

Predicting U.S. food demand in the 20th century: A new look at System Dynamics

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ABSTRACT

The paper describes a new methodology for predicting the behavior of macroeconomic variables. The approach is based on *System Dynamics* and *Fuzzy Inductive Reasoning*. A four-layer pseudo-hierarchical model is proposed. The bottom layer makes predictions about population dynamics, age distributions among the populace, as well as demographics. The second layer makes predictions about the general state of the economy, including such variables as inflation and unemployment. The third layer makes predictions about the demand for certain goods or services, such as milk products, used cars, mobile telephones, or internet services. The fourth and top layer makes predictions about the supply of such goods and services, both in terms of their volume and their prices. Each layer can be influenced by control variables the values of which are only determined at higher levels. In this sense, the model is not strictly hierarchical. For example, the demand for goods at level three depends on the prices of these goods, which are only determined at level four. Yet, the prices are themselves influenced by the expected demand. The methodology is exemplified by means of a macroeconomic model that makes predictions about U.S. food demand during the 20th century.

Keywords: System Dynamics, Fuzzy Inductive Reasoning, Macroeconomic Modeling, Food Demand Prediction

1. INTRODUCTION

Making informed predictions about macroeconomic quantities is a maddeningly difficult undertaking. Listening to different economists talk on TV about the state of the economy, it is amazing to realize how differently they interpret the very same facts, that identical observations can lead to diametrically opposite opinions about the state of the economy. Is there any science behind such predictions? It almost seems like the economy actively defies any attempt at being understood, that it eludes understanding. Economists have coined an elegant term for this elusiveness. They call it the “efficiency” of the economy. The totally “efficient” economy must be totally unpredictable by definition. The reason for this assertion is simple: as long as the economy is predictable, someone will predict it, exploit it, and get rich in the process. However, the now rich economist will have to reinvest his or her wealth in the economy. The economy will react to this massive new investment, which counteracts the economist’s capability of predicting its behavior. The economy has just become a bit more efficient.

Does this mean that any attempt at making predictions about the economy must be futile? Clearly, this is not so, because the current economy is not totally efficient. However, any insight into the workings of the economy must be fleeting, since the economy will soon counteract such knowledge. Thus, there cannot be a win situation, only a struggle.

How difficult is it to make economic predictions? In fact, this is very easy! For example, one can simply connect the last two points of an observed variable, and make a linear extrapolation one step into the future. Economic predictions are cheap and plentiful. The question is not whether predictions can be obtained. The real question is, how reliable these predictions are. A respectable model of the economy does not consist in a code that simply makes predictions . . . but in a code that assesses the quality of any prediction made. The part of the code that makes the prediction is the easy part. The heart of the modeling/simulation environment is the part that estimates the error

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of the prediction. An economic modeling tool that is not self-critical, that doesn't check the validity of its own predictions is essentially worthless.

What type of modeling methodology should be embraced? Are knowledge-based deductive models preferable, or should pattern-based inductive models be used? At one end of the spectrum are *System Dynamics* models. They are almost entirely deductive in nature. The other end of the spectrum is occupied by *Neural Network* models that are almost entirely inductive. Ironically, both types of models fail on similar grounds.

When Jay Forrester published his books on *System Dynamics*¹⁻³ in the mid 60s to early 70s, they became immediate bestsellers. Hordes of economists delved into the new technology to make models of almost anything hitherto unimaginable. A bibliography of System Dynamics written in the early eighties⁴ is more than 30 pages long and contains already more than 600 entries. System Dynamics seemed unstoppable. Yet, the predictions made were easy to check. For example, the correctness of a System Dynamics model can be tested by reverting time, simulating backward from the given initial conditions. This can be accomplished easily by inverting the sign of each rate variable (state derivative). If the prediction after only a few steps fails to reproduce the known past, clearly the model isn't trustworthy to fare any better when simulated forward through time. The main problem with the methodology is that it makes structural assumptions about the system to be modeled, assumptions that are difficult to verify or refute, yet its predictions depend heavily on these silent assumptions, and the methodology is totally blind to its own gullibility.

In recent years, it has become fashionable to employ *Neural Network* models for predicting economic quantities. In some situations, Neural Networks are better suited than econometric models or NARMAX models, because they make less stringent structural assumptions about the relationships of the variables among each other. A Neural Network is a highly non-linear set of (either static or dynamic) equations of arbitrary complexity. Using enough neurons distributed over a sufficient number of layers, basically *any* functional relationship can be approximated with arbitrary accuracy. Since the precise structure of the Neural Network doesn't matter, the structural assumptions are essentially harmless.

Yet, Neural Networks are equally oblivious to their own assumptions as System Dynamics models. The reason is the following. A Neural Network is a *parametric model*. Once the Neural Network has been trained, the system knowledge is totally contained in the network parameter values. The training data themselves are not preserved. Hence, if the system behavior suddenly changes, or if an input variable driving the system and its model suddenly leaves the range of values used in the training period, the Neural Network has no way of knowing this. It will happily continue to make predictions for any combination of input patterns, irrespective of their relationship with the training data. The structural assumptions didn't matter *before* training, but they do, once the network parameters have been frozen.

Hence the real issue is not whether to use a structural or a behavioral model. The problem of gullibility can only be overcome by a *non-parametric model* that preserves the training data during the simulation (prediction) phase, comparing the current input patterns with those that had been used in the modeling (training) phase. Structural information should be added where available in order to reduce the need for training data, but should be limited to assumptions that can be verified.

Data deficiency is a major problem in all economic predictions. The data rate is dictated by the natural time constants of the processes to be predicted. For example, population dynamics change over years, not over days. Hence, providing data more frequently than about once a year doesn't help. However, how relevant are data collected before the invention of reliable contraceptives for making predictions about the number of children per woman of childbearing age today? How many data points can be used for predicting the number of mobile telephones? Mobile telephones simply haven't been around very long. The data deprivation problem is the major stumbling block of *any* economic model. The paper shall address this issue, and put the problem into proper perspective.

Finally, any prediction is an act of *extrapolation*. Clearly, an external event, such as a war or a new invention, that is not foreseeable, cannot be predicted, and when it occurs, it immediately invalidates any prediction made prior to the event. A useful side product of being able to produce an estimate of the prediction error, is that this same estimate can be used to estimate the *horizon of predictability*, i.e., the time window into the future, for which meaningful predictions can be made, assuming that no unpredictable external events interfere.

2. SYSTEM DYNAMICS

System Dynamics (SD) starts out with the selection of a number of so-called *level variables* (state variables). “Levels” are variables that accumulate, such as population, investment, food, garbage, etc. For each level, a number of *rate variables* is defined. “Rates” are divided into *inflows* and *outflows*. Inflows contribute to the growth of the associated level, whereas outflows contribute to their decline. Once all the inflows and outflows are defined, the dynamics of the model are written as follows:

$$\frac{d(\text{level})}{dt} = \sum(\text{inflows}) - \sum(\text{outflows}) \quad (1)$$

For example:

$$\frac{dP}{dt} = (BR + IR) - (DR + ER) \quad (2)$$

The change of population with time (dP/dt) equals the *birth rate (BR)* plus the *immigration rate (IR)* minus the *death rate (DR)* minus the *emigration rate (ER)*. There is no approximation in this equation. It is a correct description of the nature of population dynamics.

One question remains to be answered: How are the values of the rates to be determined. SD proposes the introduction of a so-called “laundry list.” For each rate variable, a set of the most important factors is written down that influence the value of the rate. For example, it might be claimed that the birth rate depends on: the population, the material standard of living, the available food (both quantity and quality), education, the availability of contraceptives, as well as religious beliefs, to just mention the more important factors. Again, there is nothing wrong about choosing the variables to be considered. According to George Klir, this must in fact always be the first step in *any* modeling effort. It constitutes the “level 0” of the epistemology of levels in his *General System Problem Solving (GSPS)* framework.⁵

The “factor” variables are grouped into four classes: levels, rates, external inputs, and auxiliary variables, i.e., the influencing factors may themselves be levels and rates, i.e., variables whose dynamics are already covered by the descriptions provided earlier, or they may be external driving functions, whose values as functions of time must be known, or finally, they can be auxiliary variables. Any variable that doesn’t fall into either of the first three categories is called an auxiliary variable. It is simply added to the set of variables, for which a laundry list must be determined.

Up to this point, the SD methodology is perfectly sound. One can write that:

$$BR = f(P, MSL, FQn, FQl, Ed, Co, RB) \quad (3)$$

to encode the aforementioned laundry list for the birth rate, and although this equation is an approximation of reality, it is an acceptable approximation, because any modeling effort is inherently reductionistic in nature, and because more influencing factors can always be added to the laundry list, if it should turn out that important dynamics have been overlooked.

Unfortunately, it is at this point where the SD methodology, as proposed by Forrester, becomes questionable. Because Forrester didn’t know how to handle an equation as complex as the one presented above, he proposed to “rewrite” the above equation as follows:

$$BR = BRN * P * f_1(MSL) * f_2(FQn) * f_3(FQl) * f_4(Ed) * f_5(Co) * f_6(RB) \quad (4)$$

i.e., he pulled out the *normal birth rate constant (BRN)* as well as the population, and then described the “small signal behavior” of the variations imposed by the remaining factors. His assumptions are that each rate equation is purely static in nature, and that the influencing factors are independent of each other. These are a lot of assumptions that can hardly ever be justified, and that almost invariably lead to behavioral patterns in simulations that have little in common with reality.

First, it should not be assumed that the rate equations are static in nature. There exist natural state variables in systems that don't fall into the category of things that accumulate. For example, in mechanics:

$$\frac{dx}{dt} = v \quad (5)$$

$$\frac{dv}{dt} = a \quad (6)$$

The position, x , and the velocity, v , are natural state variables, whereas the acceleration, a , is not. Yet, it doesn't make sense to proclaim that positions and velocities accumulate, or that velocity is an inflow or outflow of position. These secondary dynamics can be captured by allowing the rate equations to be themselves dynamic.

Second, the assumption of independence of different influencing factors is ludicrous. This assumption cannot be justified on any grounds. However, it was precisely this assumption that made many economists embrace this technology at first, because it makes the modeling effort tractable. It eliminates the need for large quantities of measurement data.

This is precisely where the proposed methodology departs from the System Dynamics approach. No structural assumptions are being made that are not justifiable on the basis of meta-knowledge or at least common sense. Instead, the proposed methodology identifies a dynamic *Fuzzy Inductive Reasoning* model for each of the rate variables and each of the auxiliary variables in the laundry list.

3. FUZZY INDUCTIVE REASONING

*Fuzzy Inductive Reasoning (FIR)*⁶⁻⁸ is a qualitative inductive non-parametric modeling and simulation methodology. It is assumed that training data are available for all variables in the laundry list. In reality, since measurement data are difficult to come by, structural assumptions, in this modeling approach, are often based on the availability of training data, more than on any other consideration.

FIR has the same range of applications as a Neural Network. It creates inductive (either static or dynamic) models of a system from observations of input/output behavioral patterns. However, and contrary to Neural Networks, FIR uses a non-parametric approach. FIR has a history of success in identifying dynamic models of complex systems.⁹⁻¹¹ Most importantly, the methodology contains an inherent self-validation capability, i.e., it rejects making predictions that are not justifiable on the basis of the available facts,¹² a feature that can also be used to estimate the horizon of predictability.¹³

FIR contains four modules. The first module is the *fuzzification* module. FIR fuzzifies real-valued variables by assigning a *class* value, a *fuzzy membership* value, and a *side* value to each observation.⁶⁻⁸ For sufficiently smooth variables, three to five classes are usually sufficient.

The second module is the *qualitative modeling* engine. FIR reasons about observed input/output patterns in terms of their class values. It constructs a finite state machine of observed input/output patterns. For each output to be explained, FIR selects among the available input variables those that lead to as deterministic a finite state machine as possible, i.e., different observations of the same input pattern should lead as often as possible to an identical output pattern. The selection of variables is the qualitative model. It is reported back to the user in the form of a so-called *optimal mask*.

The third module is the *qualitative simulation* engine. FIR makes predictions by comparing the newly observed input pattern with all the input patterns in the experience data base (the training data), and finds the *five nearest neighbors*. It then predicts the most likely class and side values, and calculates the membership value as a weighted average of the membership values of the five nearest neighbors. In this way, reasoning is done using the (discrete) class and side values only, whereas the concrete quantitative information is preserved by interpolating among the (real-valued) membership functions of the five nearest neighbors.

The fourth and final module is the *defuzzification* module. Here, the predicted class, side, and membership values are converted back to real-valued quantitative predictions using the inverse operation to the fuzzification.

FIR's *confidence* measure has two components. FIR measures the distance between the new data point to be predicted from its five nearest neighbors in the input space. If the distance is small, only little interpolation needs

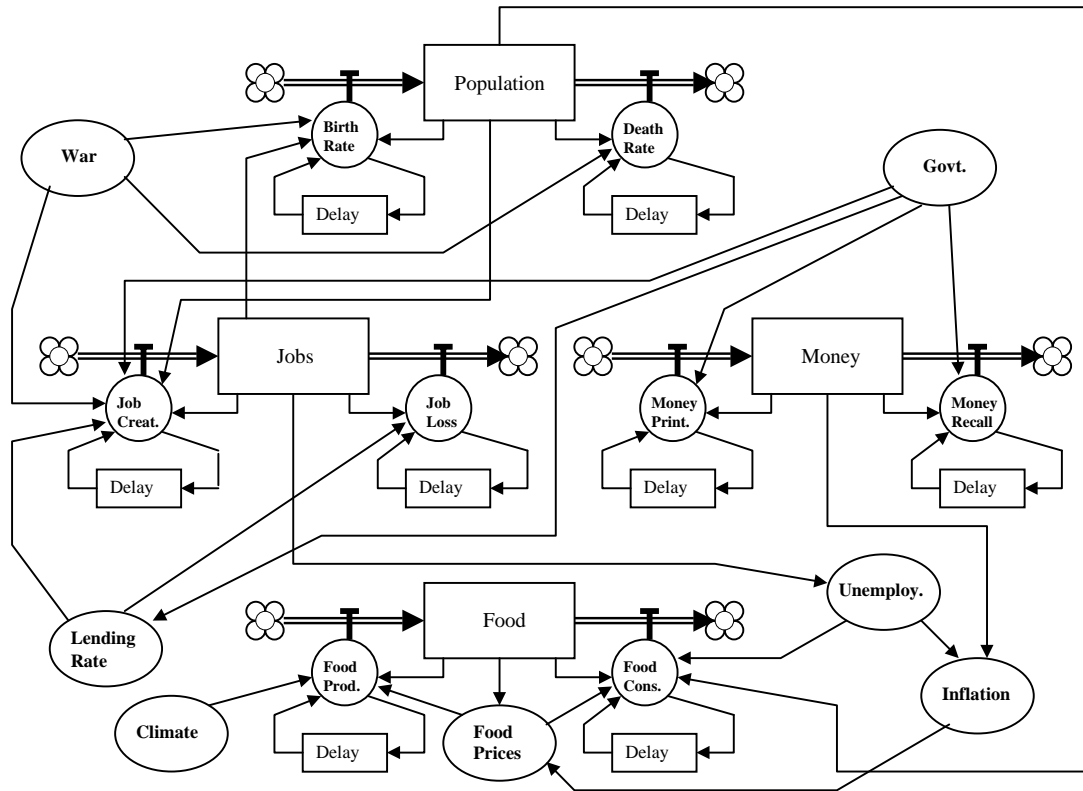


Figure 1. System Dynamics Model of U.S. Food Demand

to be done, and FIR is more confident that the proposed prediction is accurate. Secondly, it looks at the dispersion among the outputs of the five nearest neighbors. If the dispersion is small, FIR is confident that it can predict accurately the new output value. If it is large, it cannot know which of the neighbors is right, and therefore, assigns a lower value to the confidence measure.¹²

FIR, although internally operating as a *qualitative* technique (reasoning about discrete class values), looks from the outside like a *quantitative* technique thanks to its fuzzification and defuzzification engines. FIR is therefore compatible with quantitative approaches, such as System Dynamics. FIR submodels can be easily embedded in SD models, as proposed in the advocated methodology.

4. FOOD DEMAND MODELING

Fig. 1 shows a highly simplified *System Dynamics* macroeconomic model that may be used to predict aspects of U.S. food demand in the 20th century. This is a rather naïve model, but it may serve for illustrative purposes.

The amount of food available on the market, a *level* variable, depends on food production and consumption, two *rate* variables. Both food production and consumption are heavily influenced by the food prices, an *auxiliary* variable. The food prices depend primarily on the amount of food currently on the market, but also on the state of the economy, here reflected by another auxiliary variable, the inflation. Both the economy (here represented by the unemployment rate) and the population (the prospective buyers) influence food consumption. The two delay boxes represent secondary dynamics. They reflect the inertia of both food production and consumption, as neither of them will change abruptly over night.

In order to be able to predict food demand and supply, it is necessary to know something about the state of the economy and population dynamics. The economy is represented by two level variables, the number of jobs, and

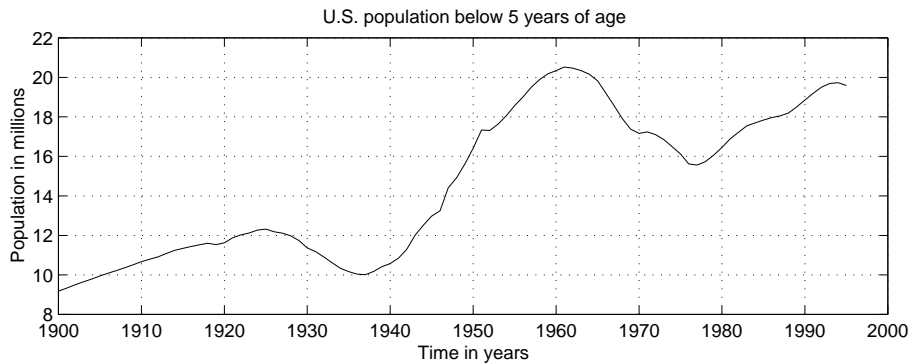


Figure 2. U.S. Toddler Population Dynamics in the 20th century

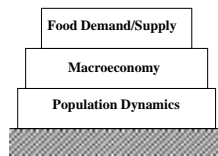


Figure 3. The Layered Model Architecture

the volume of money. Although there exist tight interactions between these variables, they can be modeled almost independently. The reason is that the number of jobs (or rather the unemployment rate) is a *controlled variable*. The government tries to keep it always around 5%. If the unemployment rate climbs, the lending rate is lowered; this provides incentive for the construction industry, which absorbs the surplus unemployed. If the unemployment rate decreases much below the 5% level, the lending rate is increased, which dampens the construction industry, which makes more workers unemployed. The reason is simple: if there are too few unemployed workers, the employers have to raise the salaries in order to attract employees, which leads to an increased inflation rate.

Knowledge of the population dynamics, and in particular the number of young adults, helps with predicting unemployment. Once the unemployment is predicted, it can in turn be used as a driver for predicting the inflation rate.

The population dynamics are influenced by the state of the economy, but only to a minor extent. Only during the great recession of the 30s, a notable change in birth rate patterns could be observed as a consequence of a poor economy. The other anomaly are the years of the Vietnam war, when many potential fathers were abroad for years in a row, and therefore, could not sire children in the U.S. The U.S. toddler population dynamics are shown in Fig. 2.

To summarize, it makes sense to postulate a hierarchical model, whereby the population dynamics (level 1) are explained only from their own past, whereas the economy (level 2) is explained from its own past *and* the already predicted population dynamics. Finally, the food model (levels 3/4) is predicted by its own past *as well as* all the previously predicted variables of the population dynamics and economy layers. The three-layer hierarchy is shown in Fig. 3. For reasons to be explained further down, the top two layers (food demand and supply) were lumped into a single layer for the purpose of this research effort.

An additional advantage of the layered architecture is that the models at levels 1 and 2 are *generic models* that can be created once and for all. They do not depend on the application to be predicted at level 3, i.e., if there should suddenly be a need to predict the demand for used cars rather than powdered milk, the bottom two layers of the architecture will remain the same. Only the top layer changes.

4.1. The Population Dynamics Layer

The *System Dynamics* methodology stipulates that equations need to be found that predict the rate variables. The level variables then follow by integration. Yet in practice, it is much easier to gain access to good measurement data for level variables than for rate variables. Therefore, it may be easier to predict the level variables directly.

The data available to us for this study include the total U.S. population recorded (estimated) annually since 1910. They also include the percentages of the population in different age brackets, as well as the demographic distribution.

The idea was to create a *Fuzzy Inductive Reasoning* model that predicts each of these variables from its own past and from past values of the other population dynamics variables. For example the number of newly borns depends on the population of childbearing age, whereas the population of teenagers depends on previous values of the population of toddlers, etc. The data from 1910 until 1970 were to be used as training data, whereas the remaining 25 years should be used to validate the model.

One problem was that FIR is totally pattern-based, i.e., FIR can only predict what it has been shown before. Yet, the population is non-stationary. It grows almost exponentially. FIR certainly is not capable of predicting such a growth variable. This problem was solved with a simple trick. Since the population grows almost exponentially, it makes sense to postulate the model:

$$\frac{dP}{dt} = k(t) \cdot P \quad (7)$$

If k were a positive constant, the population, P , would grow exponentially. By allowing $k(t)$ to be time-dependent, the actually observed population dynamics can be modeled. However, whereas P is a growth variable, k is essentially stationary.

The population derivative can be approximated as:

$$\frac{dP}{dt} \approx \frac{P(n) - P(n-1)}{\Delta t} \quad (8)$$

and since $\Delta t = 1$:

$$k(n) \approx \frac{P(n) - P(n-1)}{P(n)} \quad (9)$$

Since $k(t)$ is stationary, k can be predicted from its own past and from past values of other population dynamics variables. However, once $k(n+1)$ is predicted, Eq.(9) can be shifted by one year into the future and solved for $P(n+1)$:

$$P(n+1) \approx \frac{P(n)}{1.0 - k(n+1)} \quad (10)$$

Fig. 4a shows one, three, and five year predictions of the U.S. toddler population plotted together with the observed data for the years 1970 until 1995. Fig. 4b shows the average relative error as a function of the number of years to be predicted. Similarly good results have been obtained for the populations in age brackets and for the demographics.

The forecast is non-trivial, because the onset of the forecasting period coincides with the anomaly of the Vietnam war. Several trivial predictions were tried also. Their prediction errors were always larger by at least a factor of four in comparison with the FIR predictions.

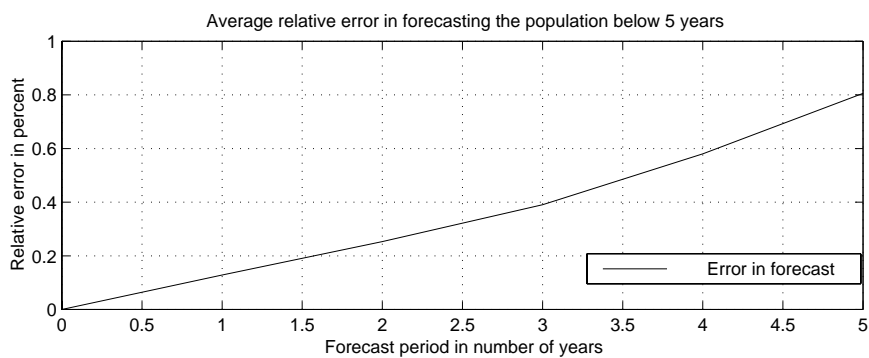
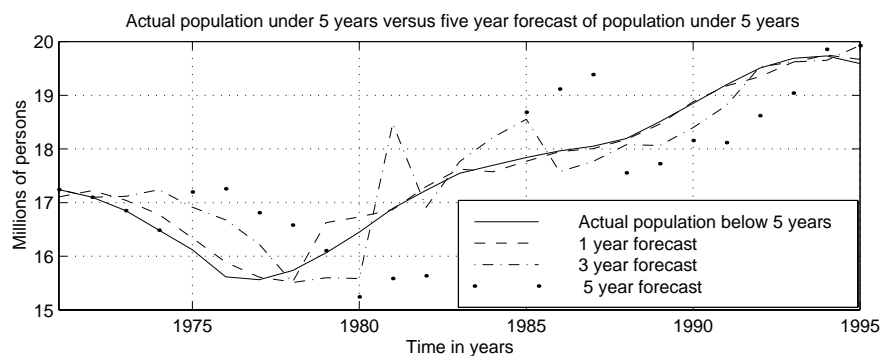


Figure 4. Toddler Population Forecast and Error Curves

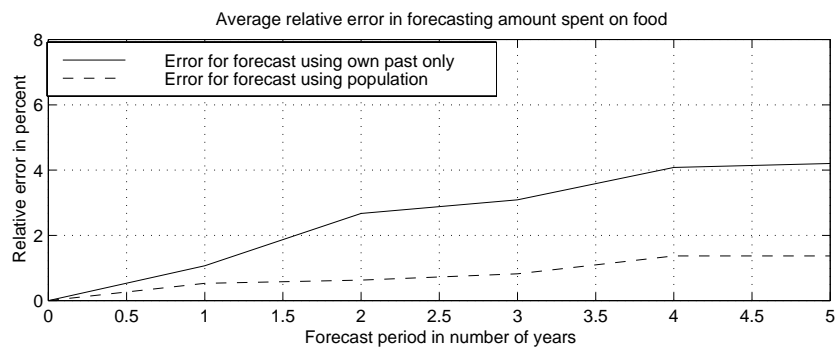
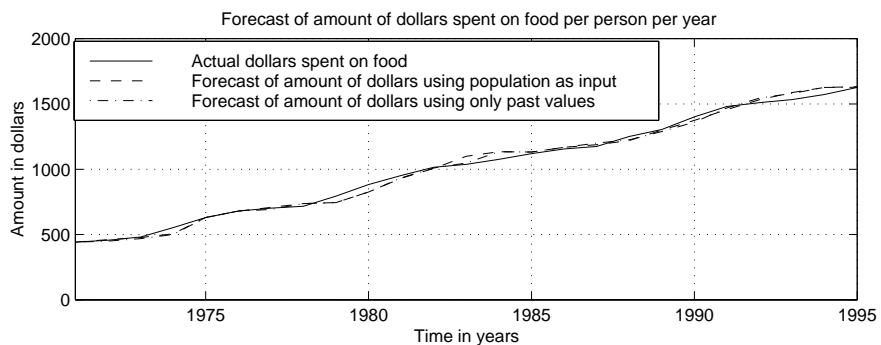


Figure 5. Inflation Forecast and Error Curves

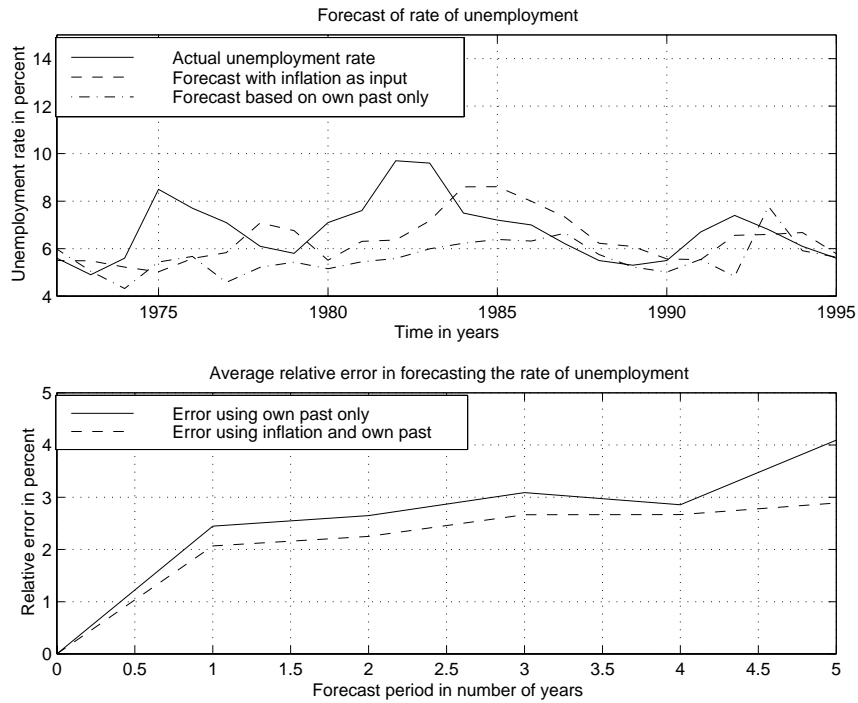


Figure 6. Unemployment Forecast and Error Curves

4.2. The Economy Layer

Whereas the population dynamics layer is quite sophisticated, the economy layer is still rudimentary. Until now, *unemployment rate* and *inflation* were used to represent the state of the economy. Other important economic drivers, such as import/export statistics and national debts were ignored.

Fig. 5a shows the three year prediction of the inflation, represented by the total cost of food spent per person per year, predicted from its own past alone and predicted using the already predicted population dynamics as additional input. Fig. 5b shows the corresponding error curves as a function of the years of prediction. Again, the lower level aided the prediction. The same trick was used for the inflation (another growth variable) that had been used in the case of the population dynamics.

Fig. 6a shows the three year prediction of the unemployment rate predicted only from its own past, and also predicted using the predicted population dynamics as well as the predicted inflation rate as additional inputs. Fig. 6b shows the corresponding relative error curves as a function of the years of prediction. As postulated, knowledge of the lower levels helped reduce the prediction error.

4.3. The Food Demand/Supply Layer

Food data are available in four different categories¹⁴:

1. dairy products,
2. meats, fish, and poultry,
3. fruits and vegetables, and
4. miscellaneous foods.

Each category is subdivided further into individual products. For each product, there are available data about the amount of consumed goods as well as the prices that they were sold at. Hence there are lots of data available to base the food-layer model upon.

For the purpose of this paper, only a few individual products, one from each category, were more or less arbitrarily picked out. Models were obtained for:

1. fresh milk and cream,
2. fish,
3. fresh vegetables, and
4. cereal, grains and bakery products.

Food prices and volume cannot be decoupled from each other. The food prices depend on the amount of food available, yet the food consumption depends on the price. One problem, of course, is that the time constants for food prices and consumption are much shorter. The food prices change over the year, and so does consumption. With food consumption being lumped and food prices being averaged over an entire year, important dynamics are being lost.

In order to come up with a decent model at such a high aggregation level, the relationship between prices and volume must be considered to be immediate. The food prices depend on the *current* food consumption, and vice versa. In order to tackle this interdependence problem, the following approach could be used. The prices are first fixed at the previous year's level, and the amount of food sold at those prices, given the current population dynamics and economy data, can be calculated. From the estimated consumption, the profit of the producers can be obtained. This model is embedded in an optimization layer, in which the food prices are treated as parameters, and the profit is the performance index to be maximized.

Yet, in this first study, a much simpler approach was chosen. It was assumed that:

$$\begin{aligned} price(n) &= f_p(price(n-1), volume(n-1), inflation(n)) \\ volume(n) &= f_v(volume(n-1), price(n), inflation(n), population(n)) \end{aligned} \quad (11)$$

where n means "up to year n ", and $n-1$ signifies "up to year $n-1$," i.e., dependences on earlier years are always allowed as well. In this way, the costly optimization was avoided. However, the assumption that this year's food prices depend on last year's volume is certainly not justifiable, and will probably lead to a significant reduction in overall prediction quality.

As in the case of the economy layer, predictions using only the past of the variable to be predicted, i.e.:

$$volume(n) = f(volume(n-1)) \quad (12)$$

were used as reference. Fig. 7a shows the three year prediction of the volume of fresh milk and cream predicted using Eqs.(11) on the one hand, and Eq.(12) on the other. Fig. 7b shows the prediction error as a function of the number of years of prediction for the two models.

Again, the more complex model performed better in the case of fresh milk and cream, but this wasn't the case with all variables. Also, the improvement is not very large.

In order to obtain yet better results, it will be necessary to implement the aforementioned optimization scheme. Also, it may make sense to allow past values of the overall amount of food in a given category to be used as additional input for predicting the consumption of a particular food item within the same category. This modification will allow to take into account replacement foods. Whereas the total intake of calories per person per year is constant, people may replace one food item by another within the same category if the prices of the individual items change.

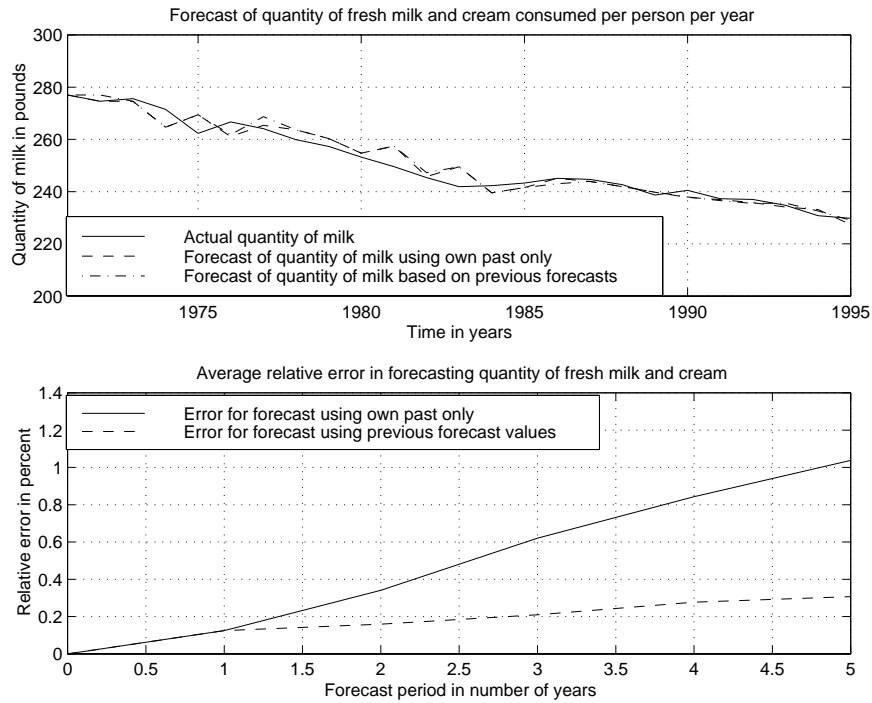


Figure 7. Fresh Milk and Cream Forecast and Error Curves

5. SUMMARY AND CONCLUSIONS

In this paper, a new mixed quantitative and qualitative approach to modeling macroeconomic systems for the purpose of short-term prediction (one to five years) was presented. A three-layer architecture was proposed. It was shown that fairly accurate predictions of macroeconomic variables can be obtained using this layered architecture.

What are the main advantages of a mixed SD/FIR approach? Pure SD is attractive because it requires very few training data, but the methodology is treacherous, because it doesn't offer any self-assessment capabilities. Pure FIR is attractive because of its sheer generality and ease of use, but it has the problem of requiring lots of data, and without any underlying structure, the modeling effort needs to be started from scratch for each new application. The mixed SD/FIR approach combines the best of both worlds. It saves of SD what is worth saving, but adds FIRs self-assessment capabilities and reduces drastically the assumptions made on the model.

It is amazing how well the methodology worked, given the fact that the model had to operate in a mode of *severe data deprivation*. Annual data from 1910 to 1970 were used as training data, i.e., only 61 data records were available for training the model.

It would be possible to overcome the data deprivation problem by interpolating between the measurement data points using e.g. spline interpolation (available in Matlab). Clearly, adding more data points by means of interpolation doesn't add any additional information to the data set. The new data are *derived data*, and one shouldn't expect that the model would improve as a consequence of such data. Yet, they may actually help for two reasons.

First, FIR uses the five nearest neighbors for predicting fuzzy membership values. Because there are only 61 data records in the training data base, the neighbors will be far away, and therefore, a lot of interpolation has to be done. By generating e.g. three new artificial data points for each measured one, the system would now have 241 data points to work with. Therefore, the five nearest neighbors will be much closer to the current data point, and consequently, much less interpolation will be needed.

Second, FIR tries to have at least five recordings for each discrete state. With 61 data records, only 12 different states can be recorded 5 times each. This means that FIR will always pick extremely simple models with one to three

ternary input variables only. If FIR is offered four or five possible input variables, it will pick the most relevant ones, and discard the others, although they might carry useful information. If the data deprivation problem is reduced, FIR might pick a mask of higher complexity, and thereby also exploit the information contained in less important variables.

How does this study help with predicting other variables, such as the demand for used cars, or the prices of telephone calls? The two bottom layers of the architecture are independent of the application at hand. Only the top layer (demand and supply) needs to be reidentified for each new application. This certainly helps.

Many technological variables have a much shorter history. For example, cellular phones or the world wide web simply haven't been around very long. Yet, their time constants are considerably shorter also, and therefore, data can be recorded more frequently. If monthly data are meaningful (because the time constants are months rather than years), only about six years worth of data would be needed to get 60 data points. In this case, a spline interpolation on the lower levels serves an additional purpose. It can be used to provide the intermediate data points needed to feed the faster changing technological variables of the top layer.

Finally, although the bottom layers are certainly specific to the U.S., the three-layer architecture itself is not. For each new country or region, the two bottom layers will have to be reidentified, yet, the structure of the architecture will remain the same.

6. ACKNOWLEDGMENTS

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