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PEAK LOAD PREDICTION IN AN ELECTRIC POWER SYSTEM

by

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Abstract

In the operation and maintenance of an electric power system, it is very useful to know the load, especially the peak load, in advance. In this paper we consider the difficult problem of peak load prediction (PLP) in an electric power system. We propose a discrete, complex dynamical model for PLP, similar to those proposed recently for macroeconomic prediction, in the spirit of complex dynamical systems (CDS) theory.

1 Introduction

The background for this work is the problem of the stability of an electric power system. See [20] and the references therein for the history of research in this area. Many difficulties arise from an unexpected increase in the peak load, due to *exogenous factors* such as climate (for example, air-conditioning demand during summer) or social habits (for example, TV demand during baseball or soccer games). Our approach for the prevention of service problems involves the modeling and prediction of the overall peak load of the grid. This power consumption factor fluctuates widely, presenting the utility management with many practical problems. Some exogenous factors create predictable perturbations in the distributed parameters of the grid while other exogenous factors may be unpredictable.

2 Applications of chaos theory

The methods of chaos theory might be used to make short-term predictions (such as one day or a few days in advance) of the peak load as follows.

1. Assume a massively detailed, continuous, CDS model for the power system, with all its buses of generators and loads. The creation of a useful model, capable of rapid simulation on a hybrid or massively parallel supercomputer, is a nontrivial task.

2. Given such a model, we could assume a reasonable coupling of exogenous factors to the distributed loads within the grid.

3. From existing data for the exogenous factors, we would make a short-term (such as one day) prediction of the exogenous parameters, using the techniques of chaos theory.

4. Then we may simulate the effect of these predicted forcing terms with the computer model.

This program has been considered in the recent literature on voltage collapse [6] [8] [9] [10] [13] [15] [18]. But our task in this paper is only to consider the third step of this sequence [17]. And our method will be that of discrete CDS, using a time increment of one day. We will describe a model to predict peak load, which could be used in a practical way to give warning of unusually heavy loads, and thus prevent outages. The technique to be described has been used to model real economic data, with encouraging results [19].

In the future, we will try to obtain detailed peak power data for a real power grid, to apply the modeling strategy of this paper to adapt a discrete, CDS model to the data, and to relate the exogenous factors of the consumer population (temperature, sports events, etc.) to the parameters of the model. Assuming, eventually, some success in this program, an experimental intervention in a real power system could be considered, attempting to avert a voltage collapse or outage due to excess loading.

Although there are some dangers inherent in any intervention in a real system by an experimental method, we may emphasize that the methods envisioned here may involve only very subtle variations in the load parameters at a few key nodes of the grid. Certainly this is safer than a electro-surgical manipulation of a human heart in a living and critically ill patient [15]. And in fact, methods perfected in the power grid of a large urban area, besides obtaining greater reliability for the consumer network, may provide theoretical and technical byproducts for the other technologies (physical, biological, social, economic, psychological, etc.) which share the basic structure of the electric power grid: a massively parallel, distributed, and chaotically driven, CDS.

3 CDS economic models

There is increasing interest in modeling the world economy as a spatially-distributed CDS, which may then be coupled to a similar CDS model of the environment. This effort is the dynamical approach to environmental economics [2] [19]. In these projects, each nation is divided into regions, in which there are a standard set of sectors (the new United Nations System of National Accounts uses 40 sectors), which are fully coupled, like a neural net. Actual economic data may be used to set the parameters in the dynamical model for each sector of each region, and the parameters of the coupling, as in input/output matrix models. In the models referred to, the standard sector model is a two-dimensional discrete dynamical system, with variables labor and capital, or value-added and investment.

We may distinguish two different levels of economic modeling: detailed models and reduced models. The modeling strategy developed by Jay Forrester is exemplary of the detailed approach [14]. The actual dynamics of each sector (or possibly, each factory, bank, or service unit) is modeled in the input/output style of system dynamics.

In the reduced modeling strategy, only the aggregate financial records of the sectors (or perhaps, smaller economic units) appear in the model. The economic CDS model described above is of this second type. The greater region is divided into smaller regions, for which economic records are available. And each smaller region is divided into sectors, that is, different types of economic activity. For example, the greater region of Italy is divided into North and South Italy, or into a larger number of provinces. In each smaller region, there are sectors such as industry, banking, government, and so on. For each sector of each region, there is a node of the CDS model, and thus, a discrete dynamical system. In this example, the state variables of each node might be capital and labor, or value and investment.

The basic data of a CDS model comprise a directed graph, or network, a dynamical system at each *node*, and an explicit coupling (output-to-input) function at each directed edge, or *link*. In the example above, we have a polynomial map at each node, in which the coefficients depend on the state variables at all of the other nodes. This is a cellular dynamical system, somewhat like a neural net.

4 The PLP model

In place of the geographic regions and economic sectors of the economic model, we now have geographic regions of electrical power, and classes of power consumers, such as transportation, industry, etc. The consumer nodes of the economic model correspond almost exactly to the consumer nodes in the electrical power model, except that we now have a special class of nodes in the electrical context, namely generators, which primarily supply power.

In the place of the state variables such as capital and labor in the economic model, we will now have electrical power consumption as the (single) state variable at each node of the electrical power model. Thus, the state variables of the CDS model would provide precise information on the space-time distribution of power demand in the full power grid.

We may try to construct a discrete dynamical model for the power demand from data on record. Chaos theory suggests that this sort of direct model may succeed, if the power demand of a given sector, for the next time interval, is modeled by a function of the demand in the present time interval, and possibly, the demand of the preceding time interval as well. Of course, exogenous parameters, such as temperature and holidays, must be included. We now propose such a strategy.

Suppose that daily records of peak power load for each sector are available, as well as some exogenous variables, such as the average temperature, number of people on holidays, etc. Following the modeling methods of [19] we construct, for each sector, a discrete dynamical system of the form:

$$x' = p(x)$$

where x denotes the peak load of the sector in a given day, and x' denotes the peak load of the following day. The function p might be a polynomial, its coefficients to be determined so as to minimize the difference between the prediction of the model and the actual peak load data. Polynomials of degree one (linear), two (quadratic), and three (cubic) all have interesting dynamical behavior, when coupled in a CDS network with nonlinear coupling functions. A net of linear nodes (continuous dynamics) with sigmoid coupling functions may have chaotic behavior, see [5]. A net of quadratic nodes with linear coupling also has complicated dynamical beharior, see [3]. And a net of cubic nodes with linear coupling functions is even more complex, see [4].

The method of least squares may be used to fit the coefficients to the available data. These local dynamical systems relate each day's peak load to the previous day's peak load, without consideration of the exogenous factors, or the peak loads at the other sectors.

The coupling functions must now relate the coefficients of the polynomial of a given node to the values of the peak load at other nodes, and to the ambient variables such as local temperature. Strategies for determining these coupling functions are a fine art, and pose the main difficulty of this modeling strategy.

5 An example

As an example, we now consider the Kansai region of Japan. Considering the actual power grid, the second largest in Japan, we may divide the power system into 165 generating stations and 9 local load dispatching centers. This system is treated as a simple network of sources and loads. The sources, being controlled by the central load dispatching center of the power company, are regarded as control parameters in the CDS model for the 9 loads. The loads (that is, demands by power consumers) comprise the state variables for simulation in the model.

We further divide each local center, regarded as an ensemble of consumers, into six sectors or types: residential, commercial, industrial, agriculture, municipal, and transportation, following [12, p. 15]. Alternatively, a classification in three types (residential, commercial, industrial) might be used, following [7, p. 74]. The most useful classification scheme for consumers will depend on the data available from the local electrical utility companies, in this case, the Kansai Electric Power Company.

Our purpose in this classification is to distinguish different types of coupling to exogenous parameters, such as: average daily temperature, humidity, cloudiness or light intensity, wind, population dynamics, and social events, as well as different shapes of load curves, used as templates in the model, which are to be derived from data.

We now have a complex dynamical scheme with $6*9 = 54$ nodes, and at each node we will place a discrete dynamical scheme coupled to neighboring nodes, and to the exogenous parameters. In this model, we will use a one-dimensional map at each node, representing the increment of total power demand by the consumer sector represented by that node. The discrete time interval is a single day.

6 The dynamics

Taking an average from available data, we may obtain an exemplary daily load curve for node (i, j) for each i and j (the i-th sector of local center j) for each day of the week of a given season, and use this as a baseline for computation. Then, we may use the difference from this baseline as the primary state variable in our model. Thus at each node (i, j) we have a one-dimensional state, $x(i, j)$, at each time step. Our discrete dynamical model is generated by a one-dimensional map with parameters, which are used to fit the model to the historical data, and to describe the coupling to the exogenous factors listed above. We now propose, as a trial based upon the economic model described above, a quadratic map. Thus:

$$x' = a + bx + cx^2$$

in which the three coefficients are to be fit to data at each node. By eliminating the quadratic term, or $c = 0$, we would obtain the linear model traditionally used by power engineers in the field, but we will not make this restriction. The incorporation of exogeneous factors will be restricted to the constant term. Thus (following [12, p. 12])

$$a = W + C + E + P$$

where W denotes the weather factors, C denotes the increment due to social events (festivals, sports, etc.) and (following [7, p. 76]) E accounts for economic factors, from indicators such as the gross national product, while P reflects population growth. For example, Dhar suggests a parabolic model, the weather-load model, for W as a function of temperature, its shape determined by a least-squares fit of local data. The factors C, E and P must be determined similarly. Note that all of these exogenous factors may be estimated with existing dynamical models, so our CDS model may be embedded in a network of other CDS models. And of course, the influence of these factors upon the power grid is matched by a reciprocal influence of power consumption on the climate, economy, etc.

The coefficients b and c are to be determined by least squares fit of available data, within each node (that is, in each sector of each local center). We note that this model is complex and massively parallel, comprising a lattice of logistic functions with potentially chaotic time-series behavior. Models of this type have recently emerged in econometrics, where similar prediction problems are encountered [19]. An experimental study of logistic lattices may be found in [3]. See [2] for a similar example with two-dimensional quadratic functions at each node.

Of course, our model aspires to be useful in the day-to-day management of a large power system. But it is a massively parallel model, of the kind usually submitted to a supercomputer for batch processing. However, we now envisage the availability of massively parallel analog computers on a chip, such as Chua's Cellular Neural Net [11].

7 Conclusion

We have completed our proposal for a CDS model for the PLP, a strategy for modeling the "power economy" with a CDS model, similar to recent models for the "money economy."

What remains to be done is a test of concept in the field, that is, with real, daily, peak load data. With only moderate success, comparable to that attained by the similar CDS model for the economy of Italy, some number of power grid overload problems may be averted. Further, the way would then be open for more extensive models in which environment, economy, and electric power system may be combined in a single global model.

We also envision an experimental study of the chaotic dynamics and bifurcations of small discrete CDS networks, similar to the studies of continuous CDS networks to which we have referred above.

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