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AN INTERACTIVE FORECASTING SUPPORT SYSTEM

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Presented by R. Słowiński

In this paper an interactive computer system for long and middle range forecasting is presented. The proposed system combines judgemental forecasting with quantitative forecasting methods based on growth function models. Specifically, the proposed forecasting system calculates the upper limit time series and the most significant factors (socioeconomic and technological) which affect the upper limit. This enable the forecaster to use his experience in the form of optimistic and pessimimistic scenarios for each the significant factors, arriving in this way at a probable range for the forecasted variable. Te flexibility of the system enables the user to interact with it so that he can select a different set of factors or/and different set of optimistic/pessimistic scenarios and validate the forecasting model by doing forecasts in known time horizon. An illustrative example regarding the forecasts of the Greek Electric Energy Consumtion is also presented.

1. INTRODUCTION

Forecasting is widely used today by management, to improve the situation in several issues regarding planning, strategy and decision making. Forecasting in the future is the bridge between the organization an its environment, especially in those areas that mostly affect their present and future activities. Forecasting as an operation aims at providing information about other operations, such as production, marketing finance, so that a rational policy for their can be set down. Forecasting may be divided according to the decisions taken in an organization, to short, medium or long term. This classification is however arbitrary since long or medium term forecasts are used as short ones (as is the case in desired production levels or types and quantities of stock supplies).

Current forecasting methods are well classified [9, 11, 12, 13]. In his

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excellent review of forecasting Makridakis [10] classifies the forecasting methods as follows:

- Judgemental forecasting methods
- Econometric methods
- Sophisticated methods
- Adaptive methods
- Least squares methods.

One on the basic conclusions is that the gains in accuracy from sophisticated methods are usually small. Evenmore he suggests among the future directions in forecasting, the development of forecasting system. These systems should find effective ways to incorporate human judgement with the quantitative methods of forecasting. The advantages of these systems, are:

- To introduce the forecasters the quantitative forecasting methods, which were regarded up to now as unintelligible and difficult to use (black box).
- To develop appropriate data bases with historical data and judgemental information, without which forecasting is not possible.
- To help forecasters in getting a deeper understanding of the forecasting problem, while by exploiting their experience, a better forecast may result.

For the development of forecasting systems which combine the judgemental policy of the forecastens with the quantitative methods of forecasting, especially suited is the modern theory of Decision Support Systems (DSS). Indeed, the term DSS refers to a class of systems which support the process of decision making. The DSS were rapidly developped in the field of multicriteria decision making, and were succesfully applied to many fields of management (see [5, 6, 16, 17, 18, 27] for a complete description).

The process of decision making in the case of forecasting could well be the choice of the most suitable method of forecasting for the particular problem, the selection of the most significant exogenous parameters (socioeconomic and technological) which affect the forecast of an important quantity (electrical energy consumtion), the selection of the most probable scenario (according to the forecaster's experience) for the evolution of a parameter that affects the forecasted quantity etc.

The DSS appeared in the beginning of the 70'S, and since then their field of application is constantly widening (see Keen and Scott-Morton [7], Sprague and Carlson [25] for a detailed expose). Courbon [1] states with clarity the following main points that define a DSS:

- A DSS is a man-machine coupling in the form of a dialogue, where human personality is not submitted to the machine but rather directs it.
- A DSS is nothing more than another element in the decision process, which aims at making best use of an individual's judgement and experience, leading him in this way to reach a decision on anill-structured problem, through a recursive process of trial and error.

- A DSS is in no way a classical operations research model, though it can one or more of these.
- The interactive nature of a DSS consists a dialectical use of the computer and of a data base system which is not simply a data access system but also of manipulation, analysis and synthesis.

Medium and long range forecasting could well be thought of as ill-structured problems since estimates of the various model parameters are not accurate, there is a high degree of uncertainty and the socioeconomic phenomena frequently change so that they cannot be forecasted, using simple growth functions. Furthermore, medium and long range forecasts belong in the field of strategic planning, which is basically anill-structured problem (see Gorry and Scott-Morton [3] for more details).

In this paper, an interactive forecasting support system (FSS) is proposed which combines the experience and preferences of the forecaster/decsion maker (DM) with quantitative forecasting methods (related to growth functions) which aids forecasting mainly medium and longterm) of important quantities in large system (population, production, consumption, gross domestic product, new tehnologies, innovations, etc).

In section 2 the underlying theory of growth functions and the related forecasting techniques are presented.
This theoretical framework will be used in the FSS. In section 3 the FSS procedure is exposed in detail. Section 4 is a brief account of the software implementation. Section 5 presents an illustrative example of the Greek Electric Energy Consumption. In Section 6 a validation procedure is proposed, while section 7 contains the concluding remarks.

2. THE UNDERLYING THEORY OF GROWTH FUNCTIONS AND FORECASTING

The FSS presented here is based on the theory of growth functions and their application to forecasting and especially to medium and long term forecasting. In short, the theory of growth functions and the forecasting techniques which are related to growth functions are presented in the sequel.

The theory of growth functions is appled to large systems such as, socioeconomic and technological systems, which have a variety of elements-including the human beings- and their evolution or growth is in general memory-driven and every system or evolutionary case of the system is unique, providing one and only one data series for every case, (there is no way to reproduce the particular cases and results). The term large system is given to systems that are large when are compared with other systems of similar type, i.e. a local market is a small system when this market is compared with the national market or the international market which are considered as the large systems. Usually the large system show relative stability and their evolution or growth follows-in general-simple patterns. These systems can also be considered as closed systems or as open systems in which the interactions between them and other systems are weak, so that these interactions can be presented by the addition od a simple parameter in the equation of growth.

The evolution of a system follows two basic ways: a) the development by means of structural changes into the system that make the system more effective; the development of a system leads more easily to the realization of its goals, b) the growth, which is the movement of the system or better of some characteristics of this system from lowe to higher bounds. This growth movement is usually monotonous, which means that the rate of growth or the first derivate of the growth function is a continuous positive function over time.

Growth is bounded. A lower bound appears at zero or in a low level but it is also reasonable to assume that almost all growth phenomena in nature there will appear an upper limit which is denoted by capital letter F.

The analytical mathematical tools or functions that describe the growth of a system (or of some characteristics of this system) are called growth functions. However, as regards the underlying philosophy of growth, two basic types of functions or models appear: a) models that used as laws and have explanatory and forecasting ability and b) models that are used as tools and have forecasting ability.

The models used as laws are manily the so-called binomial models. These models describe the magnitude of one part-say f-of system versus the magnitude of another part or of the whole (magnitude versus magnitude or fvf). The general differential equation which describes the fvf type of growth is:

$$\frac{df}{dt} = z(f). \tag{1}$$

The models used as tools describe the magnitude f versus time (fvt). The general differential equation of this type is

$$\frac{df}{dt} = z(t) \tag{2}$$

The models and the related functions in use are divided into continuous or disctrete, deterministic or stochastic and simple or complicated. Regarding simplicity, the rule "the simplest (is) the best" applies in general when the models are used for forecasting purpose. When the models are used to explain the behavior of the system under consideration this rule has only relative importance. In such cases the main effort is centered on the explanatory behavior of the models. A complicated model might explain better a specific situation although the future fluctuactions of the system might reduce the predictive ability of this model. In other words the search for laws of growth in the socioeconomic and technological systems could not be based on the predictive ability of the models.

The traditional of growth functions was based on techniques which estimate the parameters of the growth function from a set of data (or data series) After this step the future predictions are usually done by simple extrapolation based on the already "estimated" growth function.

The first estimation technique on three data points was used by P.-F. Verhulst [26] to estimate the three parameters of his logistic equation and to make population predictions (population of France). Pearl and Reed [15] made an improvement by introducing a simple regression technique for the estimation of the parameters of the logistic function and made predictions of the population of the United States. The basic non-linear analysis technique for the estimation of the parameters of the logistic equation and other non-linear models was proposed by Marquardt [14]. For non-linear technique related to binomial models, see Skidas [19]. If the system under consideration is "consistent", then he use non-linear regresion analysis techniques leads to reliable estimations of the parameters of the appropriate growth function and to satisfactory forecasting by extrapolation. When the system is "inconsistent"-that the laws of growth are not entirely applicable-the parameters of the growth functions change over time and explicit estimation by a regression technique of these parameters may lead to erroneous forecasts (an improvement was done by introducing Kalman filtering techniques). The most sensitive parameter is that of the saturation level. In human population forecasting, Leach [8] found out that parameter expressing the upper limit of the population changes over time following a bell-shaped pattern in the case of G. Britain. Leach showed that could improve the predictions based on the logistic growth function by taking into account the systematic changes of the saturation level. He mainly treat parameter F as a function of time, that is,

$$F = F(t). \tag{3}$$

The ideas of a varying saturation can also be found in another approach done by Skidas [19], [21], [22] who finded out that introduction of a varying saturation level of the type,

$$F = F(f), \tag{4}$$

(where f is the growth function)
in the logistic equation of growth, would lead to Von Bertalanffy's model to the GRM1 model according to the type of the function for F introduced. In these ideas the knowledge of the systematic variability of the saturation level leads to the advance of the existing growth functions by formulating new ones or by improving their explanatory ability. Regarding forecasting based on the varying saturation level, one direction is that using the complicated functions which arise the simple logistic-or other simple function-after the introduction

to their equation of the equation for the varying upper limit. Another attempt is to use the logistic function with an upper limit which is proestimated or which is corrected for some steps of the forecastin horizon.

Another technique was based on some semi-sigmoid functions [20, 23] which express growth in the early and middle stages, whereas in the long-run tend to overestimate the situation. However, these functions, having no parameter expressing the upper limit, show more stable ability than the traditional S-shaped functions and are useful for medium and short run forecasting, whereas in the long-run tend to keep the left side of a data point series in an (f,t) diagram. In other words the semi-sigmoid functions can be used as an upper asymptote of the forecasting horizon of data-series.

There is no question that the knowledge of the behavior of the upper limit or saturation level in a varying logistic process would lead to a better understanding of the behavior of the system under consideration and to the improvement of future forecasts. However the work regarding the varying saturation level is limited. Moreover there lack of information regarding the reasons which cause changes in the parameter F expressing the upper limit. In a recent paper [24] a work was presented in which the parameter F was correlated to some other variables that measure characteristic phenomena of the system under consideration. The aim was to the direction of: a) clarification of the reasons that force a system or some parameters of a system to changes (systematic or not) and b) finding some rules that could become useful in doing forecasts. The consumption of electric energy in Greece, was used as a test case for these ideas.

If the system under consideration is a large system it is expected to show a relatively simpler bahavior than the small system. Evenmore, the system could be considered as closed. The simplest growth function which could be applied in such a case is the sigmoid logistic function which is defined by

$$f(t) = \frac{F}{1 + \left(\frac{F - f_o}{f_o}\right)e^{-bt}} \tag{5}$$

where f_o is the value of $f(0)$ and b is the growth parameter and F is the upper bound.

The upper bounds of the forecasting horizon might cover the S-4 model whose equation is

$$k\,ln f + f - \frac{k_1}{f} = k\,ln f_o + f_o - \frac{k_1}{f_o} + \mu t, \tag{6}$$

where the parameter μ provides the maximum growth rate (df/dt) of the process and parameters k, and k_1 characterize the shape (curvature) of the function.

3.THE FORECASTING SUPPORT SYSTEM (FSS)

The FSS comprises of the following major components: 1) The data base, 2) the model base and 3) te basic software system. Figure 1 illustrates the overall architecture of the FSS.

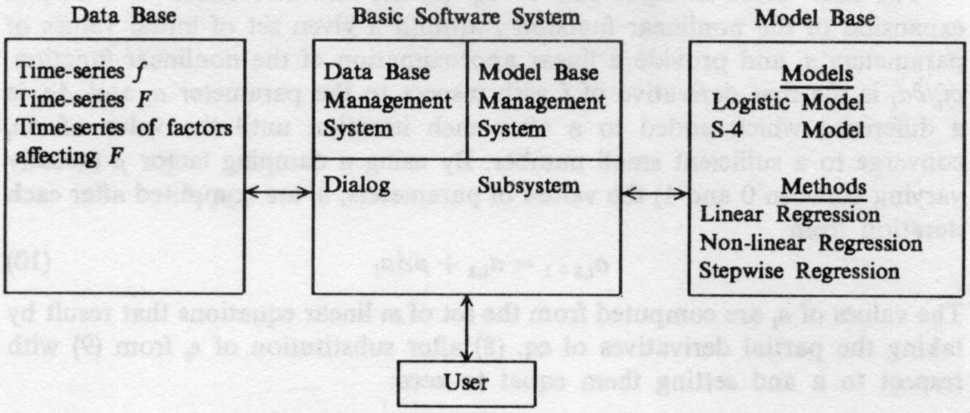

Fig. 1. Components of the Forecasting Support System

The data base subsystem stores and processes information related to the quantity f for which predictions are needed. The time-series f is input, whereas the time-series for the upper limit F is calculated from the Logistic model by a technique described in [22, 24]. The data-series of the factors which might affect the upper limit of the logistic model (F) are also input and stored in the data base subsystem.

The model base consists of two non-linear models (Logistic and S-4) and three methods of regression analysis (linear regression analysis, iterative non-linear regression analysis and stepwise multiple regression analysis). The stepwise method estimates the parameters of an equation of the form.

$$F = \beta_o + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \qquad (7)$$

where $\beta_o, \beta_1, \ldots, \beta_n$ are parameters and $x_1, x_2, \ldots, x_n$ are the factors which affect the upper limit F, (by using the stepwise regresion analysis technique, only the most important factors, x_i, are retained in the above equation).

The iterative non-linear analysis method estimates the parameters of the logistic equation (5) and also the parameters of S-4 model (6), whereas the linear regression analysis method provides the first values of the parameters needed to proceed to the non-linear iterative procedure. The parameters, say a_i, $i = 1, \ldots, m$, of the Logistic and S-4 models (F, b, f_o, k, k_1, μ) are estimated by iterative direct nonlinear least-squares by minimizing the sum of squared errors:

$$S = \Sigma \varepsilon_t^2, \qquad (8)$$

ε_t is the error term of the stochastic equation:

$$y_t = f_t + \sum_{i=1}^{m} \frac{\partial f_t}{\partial a_i} \Delta a_i + \varepsilon_t, t = 1, 2, \ldots, n \text{ (n observations)} \tag{9}$$

where y_t denotes provided data.

The first terms in right side of eq. (9) are the first terms of a Taylor expansion of the nonlinear function f around a given set of initial values of parameters a_i and provide a linear approximation of the nonlinear function. $\partial f_t/\partial a_i$ is the first derivative of f with respect to the parameter a_i and Δa_i is a difference which added to a after each iteration until the value of Δa_i converge to a sufficient small number. By using a damping factor ρ (usually varying between 0 and 1) the values of parameters, a_i are computed after each iteration from

$$a_{i,k+1} = a_{i,k} + \rho \Delta a_i \tag{10}$$

The values of a_i are computed from the set of m linear equations that result by taking the partial derivatives of eq. (8) after substitution of ε_t from (9) with respect to a and setting them equal to zero:

$$\frac{\partial s}{\partial a_i} = 0, \tag{11}$$

$(i = 1, 2, \ldots m)$

The Basic Software System includes the Data Base Management System, the Model Base Management System and the Dialog Subsystem.

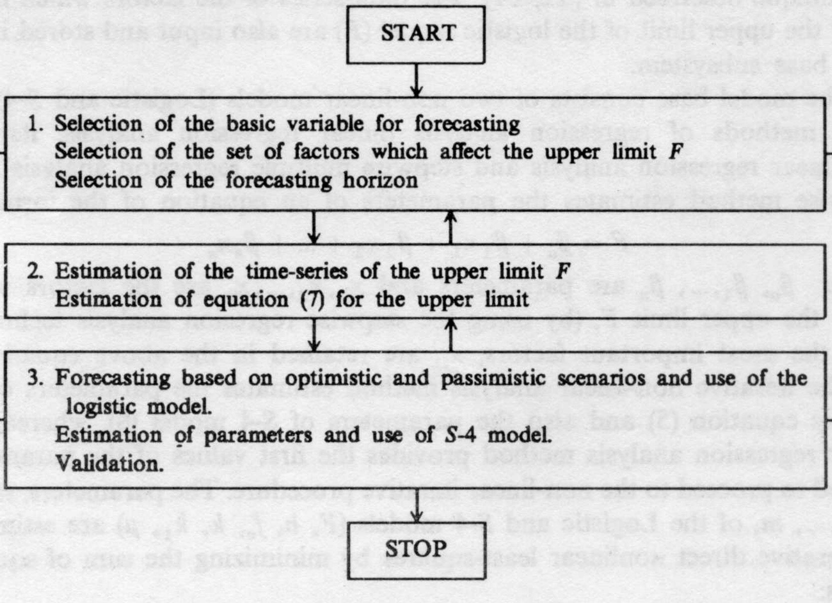

Fig. 2. Procedure of the FSS

The procedure for the FSS is presented in Figure 2. The system has three phases:

Phase 1. Selection of basic variable, set of factors and forecasting horizon

1.1. The Decision Maker (DM) inputs the time-series into the data base

1.2. The DM selects the set of factors which may affect the upper limit

1.3. The DM selects the forecasting horizon

Phase 2. Estination of the time-series of the upper limit and its regression equation

2.1. The FSS estimates the time-series of the upper limit F using the logistic equation (5).
Each term $F(t)$, is estimated from the logistic equation using the data series $(f_1, f_2, \ldots, f_t)$ for $t = n,\ n-1, \ldots,\ 3$, where n is the number of data points for $f(t)$.
The search stops when no-convergence is attained whereas the values of $F(t)$ which exceed the computed asymptotic standard errors are automatically excluded from the series.

2.2. The FSS estimates the multiple equation (7) for the upper limit F by using the stepwise regression analysis method [4]. Only the basic factors which affect the upper limit F are retained, according to prespecified entrance and deletion significance levels. These are usually set at 0.05 [2]. If the DM is not satisfied by the selected factors he may return to step 1.2, otherwise goes on to phase 3.

Phase 3. Forecasting based on optimistic and pessimistic scenarios.

3.1. The DM-based on his experience-proposes optimistic and pessimistic scenarios for every one of the selected factors affecting F. The scenarios are given as percentages of the rate at which the DM expects the various factors to change.

3.2. The time varying effect of every factors is presented graphically and the DM can decide if he is satisfied by the scenario he already proposed.

3.3. The FSS illustrates the time varying effect if the basic variable and the development of the upper limit for every case, both pessimistic and optimistic, selected. It is obvious that-in the long run-the basic variable f and the upper limit F tend to coincide.

3.4. The FSS estimates the parameters of S-4 model and makes forecasts of the basic variable for the selected time horizon. The DM may then compare the results with those given by the logistic model in both optimistic and pessimistic cases. If the DM is not satisfied by the forecasts he may return to step 3.1, otherwise the procedure is ended.

Feedback, consistency and validation. The DM can also follow a validation procedure by going back a few years. Then the DM can try to do forecasts into the already known time horizon and check his predictions by doing comparisons with the existing data. After several attempts the DM will be able to check how well his experience fits into te FSS. This Feedback procedure would improve the consistency of predictions and avlidate the models in use.

4. COMPUTER IMPLEMENTATION

The FSS is implemented on a microcomputer supporting the MS-DOS operating system. It is written in the Microsoft Quick basic environment and takes up 100 kb of disk space.

An IMSL routine is used to calculate the stepwise multiple regression coefficients. The software supports both monochrome and colour displays while hardcopy output is available through the Print Screen Utility.

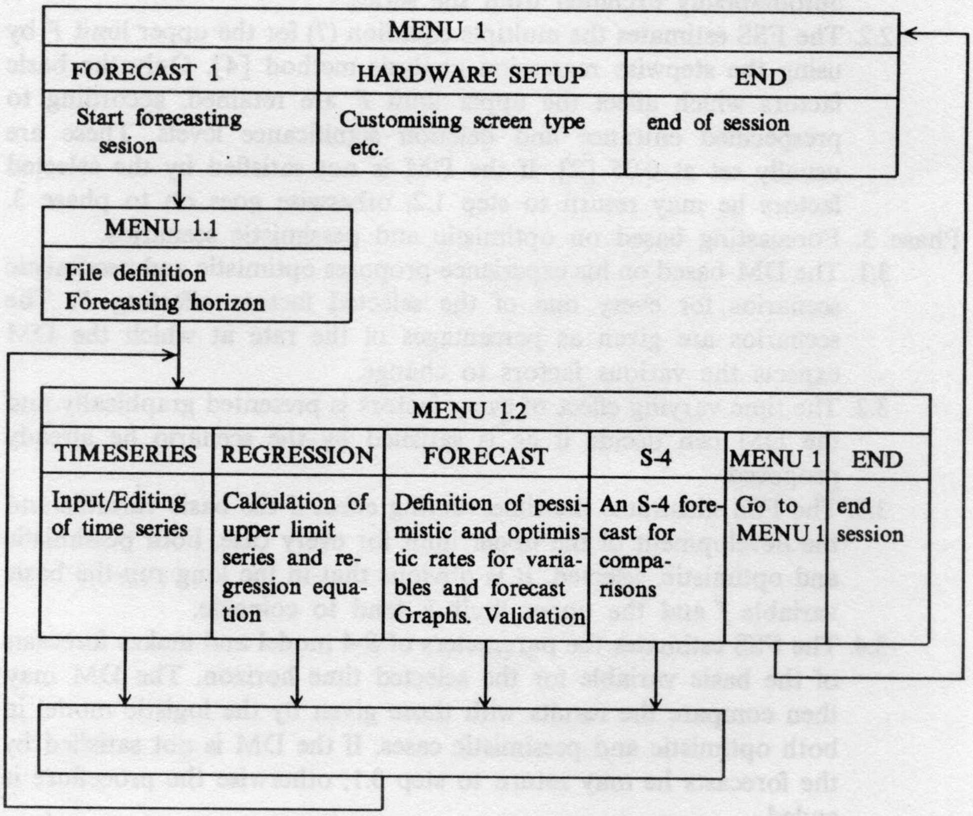

Figure 3. Menu diagram of software program

The number of data points for each time series and the number of time-series depend on the computer's available memory (256k support 200 data points X 30 time-series).

The software is menu-driven and therefore easy to learn and use friendly. Its basic steps and menus are illustrated in Figure 3.

5. AN ILLUSTRATIVE EXAMPLE: FORECASTING THE GREEK ELECTRIC ENERGY CONSUMPTION

The following application uses the data for the consumption of electric energy in Greece from 1961 to 1986.

PHASE 1

1.1. The DM inputs the basic variable for forecasting, f, and the data-series in the data base (see Table 1).

1.2. The DM selects the set of factors which may affect the upper limit F. These are the following:

Socioeconomic Factors	
GT	: Gross Domestic Product
PI	: Industrial Production Index
IT	: Total Investment
IM	: Investment in Industry (Manufacturing)
IR	: Investment in Housing
NRC	: Number of Household Consumers
TEP	: Mean Total Electric Price
ITEP	: Index of Mean Total Electric Price (1975 = 100)
IGP	: General Price Index (1975 = 100)
IRTEP	: Index of Relative Total Electric Price (ITEP/IGP)·100
REP	: Mean Household Electricity Price
IREP	: Index of Mean Household Electricity Price (1975 = 100)
IRREP	: Index of Relative Household Electricity Price = (IREP/IGP)·100

1.3. The forecasting horizon is set at $t = 5$ years

PHASE 2

2.1 The FSS calculates the upper limit series F (if not already calculated) and stores it in the data base with a name given by the DM (in this case, f upper).

2.2 The FSS calculates the multiple equation (7) for the upper limit F. The stepwise procedure gives the following equation,

$$F = 3.428.10^{-4}\ \mathrm{IT} + 1.086.10^{-2}\ \mathrm{ITEP} - 7.735$$

Table 1

Basic Time-Series

06 - 11 1989

year	f	gt	pi	it	im	ir	nrc	tep	itep	igp	irtep	rep	irep	igp	irrep	fupper
1961.0	2.1030															
1962.0	2.3670															
1963.0	2.6930															
1964.0	3.2100															
1965.0	3.7450															
1966.0	4.9870															
1967.0	5.9790															
1968.0	6.4790	217895	81.000	60397.0	7245.0	19445.0	1940.0	0.94000	63.385	53.087	119.40	1.2130	68.300	53.087	128.66	
1969.0	7.4340	238201	90.500	71653.0	8426.0	23212.0	2109.0	0.92300	62.239	54.410	114.39	1.1830	66.610	54.410	122.42	16.996
1970.0	8.3570	258000	100.00	70663.0	10044.0	19740.0	2280.0	0.92000	62.036	56.000	110.78	1.1770	66.273	56.000	118.35	15.530
1971.0	9.8220	278551	111.30	80558.0	11198.0	23641.0	2475.0	0.90800	61.227	57.672	106.16	1.1490	64.700	57.672	112.18	21.044
1972.0	11.184	303973	127.10	92977.0	13228.0	29964.0	2575.0	0.91200	61.497	60.140	102.25	1.1550	65.034	60.140	108.14	26.550
1973.0	12.701	329269	146.60	100093	14457.0	30576.0	2724.0	0.98900	66.689	69.490	95.971	1.2370	69.651	69.490	100.23	31.762
1974.0	12.846	323307	144.30	74500.0	14914.0	15869.0	2834.0	1.3320	89.818	88.190	101.85	1.6270	91.610	88.190	103.89	21.354
1975.0	13.608	339833	150.60	74660.0	13132.0	20476.0	2946.0	1.4830	100.00	100.00	100.00	1.7760	100.00	100.00	100.00	19.091
1976.0	15.028	360399	166.50	79750.0	13288.0	21909.0	3047.0	1.6180	109.10	113.32	96.283	1.8850	106.14	113.32	93.665	19.710
1977.0	10.057	371022	169.90	85950.0	12599.0	26428.0	3164.0	1.7510	118.07	127.07	92.917	2.0680	116.44	127.07	91.634	20.439
1978.0	18.219	394803	182.70	91100.0	12244.0	30074.0	3271.0	1.9190	129.40	143.03	90.468	2.1110	118.86	143.03	83.101	23.678
1979.0	19.174	409075	193.80	99121.0	13824.0	31572.0	3392.0	2.3090	155.70	170.19	91.483	2.3030	129.67	170.19	76.192	25.673
1980.0	20.064	417510	195.70	92705.0	14899.0	27290.0	3517.0	3.0880	208.23	212.23	97.979	2.9180	164.30	212.52	77.310	26.531
1981.0	20.289	418271	197.27	96750.0	13973.0	21452.0	3642.0	4.2200	284.56	264.55	107.56	4.5090	253.88	264.55	95.969	25.800
1982.0	20.509	420641	199.03	84100.0	13120	20398.0	3755.0	5.0830	342.75	320.02	107.10	5.2130	293.52	320.02	91.721	24.896
1983.0	21.940	422351	198.44	8300.0	12208.0	21124.0	3870.0	5.9110	398.58	384.66	103.62	5.8100	327.14	384.66	85.047	25.229
1984.0	23.052	434726	203.14	78300.0	12101.0	17083.0	3967.0	6.7760	456.92	455.73	100.26	6.6330	373.48	455.73	81.952	25.883
1985.0	23.725	448710	209.79	82290.0	11052.0	17097.0	4062.0	7.9590	536.68	543.74	98.702	7.7200	434.69	543.74	79.944	26.393
1986.0	24.064	455000	210.57	78300.0	12555.0	19910.0	4135.0	9.9670	672.08	668.87	100.48	9.8450	554.34	668.87	82,876	26.608

PHASE 3

3.1 DM proposes optimistic and pessimistic scenarios for IT and ITEP:

	OPTIMISTIC VALUE	PESSIMISTIC VALUE
IT	2	1
ITEP	1	2

3.2 The FSS, if wanted, presents graphical output of the secioeconomic variables IT and ITEP (see Figures 4 and 5).

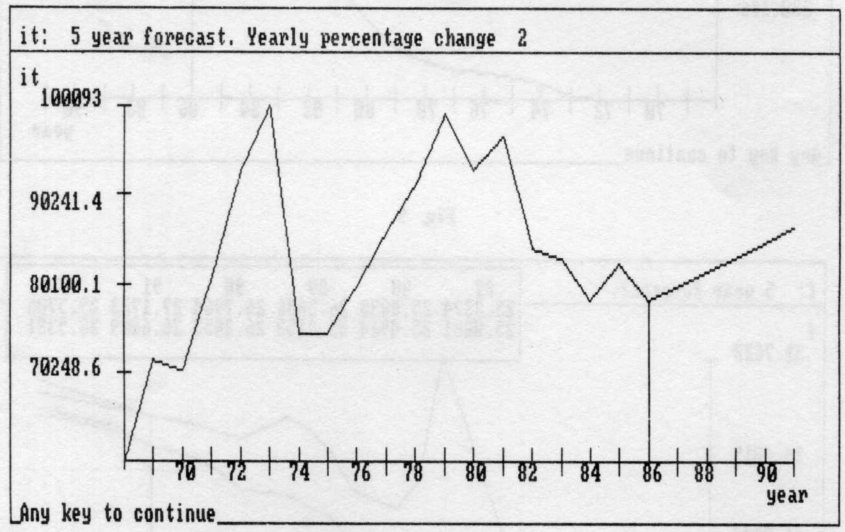

Fig. 4

3.3 The FSS illustrates the time varying effect of the consumption od electric energy in Greece and the varying upper limit *F* (see Figure 6) the forecasts according to the two scenarios selected are also presented (1986 - 1991). At the upper part of the screen appear the optimistic and pessimistic values for the consumtion od electric energy, as well as the values for the upper limit *F* for the year 1991 (optimistic and pessimistic respectively)

3.4 The DM decides to compare the results with the forecast based on the *S*-4 model (see Figure 7). The estimated value for 1991 is 29.979 GWh. This value is close to the mean of the estimated values of the upper limit F for 1991:

$(29.571 + 28.533)/2 = 29.052.$

On the other hand the estimation based on the *S*-4 model (for 1991) is much higher than that based on the logistic model which for the optimistic case estimates 27.172 GWh per year.

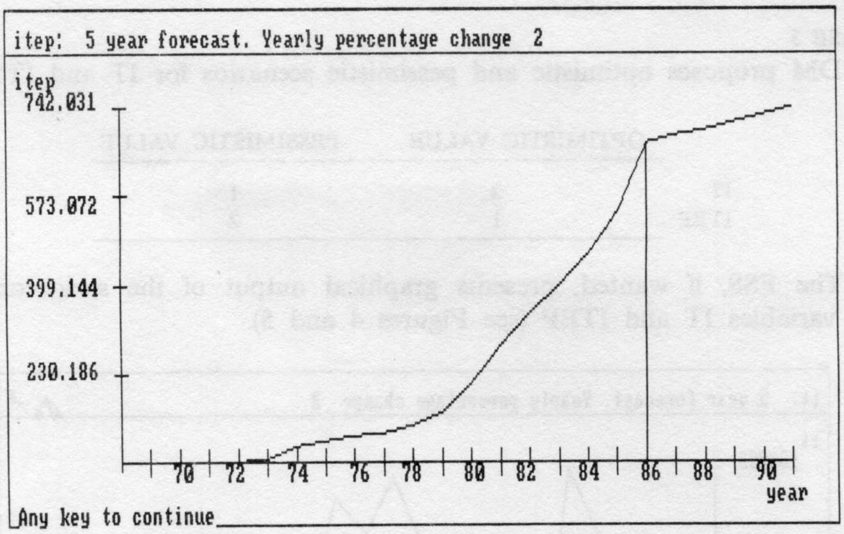

Fig. 5

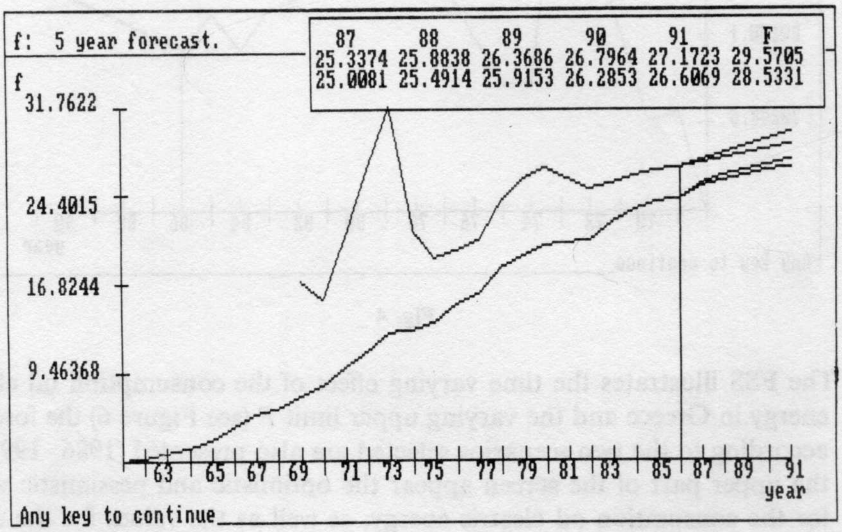

Fig. 6

Perhaps, here, the decision maker followed a rather passimistic scenario in both optimistic and pessimistic cases selected. In such a case the DM may return to 3.1 and select new scenarios.

Going back at stage 3.1 the optimistic and pessimistic values of ITEP are set at 15% and 8% respectively whereas, the values for IT are left the same. The optimistic case for ITEP is illustrated in Figure 8 and the forecasts appear

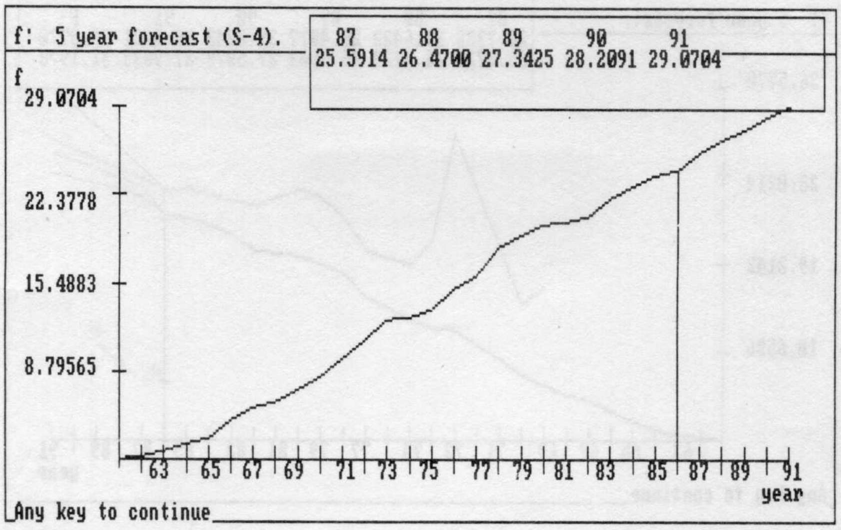

Fig. 7

in Figure 9. The pessimistic value for 1991 is 27.969 GWh and the optimistic value is 30.002 and their mean value is 28.986 which is very close to that estimated by using the *S*-4 model (29.070 GWh).

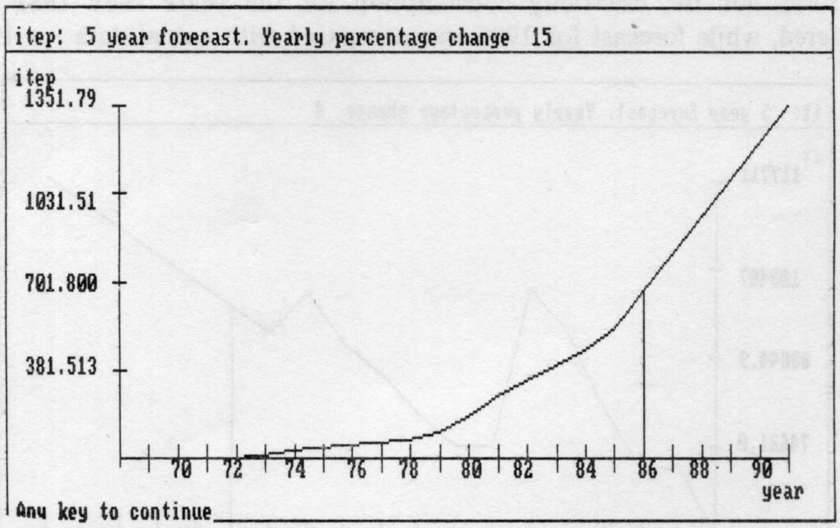

Fig. 8

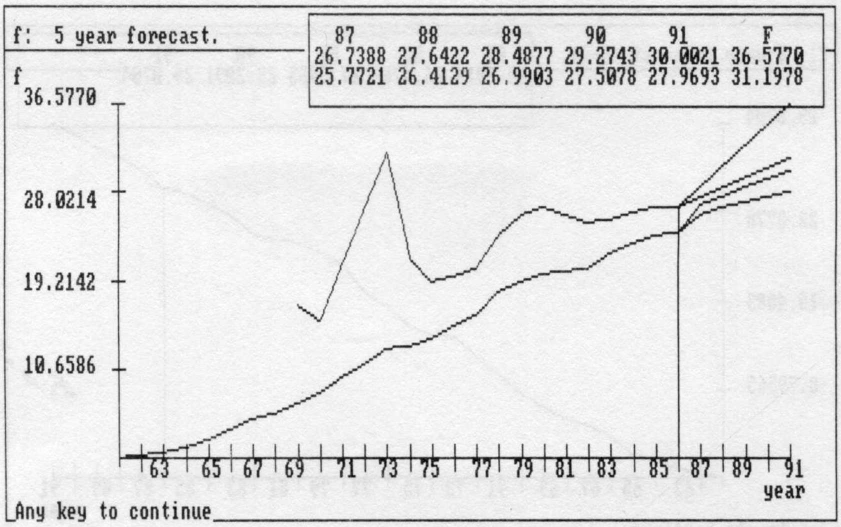

Fig. 9

6. VALIDATION

The DM also follows a validation procedure by going back a few years. The time series for the electricity consumption for the years 1961 - 1981 was considered, while forecast for 1986 was compared with actual data for 1986.

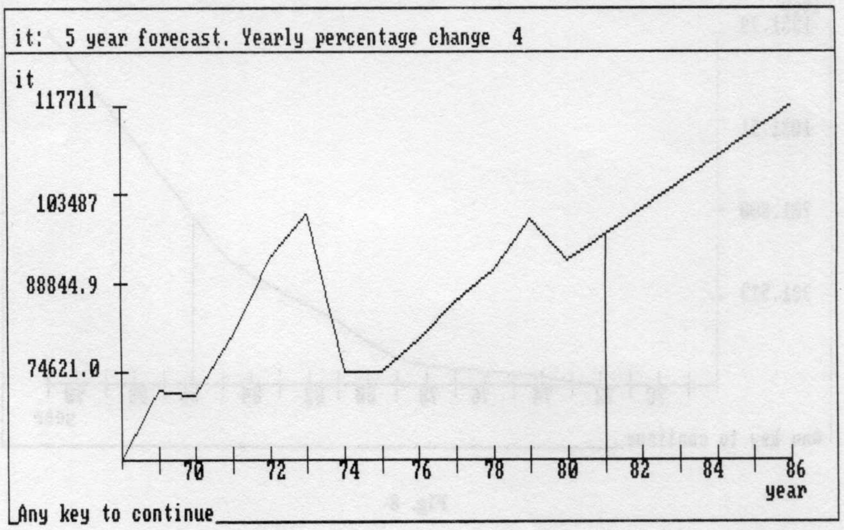

Fig. 10

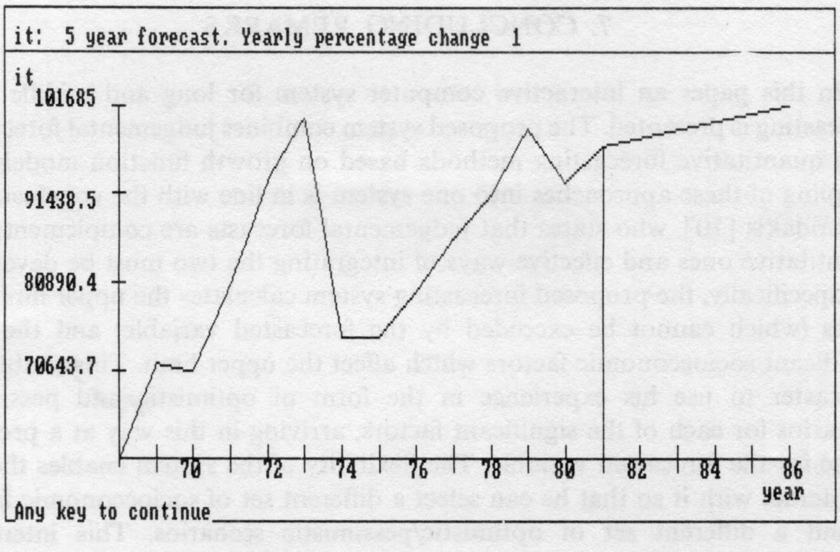

Fig. 11

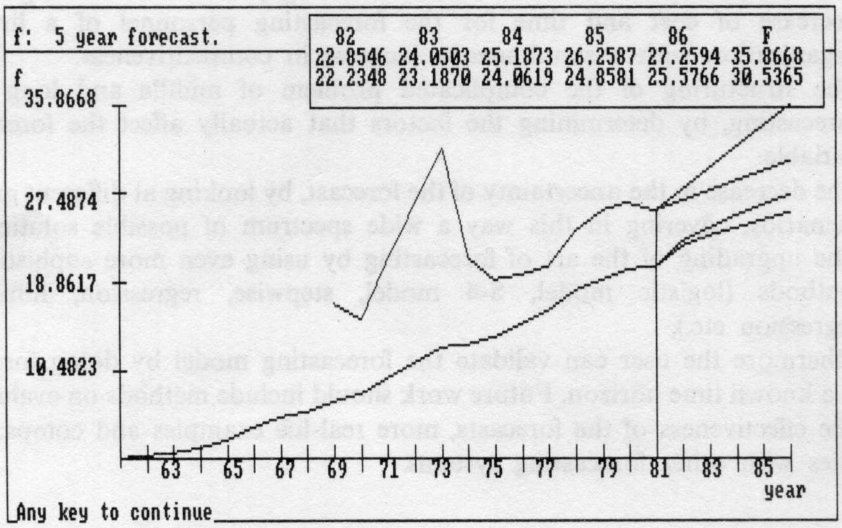

Fig. 12

The optimistic and pessimistic scenarios (step 3.1) for IT were 4% and 1% respectively. (See Figures 10 and 11) and the forecast (step 3.3) is presented in Figure 12. The true value for 1986 is 24.064 GWh which is lower than that estimated by the pessimistic scenario (25.577 GWh) and the DM may return to step 3.1 to choose more pessimistic scenarios and then to proceed to step 3.3.

7. CONCLUDING REMARKS

In this paper an interactive computer system for long and middle range forecasting is presented. The proposed system combines judgemental forecasting with quantitative forecasting methods based on growth function models. The coupling of these approaches into one system is in line with the conclusions of Makridakis [10], who states that judgemental forecasts are complementary to quantitative ones and effective ways of integrating the two must be developed.

Specifically, the proposed forecasting system calculates the upper limit time series (which cannot be exceeded by the forecasted variable) and the most significant socioeconomic factors which affect the upper limit. This enables the forecaster to use his experience in the form of optimistic and pessimistic scenarios for each of the significant factors, arriving in this way at a probable range for the forecasted variable. The flexibility of the system enables the user to interact with it so that he can select a different set of socioeconomic factors or/and a different set of optimistic/pessimistic scenarios. This interactive capability leads the user to more satysfying solutions.

The system also contributes to:

- The computerization of the entire forecasting procedure, resulting in the decrease of cost and time for the forecasting personnel of a firm or organization with a simultaneous increase in competitiveness.
- The structuring of the complicated problem of middle and long term forecasting, by determining the factors that actually affect the forecasted variable.
- The decrease in the uncertainty of the forecast, by looking at different growth scenarios, covering in this way a wide spectrum of possible solutions.
- The upgrading of the art of forecasting by using even more sophisticared methods (logistic model, S-4 model, stepwise, regression, nonlinear regression etc.).

Furthermore the user can validate the forecasting model by doing forecasts into a known time horizon. Future work should include methods on evaluation of the effectiveness of the forecasts, more real-life examples and comparative studies with other forecasting systems.

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