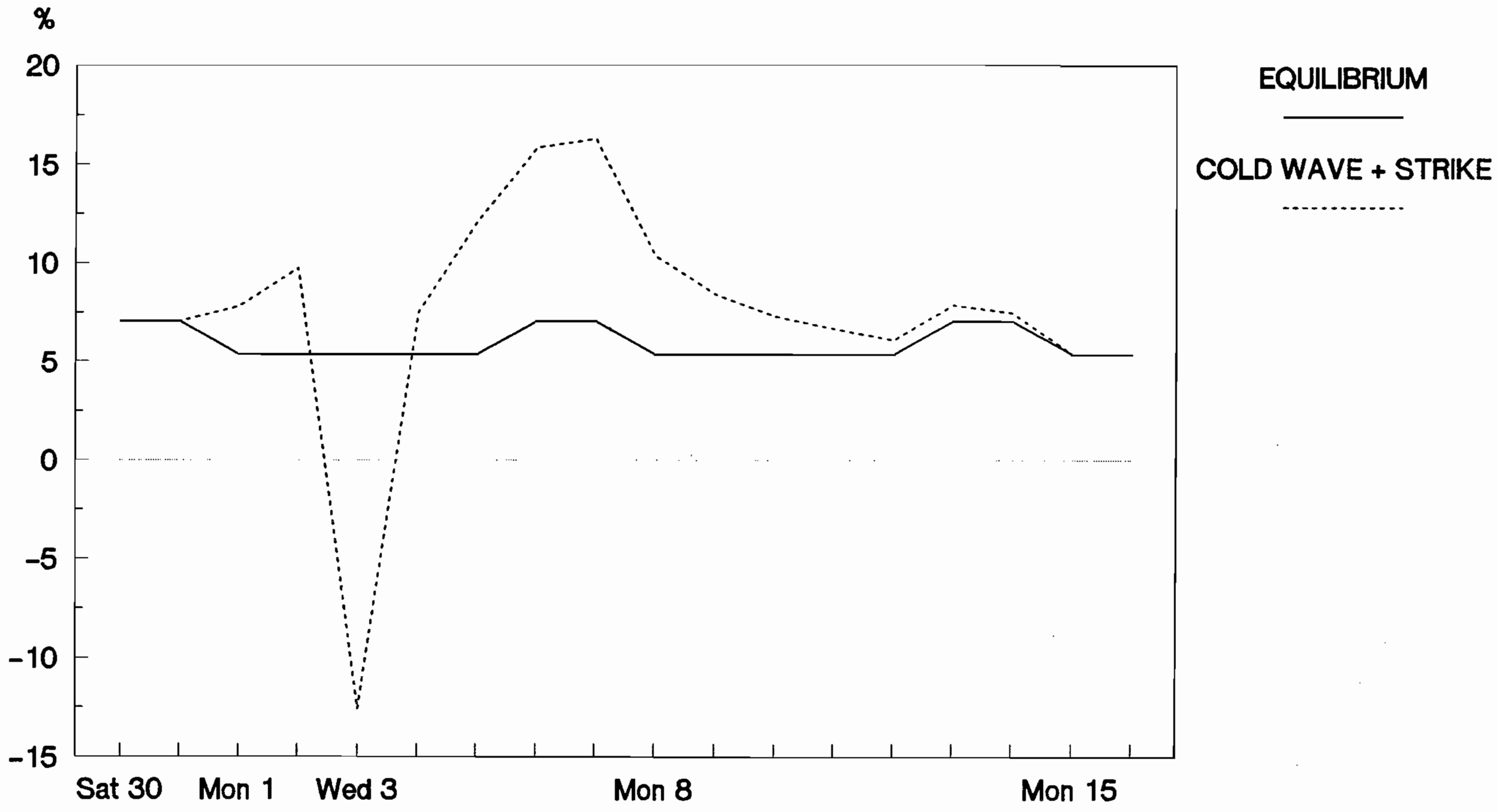
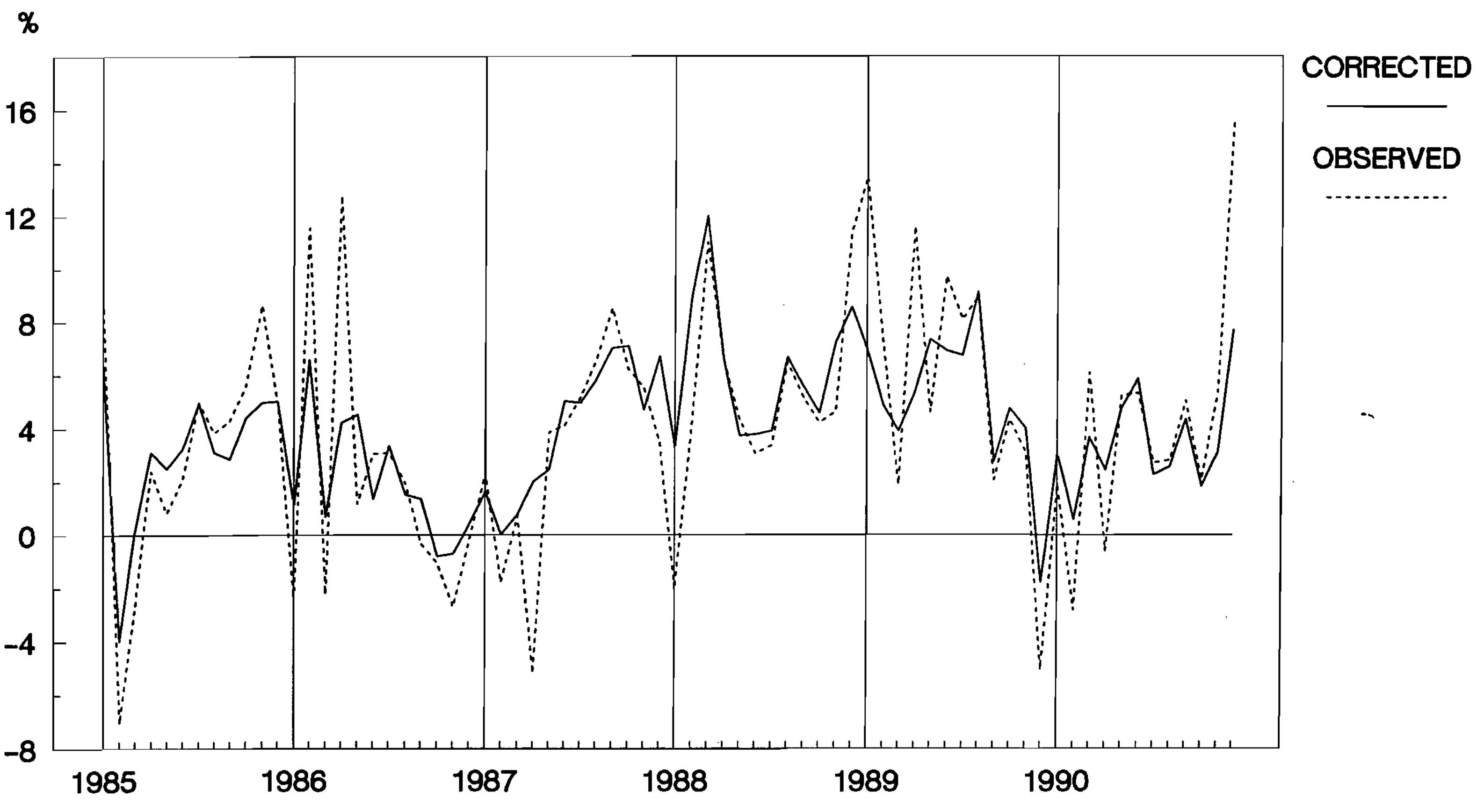


FIGURE 2. - OBSERVED AND CORRECTED GROWTHS OF THE MONTHLY CONSUMPTION OF ELECTRICITY IN SPAIN



NOTE: Growth is computed as relative change with respect to the same month of the previous year