Short-Term Load Forecasting

GEORGE GROSS, SENIOR MEMBER, IEEE, AND FRANCISCO D. GALIANA, SENIOR MEMBER, IEEE

Invited Paper

This paper discusses the state of the art in short-term load forecasting (STLF), that is, the prediction of the system load over an interval ranging from one hour to one week. The paper reviews the important role of STLF in the on-line scheduling and security functions of an energy management system (EMS). It then discusses the nature of the load and the different factors influencing its behavior. A detailed classification of the types of load modeling and forecasting techniques is presented. Whenever appropriate, the classification is accompanied by recommendations and by references to the literature which support or expand the discussion. The paper also presents a lengthy discussion of practical aspects for the development and usage of STLF models and packages. The annotated bibliography offers a representative selection of the principal publications in the STLF area.

INTRODUCTION

The close tracking of the system load by the system generation at all times is a basic requirement in the operation of power systems. For economically efficient operation and for effective control, this must be accomplished over a broad spectrum of time intervals. In the range of seconds, when load variations are small and random, the automatic generation control (AGC) function ensures that the on-line generation matches the load. For the time scale of minutes, when larger load variations are possible, the economic dispatch function is used to ensure that the load matching is economically allocated among the committed generation sources. For periods of hours and days, still wider variations in the load occur. Meeting the load over this time frame entails the start-up or shutdown of entire generating units or the interchange of power with neighboring systems. This is determined by a number of generation control functions such as hydro scheduling, unit commitment, hydro-thermal coordination, and interchange evaluation. Over the time range of weeks, when very wide swings in the load are present, functions such as fuel, hydro, and maintenance scheduling are performed to ensure that the load can be met economically with the installed resource mix. In addition, to ensure the secure operation of the power system at some future time requires the study of its behavior under a variety of postulated contingency conditions by the off-line network analysis functions. All these functions have in common the need to know the system load. In the real-time environment, state estimators are used to validate telemetered measurements from which the estimated values of the voltage magnitude and angle at each bus are determined. These values may be used to compute estimates for the instantaneous load. Procedures for very-short-term load prediction are embedded in the AGC and economic dispatch functions with lead times of the order of seconds and minutes, respectively. The load information for the hydro scheduling, unit commitment, hydro-thermal coordination, and the interchange evaluation functions is obtained from the short-term load forecasting system. The fuel and hydro allocation and maintenance scheduling functions require load forecasts for periods longer than one week. These load predictions are obtained from operational planning forecasting systems with lead times as long as one to two years.

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G. Gross is with Pacific Gas & Electric Co., San Francisco, CA 94106, USA.
F. D. Galiana is with the Department of Electrical Engineering, McGill University, Montreal, Que., Canada H3A 2A7.
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Definition and Scope

This paper is concerned with the area of short-term load forecasting (STLF) in power system operations. Throughout the paper, we use the term "short" to imply prediction times of the order of hours. The time boundaries are from the next hour, or possibly half-hour, up to 168 h. The basic quantity of interest in STLF is, typically, the hourly integrated total system load. In addition to the prediction of the hourly values of the system load, an STLF is also concerned with the forecasting of

- the daily peak system load
- the values of system load at certain times of the day
- the hourly or half-hourly values of system energy
- the daily and weekly system energy.

In this paper, we include under the scope of STLF the prediction of the hourly or half-hourly load up to 168 h as well as any and all of these quantities (for those systems where the basic quantity is the half-hourly system load, the forecasting is done on a half-hourly basis).

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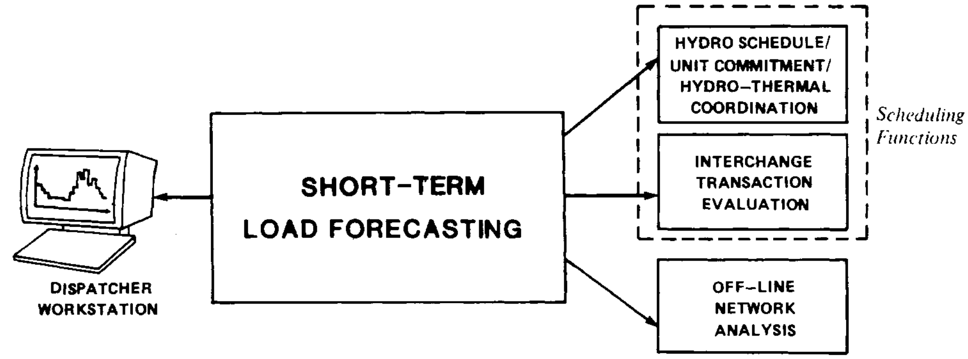

Fig. 1. Major uses of the short-term load forecasting function are to provide dispatcher information and to be primary inputs to the scheduling functions and off-line security analysis.

The Importance of STLF

STLF plays a key role in the formulation of economic, reliable, and secure operating strategies for the power system. The principal objective of the STLF function is to provide the load predictions for

- the basic generation scheduling functions
- assessing the security of the power system at any time point
- timely dispatcher information.

The primary application of the STLF function is to drive the scheduling functions that determine the most economic commitment of generation sources consistent with reliability requirements, operational constraints and policies, and physical, environmental, and equipment limitations. For purely hydro systems, the load forecasts are required for the *hydro scheduling* function to determine the optimal releases from the reservoirs and generation levels in the power houses. For purely thermal systems, the load forecasts are needed by the *unit commitment* function to determine the minimal cost hourly strategies for the start-up and shutdown of units to supply the forecast load. For mixed hydro and thermal systems, the load forecasts are required by the *hydro-thermal coordination* function to schedule the hourly operation of the various resources so as to minimize production costs. The hydro schedule/unit commitment/hydro-thermal coordination function requires system load forecasts for the next day or the next week to determine the least cost operating plans subject to the various constraints imposed on system operation. A closely associated scheduling task is the scheduling and contracting of interchange transactions by the *interchange evaluation* function. For this function, the short-term load forecasts are also used to determine the economic levels of interchange with other utilities.

A second application of STLF is for predictive assessment of the *power system security*. The system load forecast is an essential data requirement of the off-line network analysis function for the detection of future conditions under which the power system may be vulnerable. This information permits the dispatchers to prepare the necessary corrective actions (e.g., bringing peaking units on line, load shedding, power purchases, switching operations) to operate the power systems securely.

The third application of STLF is to provide system dispatchers with *timely* information, i.e., the most recent load forecast, with the latest weather prediction and random behavior taken into account. The dispatchers need this information to operate the system economically and reliably. Fig. 1 summarizes the major applications of STLF.

STLF within the EMS

The manual forecasting previously performed by the system dispatchers has been replaced by STLF software packages in the modern energy management system (EMS). The major components of an STLF system are the STLF model, the data sources, and the man–machine interface (MMI). The STLF model implements the system load representation and the STLF algorithms. The data sources are the historical load and weather databases, the parameter database, the manually entered data by the dispatchers, and the real-time data obtained from the AGC function of the EMS and the data link to a weather forecasting service. Fig. 2 illustrates the data inputs to the STLF function. The manually entered data may include weather updates, load forecast parameter data, or execution commands. In general, the STLF models use integrated load (MWh) data. The telemetered measurements in the real-time database are used by the AGC to determine the "measured" loads which are, typically, integrated (and consequently smoothed) before they are used by the STLF model. The outputs of the STLF are provided to the dispatcher workstations and the other EMS functions that require the load forecasts (see Fig. 1).

The timeliness and accuracy of short-term load forecasts have significant effects on power system operations and production costs. System dispatchers must anticipate the system load patterns so as to have sufficient generation to satisfy the demand. At the same time, sufficient levels of spinning reserve and standby reserve are required to mitigate the impacts of the uncertainty inherent in the forecasts and in the availability of generating units. The cost of reserves is high since the units that make up the reserves are not fully loaded and consequently may be operating at less than their maximum efficiencies. The spinning and standby reserve capacities are set at levels dictated by the desired measure of security and reliability for the power system operation. Thus by reducing the forecast error, reserve levels may be reduced without affecting the reli-

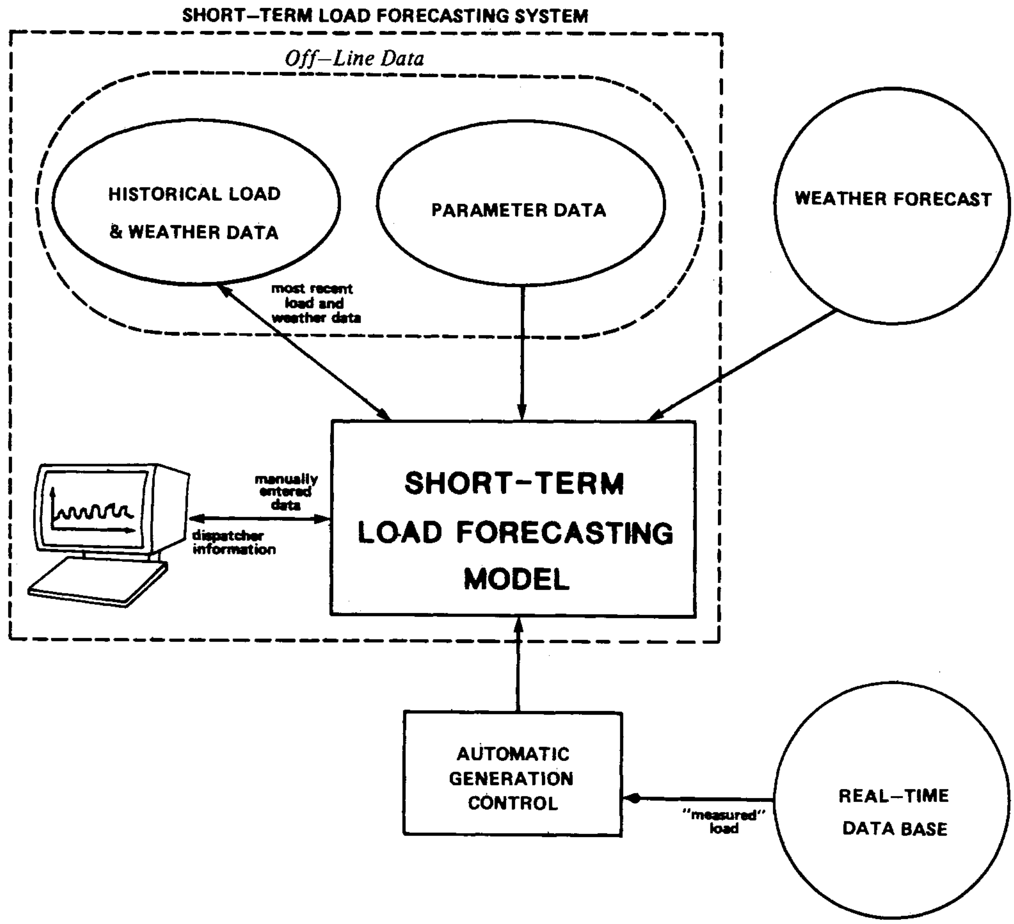

Fig. 2. Input data sources for the short-term load forecasting model.

ability and security of the system. In this way, the operating costs are reduced.

In addition, forecast error in load predictions results in increased operating costs. Underprediction of load results in a failure to provide the necessary reserves which, in turn, translates to higher costs due to the use of the expensive peaking units. Overprediction of load, on the other hand, involves the start-up of too many units resulting in an unnecessary increase in reserves and hence operating costs. In the year 1985, for the predominantly thermal British power system, it was estimated that a 1-percent increase in the forecasting error was associated with an increase in operating costs of 10 million pounds per year [10].

Forecasting Models and Techniques

The technical literature displays a wide range of methodologies and models for STLF. Since no two utilities are identical, there is limited portability of an STLF model from one utility to another. On the other hand, the wide spectrum of techniques—standard algorithms tailored to the particularities of a specific system or new procedures developed for STLF—appearing in the literature has a much broader capability to be portable from one utility to another. This paper reviews a representative sample of STLF models and techniques.

There are allied forecasting functions such as area load and bus load forecasting. Both are concerned with the further disaggregation of the system load. For utilities with a wide range of geographical zones or structural subunits with climatic diversity, usually called areas, the area load forecasting function provides the forecast of the total area load. These area short-term forecasts are required for the regulation of flows on tie lines between the areas, for area generation scheduling, and for bus load forecasting functions. The bus load forecasting provides predictions of the loads at key buses through the allocation of the system or area load forecast. The bus load forecasts are required for security analysis in both on-line and off-line modes. The area and bus load forecasting functions are not considered here because the focus of the present paper is purely on the short-term system load. One must keep in mind, however, that many of the STLF methodologies discussed here are applicable just as well to bus or area loads as to the system load.

Outline of Paper

The objective of the paper is to provide a general overview of the STLF area and to offer a representative view of the state of the art. There are five additional sections in this paper. In the next section, we discuss the nature of the system load. The focus is on the principal effects that must be considered in an STLF model. This is followed by a discussion of the various STLF models and forecasting procedures in the literature based on a classification according to the nature of the model, data and computational needs, and the forecasting requirements. The next section is devoted to a discussion of the practical considerations in the implementation and use of an STLF system in a control center environment. The Conclusions section outlines some possible future directions in the STLF area. The references cited throughout the paper form part of a bibliography annotated by a number of key STLF features. This is not a comprehensive bibliography and we apologize to any authors whose works are not included or have been misinterpreted. The bibliography does, nevertheless, offer a reasonable cross section of the present state of the art of STLF, including a number of recent publications which complement the present paper.

The System Load

The system load is the sum of all the individual demands at all the nodes of the power system. In principle, one could determine the system load pattern if each individual consumption pattern were known. However, the demand or usage pattern of an individual load (device) or customer is quite random and highly unpredictable. Also, there is a very broad diversity of individual usage patterns in a typical utility. These factors make it impossible to predict the system demand levels by extrapolating the estimated individual usage patterns. Fortunately, however, the totality of the individual loads results in a distinct consumption pattern which can be statistically predicted.

The system load behavior is influenced by a number of factors. We classify these factors into four major categories

- economic
- time
- weather
- random effects.

To model the system load, one needs to understand the impact of each class of factors on the electricity consumption patterns. We, next, briefly discuss the effects of each class.

Economic Factors

The economic environment in which the utility operates has a clear effect on the electric demand consumption patterns. Factors, such as the service area demographics, levels of industrial activity, changes in the farming sector, the nature and level of penetration/saturation of the appliance population, developments in the regulatory climate and, more generally, economic trends have significant impacts on the system load growth/decline trend. In addition, utility-initiated programs, such as changes in rate design and demand management programs, also influence the load. Typically, these economic factors operate with considerably longer time constants than one week. It is important to account for these factors in the updating of forecasting models from one year to the next or possibly from one season to another. The economic factors are not, however, explicitly represented in the short-term load forecasting models because of the longer time scales associated with them.

Time Factors

Three principal time factors—seasonal effects, weekly-daily cycle, and legal and religious holidays—play an important role in influencing load patterns. The seasonal changes determine whether a utility is summer or winter peaking. Certain changes in the load pattern occur gradually in response to seasonal variations such as the number of daylight hours and the changes in temperature. On the other hand, there are seasonal events which bring about abrupt but important structural modifications in the electricity consumption pattern. These are the shifts to and from Daylight Savings Time, changes in the rate structure (time-of-day or seasonal demand), start of the school year, and significant reductions of activities during vacation periods (e.g., Christmas–New Year period).

The weekly-daily periodicity of the load is a consequence of the work-rest pattern of the service area population. There are well-defined load patterns for "typical" seasonal weeks. Fig. 3 gives examples of typical weekly summer and winter load patterns for a summer peaking utility.

The existence of statutory and religious holidays has the general effect of significantly lowering the load values to levels well below "normal." Moreover, on days preceding or following holidays, modifications in the electricity usage pattern are observed due to the tendency of creating "long weekends."

Weather Factors

Meteorological conditions are responsible for significant variations in the load pattern. This is true because most utilities have large components of weather-sensitive load, such as those due to space heating, air conditioning, and agricultural irrigation.

In many systems, temperature is the most important weather variable in terms of its effects on the load. For any given day, the deviation of the temperature variable from

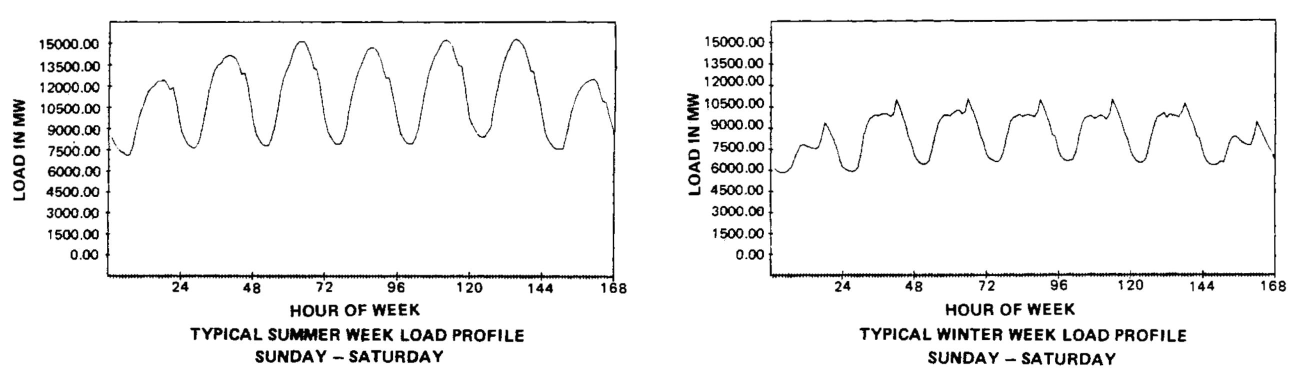

Fig. 3. Typical weekly load patterns for a summer peaking utility.

a normal value may cause such significant load changes as to require major modifications in the unit commitment pattern. Moreover, past temperatures also affect the load profile. For example, a string of high-temperature days may result in such heat buildup throughout the system as to create a new system peak. For a system with a nonuniform geography and climate, several temperature variables or several areas may need to be considered to account for variations in the system load. Humidity is a factor that may affect the system load in a manner similar to temperature, particularly in hot and humid areas. Thunderstorms also have a strong effect on the load due to the change in temperature that they induce. Other factors that impact on load behavior are wind speed, precipitation, and cloud cover/light intensity.

Random Disturbances

We group under this classification a variety of random events causing variations in the load pattern that cannot be explained in terms of the previously discussed factors. A power system is continuously subject to random disturbances reflecting the fact that the system load is a composite of a large number of diverse individual demands. In addition to a large number of very small disturbances, there are large loads—steel mills, synchrotrons, wind tunnels—whose operation can cause large variations in electricity usage. Since the hours of operation of these large devices are usually unknown to utility dispatchers, they represent large unpredictable disturbances. There are also certain events such as widespread strikes, shutdown of industrial facilities, and special television programs whose occurrence is known *a priori*, but whose effect on the load is uncertain.

Classification of the Literature

The classification of the references that follow is done with the objective of facilitating the task of the reader faced with a study or survey in the area of STLF. As can be seen from the bibliography the number of papers available in the literature is large. However, few fundamental differences exist within this group. Furthermore, because of the nature of the problem, it is difficult to judge from the available information whether any single modeling and forecasting technique stands out above the others. The reason for this is the nature of the power demand in a large utility. As described in the previous section, the system load is a random nonstationary process composed of thousands of individual components each of which behaves erratically without following any known physical law. As a result, all macroscopic models are empirical in nature and can only be objectively evaluated through extensive experimental evidence. It is our view that the best test for a load forecasting scheme is its performance in the actual control center environment over a period of time of at least two years. Only then can one evaluate the ability of the model to perform well throughout the seasonal variations, to track correctly parameter variations, to handle effectively bad or anomalous data, and to interact well with the operator. Unfortunately, if we exclude the classical operator-based load forecasting systems, only a few techniques have been implemented in a real operational enviroment, or even, for that matter, tested with real data.

The classification of the bibliography is, therefore, based on a number of significant features such as the type of load model, the data needs of the model, the computational requirements of the model and the forecasting algorithm, and the availability of experimental results. The potential user of a load forecasting scheme will have to weigh these various features and use some judgement based on the needs and types of resources available. A selected number of pertinent papers are identified under each category so that the reader does not have to wade through all available publications. Each one of the references in the bibliography contains key(s) identifying its principal features.

The reader is also referred to some of the recent survey papers in the area of short-term load forecasting [3], [10], [23], [39], [48], [53] for further classification and interpretation of the state of the field.

The classification of the literature in STLF that follows is based on the type of load model used. Some important aspects such as data needs, computational requirements, and experimental results are discussed for each load model type. The classification considers two basic models: *peak load* and *load shape* models. The peak load models are basically of a single type. We have categorized the load shape models into two basic classes each with it subtypes, namely:

1) Time of day
   - summation of explicit time functions models
   - spectral decomposition models.
2) Dynamic
   - ARMA models
   - state-space models.

We next discuss each model type in detail.

Peak Load Models

Here, only the daily or weekly peak load is modeled, usually as a function of the weather. Time does not play a role in such models which are typically of the form:

$$\text{peak load} = \text{base load} + \text{weather-dependent component} \tag{1}$$

or

$$P = B + F(W) \tag{2}$$

where the base load B is an average weather-insensitive load component to which the weather-dependent component $F(W)$ is added. The weather variables W can include the temperature at the peak load time or a combination of predicted and historical temperatures. Humidity, light intensity, wind speed, and precipitation have also been considered in such models. The function $F(\cdot)$ is empirically computed and it can be linear or nonlinear. Examples of peak load models can be found in [6], [58], [63], [69], [70].

The advantages of a peak load model are its structural simplicity and its relatively low data requirements to initialize and to update. The parameters of the model are estimated through linear or nonlinear regression. The disadvantages of such models are that they do not define the time at which the peak occurs, nor do they provide any information about the shape of the load curve. Since the models are essentially static, dynamic phenomena such as correlation across the periods cannot be forecast.

Load Shape Models

Such models describe the load as a discrete time series (process) over the forecast interval. The load sampling time interval is typically one hour or one-half hour, while the quantity measured is generally the energy consumed over the sampling interval in MWh. Many load forecasting techniques describe the load shape since this also includes the peak load. However, since the peak load is difficult to forecast with great accuracy, combined load shape and specialized peak load models may still be desirable [6].

Basically, there exist two types of load shape models: *time-of-day* and *dynamic* models. Combinations of these two basic types are also possible.

Time-of-Day Models: The time-of-day model defines the load $z(t)$ at each discrete sampling time t of the forecast period of duration T by a time series

$$\{z(t),\ t = 1, 2, \cdots, T\}. \tag{3}$$

In its simplest form, the time-of-day model stores T load values based on previously observed load behavior. Some utilities today still use the previous week's actual load pattern as a model to predict the present week's load. Alternatively, a set of curves is stored for typical weeks of the year, and for typical weather conditions, such as wet, dry, cloudy, or windy days, which are heuristically combined with the most recent weekly load pattern to develop the forecast. Operator judgment determines the final forecast in such cases and explicit mathematical formulas are inappropriate to describe the modeling mechanism. This may be a potential area of application for an expert system which would emulate the rules followed by the operator [2]. Not much literature on this heuristic modeling approach exists; however, some related work based on cluster analysis and pattern recognition can be found in [18], [25], [28], [52].

A more common time-of-day model takes the form

$$z(t) = \sum_{i=1}^{N} \alpha_i f_i(t) + v(t), \qquad t \in \tau \tag{4}$$

where the load at time t, $z(t)$, is considered to be the sum of a finite number of explicit time functions $f_i(t)$, usually sinusoids with a period of 24 or 168 h, depending on the forecasting lead time. The coefficients α_i are treated as slowly time-varying constants, while $v(t)$ represents the modeling error, assumed to be white random noise. The model is assumed to be valid over a range of time interval τ covering the recent past, the present, and a future time period covering the maximum lead time.

When the $f_i(\cdot)$ are *a priori* selected to be explicit time functions such as sinusoids, the parameters α_i are estimated through a simple linear regression or exponential smoothing analysis applied to a set of past load observations $\{z(t), t \in \tau_{\text{past}}\}$ where τ_{past} is an interval of time from the recent past [59]. Examples of such models can be found in [17], [46], [49], [51], [57], [62], [64]. The advantages of these models are that they are structurally quite simple, and that the model parameters can be updated very simply through linear regression or linear exponential smoothing. The nature of these schemes is such that *recursive* algorithms requiring a relatively low computational effort can be devised to update the parameters, as well as the forecast, as new load data are measured. On the negative side, time-of-day models do not accurately represent the stochastically correlated nature of the load process, or its relation to weather variables. As a result, when weather patterns are changing rapidly, the coefficients α_i are not appropriate, except for a short time interval into the future. This will, in turn, cause accuracy problems for longer lead time predictions.

There exists a second class of time-of-day models, that is those based on *spectral decomposition*. The model has basically the form of (4), however, here the time functions $f_i(\cdot)$ represent the eigenfunctions corresponding to the autocorrelation function of the load time series (after removal of trends and periodicities). This method is based on the Karhunen–Loève spectral decomposition expansion [43], [71]. It has the advantage that the time functions chosen to represent the load time series are optimal in the sense that they can more closely approximate its autocorrelation function, that is, its second-order probabilistic behavior. As such, the summation of time functions in this method can represent stationary colored random loads with greater precision than with arbitrarily selected time functions. Although the coefficients α_i are estimated using linear regression techniques, the identification of the eigenfunctions $f_i(\cdot)$ requires an approximation of the process autocorrelation matrix, and the solution of the corresponding eigenvalue problem. This identification step is not as well suited for a real-time recursive algorithm because of its more intensive computational nature; however, if the process is almost stationary, the identification part is required at only infrequent intervals. This technique is also susceptible to errors under conditions of sudden and large weather variations, since these effects are not explicitly modeled. Although the spectral decomposition model is theoretically sounder than other time-of-day models, its practical advantage does not appear to have been clearly demonstrated. As a result, only a few utilities seem to rely on such a method [12], [42], [68].

Dynamic Models: Dynamic load models recognize the fact that the load is not only a function of the time of day, but also of its most recent behavior, as well as that of weather and random inputs. Dynamic models are of two basic types, *autoregressive moving average* or *ARMA* models and *state-space* models.

ARMA models: The ARMA-type model takes the general form

$$z(t) = y_p(t) + y(t) \tag{5}$$

where $y_p(t)$ is a component which depends primarily on the time of day and on the *normal* weather pattern for the particular day. This component can be represented by a *periodic* time function of the type given by (4). The term $y(t)$ is an additive load residual term describing influences due to weather pattern deviations from normal and random correlation effects. The additive nature of the residual load is justified by the fact that such effects are usually small compared to the time-of-day component. Nonlinear models describing the interaction of the periodic and residual components also exist, but are less common [11]. The residual term $y(t)$ can be modeled by an ARMA process of the form

$$y(t) = \sum_{i=1}^{n} a_i y(t-i) + \sum_{k=1}^{n_u} \sum_{j_k=0}^{m_k} b_{j_k} u_k(t-j_k) + \sum_{h=1}^{H} c_h w(t-h) \tag{6}$$

where $u_k(t)$, $k = 1, 2, \cdots, n_u$ represent the n_u weather-dependent inputs. The impact of the weather-dependent variables is considered to be significant. These inputs are functions of the deviations from the normal levels for a given hour of the day of quantities such as temperature, humidity, light intensity, and precipitation. The inputs $u_k(t)$ may also represent deviations of weather effects measured in different areas of the system. The process $w(t)$ is a zero-mean white random process representing the uncertain effects and random load behavior. The parameters a_i, b_{j_k}, and c_h, as well as the model order parameters n, n_u, m_k, and H are assumed to be constant but unknown parameters to be identified by fitting the simulated model data to observed load and weather data.

The literature presents a number of variations of the basic model described by (5) and (6). The various names encountered are *Box-Jenkins*, *time series*, *transfer function*, *stochastic*, *ARMA*, and *ARIMA*. Since there exists only a slight difference among these terms, we prefer here to take a unifying approach and concentrate on the common characteristics of these models. Accordingly, we shall refer to all these types of models as ARMA models. The reader is referred to the textbook [66] for a detailed description of ARMA models.

Some authors [13], [14], [44], [56] have chosen to explicitly represent the periodic load component as in (5), while others [8], [16], [19]–[21], [27], [30], [37], [38], [47], [60] have pre-filtered the load data so as to eliminate the periodic component as an explicit time series. The pre-filtering is basically done by defining a new load process of the form

$$z'(t) = z(t) - z(t - t_p) \tag{7}$$

where t_p is the period of the time-of-day component (usually 24 or 168 h). The resulting process $z'(t)$ is, therefore, free of periodic terms, and satisfies an ARMA equation similar to that of (6). This now has the advantage that more standard techniques can be applied to the identification of the parameters of the resulting ARMA model [37], [60], [66]. The disadvantage of pre-filtering lies in the fact that such a scheme is basically equivalent to differentiating a process which almost certainly contains measurement and modeling errors. The result is a potential amplification of measurement errors leading to corresponding modeling inaccuracies. Explicit modeling of the time-of-day component, on the other hand, does not require pre-filtering and is, therefore, not subject to this type of pre-filtering errors. However, for such models, a nonlinear parameter estimation scheme must be used to identify the model parameters. This results in a slight increase in computational effort in the parameter estimation step. The existence of constant biases or time-varying trends in the load model can also be handled by appropriate pre-filtering [19], or by its explicit representation in the time-of-day component through a polynomial in time.

Only some ARMA models include *weather* as an input (refer to those references in the Bibliography with the keys ARMA and W). Those that do not include weather, automatically update some parameters to take into account the effect of meteorological variations on the load. This approach is, however, not satisfactory during rapidly changing climatic conditions under which the assumption that the load process is stationary is no longer satisfied. In many recent STLF models, weather is explicitly accounted for. Some of the available ARMA models describe meteorological effects by additional explicit inputs as in (6) [8], [14], [19], [21], [56], while others rely on a more heuristic approach where the load process is "corrected" for temperature influences before applying an ARMA model to the corrected load [16]. The most important weather input is based on the temperature deviations, and is usually expressed as a nonlinear function of the differences between the actual and the "normal" temperatures. Such functions take into account the varying effects of temperature on load during the different seasons, deadbands, and other nonlinearities. The models relating actual weather effects and the inputs to the ARMA model are, primarily, empirically derived and vary from system to system (see the references cited in this paragraph). Certain nonlinear effects are, however, well known. Thus in the summer most systems experience higher loads due to increasing temperature, with the inverse phenomenon taking place in the winter. It is also reasonable to hypothesize that it is not the absolute value of the weather variable which affects the load, but its deviation from some "normal" level for that particular hour of the day, and for that specific day of the year. The time-of-day or periodic component will take care of the long-term seasonal effect of weather on the power consumption.

The identification of the parameters of an ARMA model is generally more computationally intensive than those of the time-of-day models; however, this extra effort is needed in order to obtain a more robust model that incorporates dynamic, weather, and random effects. In the long run, less parameter tuning is required and better forecasting performance is obtained. In any case, because of the low frequency of parameter identification (once a day), the computational burden on the EMS computers is not a major factor for the techniques being discussed here. The parameter identification for a general ARMA model can be done by a recursive scheme involving the solution of the *Yule-Walker* equations [8], [60], or using a *maximum-likelihood* approach [44], which is basically a nonlinear regression algorithm. The tunable coefficients of some forms of ARMA models are identifiable through linear regression techniques. These include those models which are AR (autoregressive) in $y(t)$ and MA (moving average) in the $u_k(t)$, but are not MA in the random input $w(t)$. Models which explicitly describe the time-of-day component generally require the application of *nonlinear regression* methods to simultaneously identify the dynamic model and the periodic component parameters [56]. One can avoid having to use nonlinear regression by leaving out the AR part of the model [14]. However, then, one loses the capability of modeling the short-term random correlation of the load. The readers are also referred to a number of excellent references which describe the above mentioned parameter identification techniques in great detail [22], [50], [59], [65].

In general, the updating of model parameters is not a very computationally demanding task, even in cases which require an iterative solution of a nonlinear estimation problem. In models where parameters may be estimated using linear regression, the parameter updating may be performed recursively on-line as new load and weather data are acquired. Such frequent parameter updating is unnecessary, unless the model is very simple, such as a pure time-of-day model, which requires continuous updating. For more elaborate model types, such as ARMA, the model structure and its parameters remain unchanged over a period of a few days. The updating of these parameters on an hourly basis may, in fact, be undesirable, particularly during periods of anomalous load behavior. In such instances, the model parameters should definitely not be updated. For ARMA models, daily parameter updating is probably sufficient. In this case, the data from the previous 24 h, after "cleaning" their anomalous behavior, are added to the data set and the oldest 24 h of data are removed. Daily parameter updating is not a critical task and can be done at a time when the computer is least busy.

State-space models: It is well known that an ARMA model can be converted into a state-space model and *vice versa* [22], so that conceptually there exist no fundamental differences between the two types of models. However, a number of state-space load models have been proposed in the literature which add a degree of structure not always present in the typical ARMA model. In these models, the load at time t, $z(t)$, is generally given by

$$z(t) = \boldsymbol{c}^T \boldsymbol{x}(t) \tag{8}$$

where

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\,\boldsymbol{x}(t) + \boldsymbol{B}\,\boldsymbol{u}(t) + \boldsymbol{w}(t). \tag{9}$$

Here the state vector at time t is denoted by $\boldsymbol{x}(t)$, the vector of weather variable-based input is $\boldsymbol{u}(t)$, while the vector of random white noise inputs is $\boldsymbol{w}(t)$. The matrices $\boldsymbol{A}$, $\boldsymbol{B}$, and the vector $\boldsymbol{c}$ are assumed constant. There exist a number of variations of this basic state-space model. In some cases, the states $x_i(t)$, $i = 1, 2, \cdots, N_s$, may represent the periodic load component for a certain day of the week at a given hour, or a parameter of this model, or a combination of load- and weather-dependent inputs. One difference between the state-space and ARMA models lies in the fact that the available techniques for state-space models assume that the parameters defining the periodic component of load are random processes. In essence, this allows one to make use of some *a priori* information about their values (a reasonable assumption in practice) which may help in the parameter estimation step via Bayesian techniques. This *a priori* parameter information could, however, also be used in ARMA models. In some of the state-space models proposed, the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ are very sparse and known [4], [26], [55], [67], while other state-space models require the identification of the full $\boldsymbol{A}$ matrix [30], [61]. The advantages of state-space models over ARMA models are not very clear at this stage and more experimental comparisons are needed. One possible area where state-space methods may prove advantageous is in the development of bus load forecasting, where the bus loads exhibit a high degree of correlation.

Summary of the State of the Art in STLF

Of the two main STLF model types—peak load and load shape models—the latter type is the more common. Load shape models have greater flexibility and are in general more accurate. The pure time-of-day models have been almost totally replaced by dynamic models, since time-of-day models do not have the capability of accurately representing time-correlated random effects and weather influences. The two major dynamic model subtypes, ARMA and state-space, use random and weather inputs. Judging from the published literature, it appears that ARMA models are more common than state-space models, possibly because the former require fewer explanatory variables and parameters. The computational effort associated with available STLF techniques varies, but in no case is it a major consideration, as both the off-line and on-line computational requirements are modest. The major missing component in the STLF literature is reports on experience with actual data, particularly in an on-line environment. Also lacking in the literature is a comparative study of the performance of various STLF approaches applied to a standard set of benchmark systems.

Practical Considerations

In this section the reader is guided through the main steps required for the development of an STLF model and procedure, considering a number of practical constraints and requirements. Whenever possible, references are cited which provide additional information and experience. Specifically, we discuss practical aspects in model formulation and selection, forecasting algorithms, performance evaluation, and implementation.

A general *load modeling and forecasting* procedure is applicable to the STLF problem with the following steps:

i) Model *formulation* or *selection*.
ii) *Identification* or *updating* of the model parameters.
iii) Testing the model *performance* and updating the forecast.
iv) If the performance is not satisfactory return to step i) or to step ii); else, return to step iii).

The model performance should be continuously monitored; however, once a reasonable model stucture has been established, a deterioration of the model performance should be corrected first by fine tuning the model parameters through step ii). Changes in the model stucture need to be made rather infrequently once the proper model choice has been made. The model state and the load forecast are updated on an hourly or half-hourly basis.

The computer requirements associated with the short-term load forecasting function are rather modest. The fraction of time spent on the forecasting part of the EMS application software is very small, since the forecasting procedure is not computationally intensive and a relatively small number of executions are performed. Adequate disk storage must be provided for the historical load and weather data used for initialization of the forecasting model and subsequently for updating.

Dispatchers like to use forecasting packages that are easy to use and that work well paticularly at critical times. Operators are much more concerned with forecasting results at peak hours than those at off-peak hours or during holidays. The model must work accurately and reliably at such critical times.

Model Formulation and Selection

The first consideration in selecting an STLF model is the objectives of the forecast, i.e., the nature of the forecast quantities, the desired lead times, and the intended uses of the forecast. More than one model may be required to forecast the daily peak system load, the system load values at specific times of the day, the hourly (or half-hourly) system load values, and/or the weekly system energy. In certain cases, more than one model can be used to predict the same quantities with the predictions being statistically combined [61]. The use of a multiple model forecasting framework provides an effective system of checks and results in increased forecasting reliability.

For a particular model under consideration, the *common sense* test is first applied. The basic questions to be answered are as follows:

- Does the model make sense?
- Are all the factors affecting the load of the particular system explicitly or implicitly accounted for?
- Is the model physically meaningful?

These questions should receive affirmative answers before proceeding further.

An important consideration in the formulation and/or selection of appropriate forecasting models is *model parsimony*. The basic issues that come into play are:

- the number of independent or explanatory variables
- ease of forecasting and the associated uncertainty of each explanatory variable
- the number of tunable parameters.

In general, models with fewer explanatory variables and tunable parameters are preferable. Such models are easier to initialize, update, modify, and operate.

A further consideration in model formulation/selection is that of *data requirements*. The data requirements associated with various models are strongly tied to the nature of the model. In general, the models requiring a large initial data set are:

- nonlinear models
- stochastic input models involving moving average terms
- models with weather descriptors
- models with many parameters.

In contrast, models whose coefficients appear in a linear relationship, such as time-of-day models, usually require a shorter period of data for initialization and update.

A dilemma exists in the data requirements. On the one hand, it is desirable to develop as permanent a relationship as possible between the dependent and independent or explanatory variables. This necessarily requires a set of historical data covering a long period. On the other hand, there is the need for the model to be flexible enough to reflect any changes in the basic underlying process. This imposes the requirement for a short data set covering only the most recent period, so that any previous processes that may no longer be operative are excluded. This consideration may be especially relevant for the incorporation into a model of the effects of conservation efforts, in particular, and new management demand programs, in general.

The highly data-intensive models have negative impacts on their ease of use and ease of updating aspects. In general, models with lesser data requirements are preferable. For example, if the model initialization requires a database of various months, one may then question whether the model is a reasonable representation of the load, given that seasonal variations and anomalies could be significant over such a period. Databases of three to six weeks are preferable in this respect. In addition, one must keep in mind that the database must also contain information about special days of the year which have a yearly periodicity.

Some judgment is clearly involved in the *formulation* of a load model or models for a particular utility. Given the state of the field of load modeling and forecasting today, it is, however, reasonable to try to develop a model with the capabilities to describe the load shape, as well as dynamic, weather, time-of-day, and random effects. Models which describe only the peak load, or which do not explicitly model weather effects, although simpler to develop and update, do not offer the accuracy and flexibility of the more general methods. At the model formulation stage, one may narrow the choice of models to those most suitable to the needs of the user based on the type of data and computational facilities available. However, one should probably keep an open mind and experiment with a few model types, since no conclusive evidence exists indicating that any one of the available models is superior to the others. It should also be noted that most of the models can be identified and operated within acceptable computational and data requirements, so that this criterion is probably not so critical. The ultimate criterion will then be the model forecasting performance with actual data, something which is difficult to predict without experimentation.

The *initialization* phase of the STLF model requires that a database of at least two to three years of hourly load and weather data be examined. Although the parameters of the model can be tracked over the seasons to some extent, the yearly load behavior has many *special days*, or discontinuities, which occur only once a year, and must, therefore, be identified and modeled as a special term of time-of-day component (holidays, switch to Daylight Savings Time, start and end of school). In addition, before proceeding with the identification phase, the load must be examined for abnormal behavior which may be caused by events such as strikes, blackouts, election days, or special television programs. Such *abnormal behavior* must be identified and left out of the "clean" initial database. At this stage, the input of experienced load forecasting operators is essential. During the initialization phase one can also establish the need for weather inputs based on previous experience, or on simple correlation tests.

Forecasting Algorithms

The forecasting algorithms are intimately tied to the type of load model formulated. Once the load model is selected, the forecasting algorithm is, therefore, essentially determined. All forecasting schemes follow the following basic steps:

a) Substitute into the load model the estimate of the model parameters obtained from the model initialization phase or from the parameter identification/update algorithm.
b) Define the prediction lead time.
c) If weather variables are involved in the model, input their forecast values, and error estimates, if available.
d) If the model is dynamic, estimate the present system state (initial conditions for the dynamic equation (6)) using a recursive linear estimation scheme [22], [59].
e) Calculate the predicted load wih the model, the estimated parameters, the specified lead time, and, if the model so requires, the forecast weather variables, and the actual state estimate as initial condition. If the model has a white random process input, then for prediction purposes it is estimated by its mean.
f) Calculate the forecast error variance if the model allows it (dynamic stochastic model).

In the time-of-day or nondynamic models, load forecasting is then a simple matter of substituting the lead time or the pertinent weather variables into the load model equations which are parametrized by the estimated coefficients. Dynamic models, on the other hand, include difference equations, which require initial condition estimates (state estimates) to start the forward simulation, and an estimate of the future inputs, i.e., the weather forecast, to proceed with the simulation forward in time. The state is estimated by a recursive linear estimation process [22], [59]. This process updates the state using the most recent values of the load and the weather variables. Since difference equations are recursive, the load forecast at some future time can only be calculated by computing all the load forecasts between the present and that time. This forecasting requirement of dynamic models, therefore, increases the on-line computational effort over nondynamic models. The extra computation is, however, well within the power of modern control center computers.

Parameter Identification

Before applying parameter identification techniques to the "clean" database, one must account for the seasonal load variations as well as possible growth/decline trends from one year to the next. One way of handling this time variation is to pre-filter the data as in (7) with a period of one year [16], [19], thereby eliminating seasonal variations from the pre-filtered load process which is then assumed stationary. A second more common approach to handle seasonal variations assumes that the load model is slowly time-varying over the seasons. A *moving time window* of data is then used to identify the model parameters which are assumed to be constant within the moving window as well as during the future forecasting time interval. Such moving windows range from three to six weeks depending on the time of the year. In order to increase the amount of data available for identification, moving windows for the same time intervals from previous years can be combined into a larger data set.

For a discussion of the various approaches used in the parameter identification step, and a number of related references, see the previous section on model classification.

Performance Evaluation

The performance of a given short-term load forecasting system may be evaluated in terms of

- the accuracy of the model
- ease of use of the application program
- the bad/anomalous data detection and correction capabilities.

Accuracy: The evaluation of the accuracy of a model requires that the forecast error, i.e., the difference between the forecast value of the load and the "measured" (actual) value of the load, be determined at each time point of the forecasting period. It is common to measure the model accuracy statistically in terms of the standard deviation of the forecast error. Other accuracy measures, such as the maximum error or a weighted squares criterion with the heaviest weights for the peak hours and declining weights for off-peak hours, are possible but not in wide use. In practice, it is difficult to find STLF systems that have a root-mean square forecast errors of less than 2 to 3 percent of the peak load for a 24-h prediction. This may constitute a statistical limit to the goodness of fit of a model and represents, by and large, the inherent noise component of the load. One should keep in mind, however, that the actual 24-h prediction error will depend strongly on the type of load, that is its mix of residential, industrial, and commercial components, its geographical location and distribution, as well as the season of the year.

In more general terms, two principal factors—the length of the lead time and the uncertainty in the explanatory variables—act to limit the accuracy of forecasting models. As the lead time increases, the accuracy of the forecast deteriorates. Also, the greater the *number of explanatory variables* in the model, the more uncertainty is introduced in the forecast. This is particularly true when the forecast explanatory variables have a large uncertainty of their own. Furthermore, one should be aware that different forecast weather variables have different forecast accuracies. For example, it is considerably easier to forecast temperature than it is to forecast the amount of precipitation. Consequently, the use of independent variables that are difficult to forecast should be avoided so as to foreclose the possibility of generating forecasts with inherently large errors.

The comparison of the accuracy of two or more different short-term load forecasting models should be evaluated under conditions approximating as closely as possible actual operating conditions. For the comparison to be meaningful, the evaluation should be carried out over a large number of subperiods of a sufficiently long period using the forecast values of the variables. This approach permits the performance of different models to be compared on a uniform basis over a wide range of data sets.

The testing of the model performance can be systematically done by verifying that the one-step prediction errors $e(t)$ form a white process, where

$$e(t) = z(t) - \hat{z}(t/t-1) \qquad (10)$$

and where $z(t)$ is the load at time t, while the variable $\hat{z}(t/t-1)$ is the load prediction at time t given measured load and weather data up to time $t-1$. Various whiteness tests can be found [50], [59], [65]. A deterioration of the model due to parameter variations or due to anomalous load behavior can be systematically detected by the whiteness test. Depending on the type of model deterioration, the model parameters can be updated, or in the case of bad or anomalous data, such data can be discarded to obtain a clean data set. Model performance should also be tested by the ability of the algorithm to adapt to interruptions in the input data, to anomalous data, and to computer breakdowns.

Ease of Application: The implementation of the short-term load forecasting models constitutes a part of the EMS application software package. To be useful to dispatchers, the forecasting software must be *easy to use*. The program must be designed to be conducive to virtually "automatic" operation by dispatchers. Desirable features include

- direct data link to a weather forecasting service
- good man-machine interface (MMI)
- bad/anomalous data detection and correction capabilities.

These features are necessary because forecasting systems have not reached the stage where completely automated operation is possible; manual intervention and the judgment of dispatchers are still necessary. From the usability point of view, it is generally advisable to avoid models that

- require excessive data entry
- are complicated and have many coefficients which require periodic updating
- need frequent parameter tuning.

A closely associated consideration is the *ease of updating* the models. Forecasting models require updating on a periodic (seasonal or annual) basis. This is carried out off-line by the dispatchers either on the EMS computer or some other computing facility. It can be effectively accomplished if easy-to-use routines are provided as part of the software package.

Bad/Anomalous Data Handling: A critically important feature of a good short-term load forecasting package is the ability to detect and exclude bad or anomalous data and to provide replacement with corrected values. For example, every forecasting package will have some manually entered data. The dispatchers, in the course of their work, will from time to time make data entry errors. The forecasting package must be "smart" enough to detect and exclude obviously flawed manually entered data and request from the dispatchers corrected values.

A more complex issue is that of anomalous data. An underlying assumption of all short-term load forecasting models is that the load is essentially in a steady-state mode of behavior. The existence of holidays and "near holidays," however, violates this assumption. For example, the peak load on Easter Sunday will generally be considerably lower than on a "normal" Sunday at that time of the year. The load pattern of the week following Easter Sunday, on the other hand, exhibits essentially normal behavior. Clearly, the actual Easter Sunday loads will not be useful in forecasting the future loads of the following week. The forecasting package must immediately detect these *anomalous* loads and exclude them from the forecasting database so as to avoid "contamination" of the database. Moreover, the program must automatically supply corrected load values or *pseudo-loads* for use in forecasting future loads. Anomalous data are detected when the deviations of the actual load from the forecast values are large. Whiteness tests of the type discussed above offer a systematic mechanism for this detection. The anomalous data correction can easily be accomplished by replacing the actual loads by their forecast values whenever the predicted value differs from the actual one by a preset quantity. Fig. 4 displays the behavior of a short-term load forecasting model without and with anomalous data detection and correction feature. More generally, the anomalous data detection and correction capability is called on whenever the system exhibits abnormal behavior. Typical examples are system component outages (e.g., a major blackout), special events (e.g., television broadcasts of the Olympics or the World Soccer Cup), and severe weather conditions, such as thunderstorms.

Usage Issues

We next focus on a set of miscellaneous issues that arise in the actual use of short-term load forecasting procedures. The short-term load forecasting program is used in two *usage modes*:

- real-time mode
- study mode.

In the *real-time mode*, the hourly (or half-hourly) values of the load for the specified forecast period are predicted. These forecast data are used to drive the basic scheduling functions of the EMS or to provide dispatcher information. Real-time mode execution of the forecasting procedure uses the historical load and weather data files, automatically or dispatcher-entered weather forecast data, and real-time telemetered data. The 24-h forecast must be generated at least once a day. In addition, in the real-time mode, there may be frequent re-forecasting whenever weather forecasts change markedly, abnormal events occur, telemetered data indicate a significant deviation of the values of the actual load from the forecast ones, or simply to update and refine the current day's forecast based on the most recent load and weather information.

In the *study mode*, the short-term load forecasting procedure is used to produce historical loads or forecast future loads within or outside the forecast period. These load data are used for security analysis of past, current, or possible future system conditions. Execution in the study mode may call for a forecast at one time point or for the length of the forecasting period. The forecast may be initialized from real-time conditions, in which case the contents of the current real-time forecast are provided. For historical loads available in the load files, the actual loads are provided. For forecasts outside the stored period or beyond the forecast period, additional data must be input to generate the requested forecasts.

Man-Machine Interface (MMI)

The system operators interface with the short-term load forecasting through the dispatcher work station. For effective usage, the forecasting system must provide a number of user-oriented features. Typical examples include syntax and range check for flagging data entries outside specified limits and dependency checks for identifying computed quantities which deviate from the average value by more

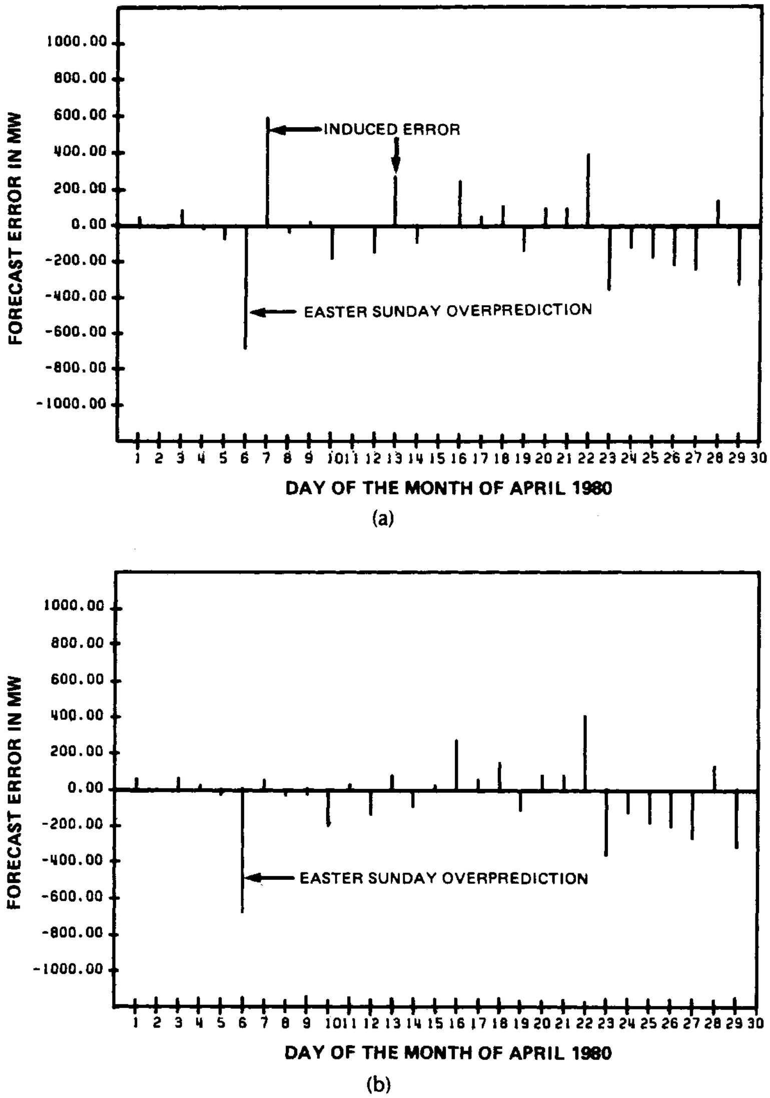

Fig. 4. The effect of anomalous data handling for forecasting the load for the month including Easter Sunday. (a) Without anomaly detection and correction. (b) With anomaly detection and correction.

than a specified amount. Well-designed CRT diplays are absolutely essential. Minimal requirements are an execution display for data entry and editing, message display, report display for presenting the real-time inputs, manually entered data, weather and load forecasts and performance statistics, and load and weather history displays.

A very useful feature is the capability to permit dispatchers to modify load forecasts prior to their use by subsequent application functions. With such a feature, dispatchers can modify an entire hourly or half-hourly load forecast or any subset thereof by simple arithmetic manipulations of addition of, subtraction of, multiplication by, and division by, a constant.

Another useful feature is an *a posteriori* error analysis capability to perform forecast error analysis after the fact. Such a capability provides a measure of the validity and goodness of the forecasts generated by the model.

Error analysis capability is particularly useful in the model formulation or selection stage. Such a feature is very helpful in the selection of the appropriate model among a number of candidate models. Typically with such a feature, the ex *post* forecasts for a specified period of the candidate models can be compared on a consistent basis by using only a part of the historical data. Good backcasting performance of a model is a strong indicator of its *ex ante* forecasting ability.

The advent of full interactive graphics brings about expanded capabilities, particularly useful for STLF in the MMI area; for example, the ability to display, using full graphics, actual and forecast load and weather data for a specified period of interest is very desirable.

Conclusions

This paper has presented a survey in the area of forecasting system load with prediction times of the order of hours and up to one week. STLF plays a key role in system operations as the principal driving element for all daily and weekly operations scheduling. The modeling of the system load and its prediction is essential for the economic and reliable performance of these functions. In addition, the load model and forecast are essential information for security analysis in both the real-time and the study modes. The survey evaluated the literature based on a classification of the state of the field according to a number of features including the type of model, the data requirements, and the parameter identification and load forecasting needs. The paper also discussed various practical considerations associated with the development of an STLF model and forecasting algorithm for use in a control center environment. The annotated bibliography constitutes a representative view of the principal publications in STLF over the last twenty years.

Because of the particular and often heuristic nature of STLF, it is not always possible to assume portability of an STLF system from one utility to another. General models and algorithms have wider applicability, but must be used cautiously and should be experimentally tested with a sufficiently lengthy data record. The detailed discussion of the advantages and drawbacks of the available STLF methodologies, the list of desirable practical features in STLF systems, and the representative annotated bibliography should help engineers in their work on specific aspects of STLF.

The STLF function provides a critically important decision tool in system operations. A good STLF system can save the utility significant sums of money by reducing the error in load predictions. Thus efforts aimed at the implementation of accurate and effective STLF are highly worthwhile. A step in the right direction is the incorporation into STLF models of meteorological effects for which better forecasts will be available in the near future. Such models will undoubtedly provide improved load predictions.

The state of the art in STLF has developed considerably over the last fifteen years. Of the many models studied and tested, the so-called dynamic models, particularly ARMA-type models, are the most popular. Such models are capable of describing time-correlated random phenomena, periodicities and trends, as well as weather effects, including heat buildup phenomena, with relatively few explanatory variables and parameters. ARMA models are relatively easily developed and updated, wih only modest computational requirements. In spite of the progress in load modeling and in load forecasting algorithms, relatively little work has been published on applications to actual load and weather data, particularly in an on-line environment over an extended period of time. More comparative work of this nature is needed. Another potentially useful area of investigation in STLF is the application of expert systems or intelligent heurisics in both the model formulation phase and in its on-line operation, particularly the problem of anomalous data detection and suppression. More work is also needed in bus and area load forecasting, and in the development of advanced MMI functions which will facilitate the input of weather data and the interaction of the operator with the STLF algorithms.

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Bibliography

Key Features in Load Forecasting Techniques

The bibliography in this survey paper is characterized by the following not mutually exclusive key features:

- PL *Peak load model.* Only the daily or weekly peak load is forecast, usually as a function of the expected weather conditions. The most recent hourly load behavior is not used by the model.
- LS *Load shape curve model.* The entire load curve is modeled over a time interval ranging from a few hours to a week.
- W *Weather-dependent model.*
- TD *Time-of-day model.* The hourly load is forecast as an explicit function of the time of day.
- DY *Dynamic model.* The load behavior is modeled as a dynamic process where the value of the load at any one time depends not only on the time of day, but on the past behavior of the load, the weather, and a random process.
- ARMA *Autoregressive moving average model.* This is a type of dynamic model where the load is modeled by an autoregressive moving average difference equation. Also known as Box-Jenkins, time series, or transfer function models.
- STA *State-space model.* A type of dynamic model described by a set of state-space difference equations.
- AD *Adaptive model.* Most time-of-day and dynamic models are also adaptive in the sense that the forecast is continuously updated as new hourly data come in.
- STO *Stochastic model.* A stochastic model provides a measure of the expected forecasting error. All techniques include this feature to some degree, however, the expected prediction error in dynamic models depends on the length of the prediction interval.
- BL *Bus load model.* The loads at individual buses are modeled.
- Q *Reactive load model.* Both the real and the reactive loads are modeled.
- PHY *Physically based model.* Model based on a microscopic analysis and modeling procedure of the various components making up the system load.
- EX *Experience with real data available.*
- RE *Real-time experience available.*
- SU *Survey paper.*
- REF *Reference textbook or journal article.*

1987

[1] M. T. Hagan and S. M. Behr, "The time series approach to short term load forecasting," paper 87 WM 044-1, presented at the IEEE Power Engineering Society Winter Meeting, New Orleans, LA, Feb. 1987. [W, DY, ARMA, AD, STO, EX]

[2] S. Rahman and R. Bhatnagar, "An expert system based algorithm for short term load forecasting," paper 87 WM 082-1, presented at the IEEE Power Engineering Society Winter Meeting, New Orleans, LA, Feb. 1987. [W, DY, ARMA, AD, STO, EX]

1986

[3] A. M. Adiata, A. B. Baker, W. D. Laing, F. Broussolle, M. Ernoult, R. Mattatia, F. Meslier, R. Anelli, and G. De Martini, "A comparison of demand prediction practices in C.E.G.B., E.D.F. and ENEL," *Bulletin de la Direction des Etudes et Recherches* (Electricite de France) ser. B, no. 3, pp. 5–20, 1986. [SU]

[4] R. Campo and P. Ruiz, "Adaptive weather-sensitive short term load forecast," paper 86 SM 305-7, presented at the IEEE Summer Power Meeting, Mexico, July 1986. [LS, W, TD, DY, ARMA, STA, AD, STO, EX]

[5] D. M. Falcao, and U. H. Bezerra, "Short-term forecasting of nodal active and reactive load in electric power systems," in *Proc. 2nd IEE Int. Conf. on Power Systems Monitoring and Control* (Durham, UK, July 1986), pp. 18–22. [LS, TD, DY, STA, AD, STO, BL, Q]

[6] T. N. Goh, H. L. Ong, and Y. O. Lee, "A new approach to statistical forecasting of daily peak power demand," *Elec. Power Syst. Res.*, vol. 10, no. 2, pp. 145–148, Mar. 1986. [PL, LS, DY, ARMA, AD, STO, BL, EX]

[7] N. J. Thadani, J. A. Findlay, M. N. Katz, B. D. Mackay, D. M. Frances, and C. T. Chan, "An integrated, hierarchical forecasting, scheduling, monitoring and dispatching system for a large hydro-thermal power system," in *Proc. IFAC Conf. on Power Systems and Power Plant Control* (Beijing, People's Rep. China, Aug. 1986), pp. 445–450. [LS, W, TD, EX, RE]

[8] S. Vemuri, B. Hoveida, and S. Mohebbi, "Short-term load forecasting based on weather load models," in *Proc. IFAC Conf. on Power Systems and Power Plant Control* (Beijing, People's Rep. China, Aug. 1986), pp. 565–570. [LS, W, DY, ARMA, AD, STO, EX, RE]

1985

[9] A. B. Baker, "Load forecasting for scheduling generation on a large interconnected system," in *Comparative Models for Electrical Load Forecasting*, D. W. Bunn and E. D. Farmer, Eds. New York, NY: Wiley, 1985, pp. 57–67. [LS, W, DY, AD, EX, RE]

[10] D. W. Bunn and E. D. Farmer, "Economical and operational context of electric load prediction," in *Comparative Models for Electrical Load Forecasting*, D. W. Bunn and E. D. Farmer, Eds. New York, NY: Wiley, 1985, pp. 3–11. [SU]

[11] D. W. Bunn and E. D. Farmer, "Review of short-term forecasting methods in the electric power industry," in *Comparative Models for Electrical Load Forecasting*, D. W. Bunn and E. D. Farmer, Eds. New York, NY: Wiley, 1985, pp. 13–30. [SU]

[12] W. D. Laing, "Time series methods for predicting the CEGB demand," in *Comparative Models for Electrical Load Forecasting*, D. W. Bunn and E. D. Farmer, Eds. New York, NY: Wiley, 1985, pp. 69–85. [LS, TD, AD, STO, EX]

[13] K. P. Rajurkar and J. L. Nissen, "Data-dependent system approach to short-term load forecasting," *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, no. 4, pp. 532–536, July/Aug. 1985. [LS, TD, DY, ARMA, AD, STO, EX]

[14] A. M. Schneider, T. Takenawa, and D. A. Schiffman, "24-hour electric utility load forecasting," in *Comparative Models for Electrical Load Forecasting*, D. W. Bunn and E. D. Farmer, Eds. New York, NY: Wiley, 1985, pp. 87–108. [LS, W, TD, DY, AD, EX]

1984

[15] C.-Y. Chong and R. Malhami, "Statistical synthesis of physically based load models with applications to cold load pickup," *IEEE Trans. Power App. Syst.*, vol. PAS-103, no. 7, pp. 1621–1628, July 1984. [PHY]

[16] M. Ernoult and R. Mattatia, "Short term load forecasting: New developments at E.D.F.," in *Proc. 8th Power Systems Computation Conf.* (Helsinki, Finland, Aug. 1984), pp. 369–375. [LS, W, DY, ARMA, AD, STO, EX, RE]

[17] H. R. Fankhauser, "A novel approach to on-line short and intermediate-term load forecasting," in *Proc. 8th Power Systems Computation Conf.* (Helsinki, Finland, Aug. 1984), pp. 376–380. [LS, W, TD, AD, EX, RE]

[18] H. Muller, "Classification of daily load curves by cluster analysis," in *Proc. 8th Power Systems Computation Conf.* (Helsinki, Finland, Aug. 1984), pp. 381–388. [LS, TD, STO, EX]

[19] K. Poysti, "Box-Jenkins method in short-term forecasting of grid load in Finland," in *Proc. 8th Power Systems Computation Conf.* (Helsinki, Finland, Aug. 1984), pp. 357–368. [LS, W, DY, ARMA, AD, STO, EX]

1983

[20] M. Ernoult and R. Mattatia, "Short-term load forecasting for production and control: New developments at EDF," in *Proc. IEE 3rd Int. Conf. on Reliability of Power Supply Systems* (London, UK, Sept. 1983). [LS, W, DY, ARMA, AD, STO, EX]

[21] A. Keyhani and S. M. Miri, "On-line weather sensitive and industrial group bus load forecasting for microprocessor-based applications," *IEEE Trans. Power App. Syst.*, vol. PAS-102, no. 12, pp. 3868–3876, Dec. 1983. [LS, W, DY, ARMA, AD, STO, BL, EX]

[22] L. Ljung and T. Soderstrom, *Theory and Practice of Recursive Identification*. Cambridge, MA: MIT press, 1983. [REF]

1982

[23] M. A. Abu-el-Magd and N. K. Sinha, "Short-term load demand modeling and forecasting," *IEEE Trans. Syst., Man Cybern.*, vol. SMC-12, no. 3, pp. 370–382, May/June 1982. [SU]

[24] T. M. Calloway and C. W. Brice III, "Physically-based model of demand with applications to load management assessment and load forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-101, no. 12, pp. 4625–4631, Dec. 1982. [PHY]

[25] A. S. Dehdashti, J. R. Tudor, and M. C. Smith, "Forecasting of hourly load by pattern recognition—a deterministic approach," *IEEE Trans. Power App. Syst.*, vol. PAS-101, no. 9, pp. 3290–3294, Sept. 1982. [LS, W, TD, AD, EX]

[26] G. D. Irisarri, S. E. Widergren, and P. D. Yehsakul, "On line load forecasting for energy control center application," *IEEE Trans. Power App. Syst.*, vol. PAS-101, no. 1, pp. 71–78, Jan. 1982. [LS, W, TD, DY, ARMA, STA, AD, STO]

[27] B. Krogh, E. S. de Llinas, and D. Lesser, "Design and implementation of an on-line load forecasting algorithm," *IEEE Trans. Power App. Syst.*, vol. PAS-101, no. 9, pp. 3284–3289, Sept. 1982. [LS, DY, ARMA, AD, STO, EX]

[28] H. Muller, "Short-term load prediction in electric power systems," *Operations Research in Progress*. Hingham, MA: D. Reidel, 1982, pp. 459–477. [LS, TD, STO]

1981

[29] M. S. Abou-Hussein, M. S. Kandil, M. A. Tantawy, and S. A. Farghal, "An accurate model for short-term load forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 9, pp. 4158–4165, Sept. 1981. [LS, W, TD, DY, STA, AD, STO, EX]

[30] M. A. Abu-El-Magd and N. K. Sinha, "Two new algorithms for on-line modeling and forecasting of the load demand of multimode power systems," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 7, pp. 3246–3252, July 1981. [LS, DY, ARMA, STA, AD, STO, BL, EX]

[31] J. H. Broehl, "An end-use approach to demand forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 6, pp. 2714–2718, June 1981. [LS, W, TD, EX]

[32] M. L. Chan, E. N. Marsh, J. Y. Yoon, G. B. Ackerman, and N. Stoughton, "Simulation-based load synthesis methodology for evaluating load management programs," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 4, pp. 1771–1778, Apr. 1981. [PHY]

[33] S. Fu, "A pragmatic approach for short-term load forecasting using learning-regression method," in *Proc. 7th Power Systems Computation Conf.* (Lausanne, Switzerland, July 1981), pp. 581–587. [LS, W, DY, AD, STO, EX]

[34] G. Heydt, A. Khotanzad, and N. Farahbakhshian, "A method for the forecasting of the probability density function of power

system loads," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 12, pp. 5002–5010, Dec. 1981. [STO]

[35] S. Ihara and F. C. Schweppe, "Physically based model of cold-load pickup," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 9, pp. 4142–4150, Sept. 1981. [PHY]

[36] F. Meslier, M. Ernoult, R. Mattatia, and P. Rabut, "Estimation of the sensitivity of the electrical energy demand to variations in meteorological conditions. History of methods and development of new approaches at Electricité de France," in *Proc. 7th Power Systems Computation Conf.* (Lausanne, Switzerland, July 1981). [LS, W, AD, EX]

[37] S. Vemuri, W. L. Huang, and D. J. Nelson, "On-line algorithms for forecasting hourly loads of an electric utility," *IEEE Trans. Power App. Syst.*, vol. PAS-100, no. 8, pp. 3775–3784, Aug. 1981. [LS, DY, ARMA, AD, STO]

[38] L. Z. Xu and J. G. Du, "Application of the innovation method of random series in power system short-term load forecasting," in *Proc. 7th Power Systems Computation Conf.* (Lausanne, Switzerland, July 1981). [LS, DY, ARMA, AD, STO]

1980

[39] IEEE Committee Report, "Load forecast bibliography phase I," *IEEE Trans. Power App. Syst.*, vol. PAS-99, no. 1, pp. 53–58, Jan./Feb. 1980. [SU]

1979

[40] General Electric and MIT, "Systems engineering for power V: Load modeling methodologies interim report," Dep. Energy Rep. HCP/T5112-01, Aug. 1979. [PHY]

[41] H. P. van Meeteren and P. J. M. van Son, "Short-term load prediction with a combination of different models," in *Proc. IEEE Power Industry Computer Applications Conf.*, (Cleveland, OH, May 1979), pp. 192–197. [LS, W, TD, DY, ARMA, STA, AD, STO, EX]

1978

[42] R. Anelli, U. Di Caprio, V. Marchese, and S. Pozzi, "Short term prediction of stationary load processes with a correlation function finite sum of exponentials," in *Proc. 6th Power Systems Computation Conference* (Darmstadt, FRG, Aug. 1978), pp. 401–408. [LS, TD, AD, STO]

[43] D. D. Belik, D. J. Nelson, and D. W. Olive, "Use of the Karhunen-Loève expansion to analyze hourly load requirements for a power utility," paper A78 225-5, presented at the IEEE Power Engineering Society Winter Meeting, New York, NY, Jan./Feb. 1978. [LS, TD, W, AD, EX]

[44] M. Hagan and R. Klein, "On line maximum likelihood estimation for load forecasting," *IEEE Trans. Syst., Man Cybern.*, vol. SMC-8, no. 9, pp. 711–715, Sept. 1978. [LS, TD, DY, ARMA, STO]

[45] H. Muller, "An approach to very short term load forecasting by exponential smoothing with trend correction based on previous day comparison and error difference smoothing," in *Proc. 6th Power Systems Computation Conf.* (Darmstadt, FRG, Aug. 1978), pp. 417–423. [LS, TD, AD]

[46] A. Quintana, J. Gomez, and N. D. Reppen, "Integration of an adaptive short term load forecast procedure into a new energy control center," in *Proc. 6th Power Systems Computation Conf.* (Darmstadt, FRG, Aug. 1978), pp. 426–431. [LS, TD, DY, AD, EX]

[47] P. Vahakyla, E. Hakonen, and P. Leman, "Short-term forecasting of grid load in Finland," in *Proc. 6th Power Systems Computation Conf.* (Darmstadt, FRG, Aug. 1978), pp. 393–399. [LS, DY, ARMA, AD, EX]

1977

[48] M. S. Sachdev, R. Billinton and C. A. Peterson, "Representative bibliography on load forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-96, no. 2, pp. 697–700, Mar./Apr.1977. [SU]

1976

[49] S. R. Brubacher and G. Turnicliffe-Wilson, "Interpolating time series with applications to the estimation of holiday effects on electricity demand," *Appl. Stat.*, vol. 25, pp. 107–116, 1976. [LS, TD, AD, EX]

[50] R. L. Kashyap and A. R. Rao, *Dynamic Stochastic Models from Empirical Data.* New York, NY: Academic Press, 1976. [REF]

[51] R. P. Thompson, "Weather sensitive electric demand and energy analysis on a large geographically diverse power system—Application to short term hourly electric demand forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-95, no. 1, pp. 385–393, Jan./Feb. 1976. [LS, W, TD, AD, EX, RE]

1975

[52] T. S. Dillon, K. Morsztyn, and K. Phua, "Short term load forecasting using adaptive pattern recognition and self organising techniques,"in *Proc. 5th Power Systems Computation Conf.* (Cambridge, UK, Sept. 1975), paper 2.4/3. [AD, STO]

[53] F. D. Galiana, "Short term load forecasting," in *Proc. Engineering Foundation Conf.—Systems Engineering for Power: Status and Prospects* (Henniker, NH, 1975), ERDA 76-66, Conf. 750867, pp. 17–22. [SU]

[54] J. H. Pickles, "Short-term load prediction using on-line data," in *Proc. 5th Power Systems Computation Conf.* (Cambridge, UK, Sept. 1975), paper 2.4/1. [LS, DY, AD, EX]

[55] K. Srinivasan and R. Pronovost, "Short-term load forecasting using correlation models," *IEEE Trans. Power App. Syst.*, vol. PAS-94, no. 5, pp. 1854–1858, Sept./Oct. 1975. [LS, W, DY, STA, AD, STO, EX]

1974

[56] F. D. Galiana, E. Handschin, and A. R. Fiechter, "Identification of stochastic load models from physical data," *IEEE Trans. Automat. Contr.*, vol. AC-19, no. 6, pp. 887–893, Dec. 1974. [LS, W, TD, DY, ARMA, AD, STO, EX]

[57] K. L. S. Sharma and A. K. Mahalanabis, "Recursive short-term load forecasting algorithm," *Proc. Inst. Elec. Eng.*, vol. 121, pp. 59–62, Jan. 1974. [LS, TD, AD]

1973

[58] S. L. Corpening, N. D. Reppen, and R. J. Ringlee, "Experience with weather sensitive load models for short and long-term forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-92, no. 6, pp. 1966–1972, Nov./Dec. 1973. [PL, W]

[59] F. C. Schweppe, *Uncertain Dynamic Systems.* Englewood Cliffs, NJ: Prentice-Hall, 1973. [REF]

[60] S. Vemuri, D. F. Hill, and R. Balasubramanian, "Load forecasting using stochastic models," in *Proc. 8th IEEE Power Industry Computer Applications Conf.* (Minneapolis, MN, 1973), pp. 31–37. [LS, DY, ARMA, AD, STO]

1972

[61] P. C. Gupta and K. Yamada, "Adaptive short-term forecasting of hourly loads using weather information," *IEEE Trans. Power App. Syst.*, vol. PAS-91, no. 5, pp. 2085–2094, Sept./Oct. 1972. [LS, TD, DY, STA, AD, STO, EX]

1971

[62] W. R. Christiaanse, "Short-term load forecasting using general exponential smoothing," *IEEE Trans. Power App. Syst.*, vol. PAS-90, no. 2, pp. 900–911, Mar./Apr. 1971. [LS, TD, AD, EX]

[63] P. C. Gupta, "A stochastic approach to peak power demand forecasting in electric utility systems," *IEEE Trans. Power App. Syst.*, vol. PAS-90, Mar./Apr. 1971. [PL, AD, STO, EX]

[64] D. P. Lijesen and J. Rosing, "Adaptive forecasting of hourly load based on load measurements and weather information," *IEEE Trans. Power App. Syst.*, vol. PAS-90, no. 4, pp. 1757–1767, July/Aug. 1971. [LS, W, TD, AD, EX]

1970

[65] K. J. Astrom and P. Eykhoff, "System identification—A survey," *Automatica*, vol. 7, pp. 123-167, 1970. [SU, REF]
[66] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*. Oakland, CA: Holden Day, 1970. [REF]
[67] J. Toyoda, M. Chen, and Y. Inoue, "An application of state estimation to short-term load forecasting," *IEEE Trans. Power App. Syst.*, vol. PAS-89, no. 5, pp. 1678-1688, Sept./Oct. 1970. [LS, DY, STA, AD, STO]

1968

[68] E. D. Farmer and M. J. Potton, "Developments of online load-prediction techniques with results from trials in the south-west region of the CEGB," *Proc. Inst. Elec. Eng.*, vol. 115, no. 10, pp. 1549-1558, 1968. [LS, TD, AD, EX]
[69] P. D. Mathewman and H. Nicholson, "Techniques for load prediction in the electricity-supply," *Proc. Inst. Elec. Eng.*, vol. 115, no. 10, pp. 1451-1457, 1968. [PL, W, EX]

1966

[70] G. T. Heinemann, D. A. Nordman, and E. C. Plant, "The relationship between summer weather and summer loads—A regression analysis," *IEEE Trans. Power App. Syst.*, vol. PAS-85, pp. 1144-1154, Nov. 1966. [PL, W, EX]

1958

[71] W. B. Davenport, Jr. and W. L. Root, *An Introduction to the Theory of Random Signals and Noise*. New York, NY: McGraw-Hill, 1958. [REF]

George Gross (Senior Member, IEEE) was born in Romania. He received his early education in Romania, Israel, and Canada. He earned the undergraduate degree in electrical engineering at McGill University, Montreal. He continued his studies at the University of California, Berkeley, where he received the Master's and Ph.D. degrees in electrical engineering and computer sciences. His graduate research was in the area of nonlinear system theory and its application to power system stability analysis.

He joined the Pacific Gas and Electric Company, San Francisco, CA, as a Computer Applications Engineer in 1974. In 1977, he established the Company's Systems Engineering Group. The work of the Group focused on the development of analytical tools for energy system operations, planning and control. In 1985, he founded the first Management Sciences Department at a utility and served as its Manager. In that capacity he was in charge of financial models, systems engineering projects, and the development of decision support systems for the Company. In May 1987, he became Manager of the Generation Planning Department. He is in charge of charting the Company's long-term electric resource plans, formulating strategic directions for its electric supply business activities, developing tactical plans for electric supply resource development, and presenting of these plans to regulatory agencies. He has been invited as a lecturer on diverse power system topics at leading universities, research institutions, and utilities throughout the world. He has taught graduate level courses on Power Systems Analysis and Control. He has organized and served on the faculty of two short courses in the areas of utility resource planning and modern power system control centers at the University of California, Berkeley. In 1986 he was invited to undertake a technical mission to Chile under the auspices of the United Nations Industrial Development Organization to assist Chilean engineers in the solution of power system problems. He was awarded the 1980 IEEE Power Engineering Society Power System Engineering Committee Award for the Prize Winning Paper. He is also a recipient of the Franz Edelman Management Science Award for 1985 from the Institute of Management Sciences.

Dr. Gross is an active member of the IEEE Power Engineering Society. He has served in several capacities on the executive of the PICA Conferences including as Executive Chairman for PICA 1985. He is currently Chairman of the Computer and Analytical Methods Subcommittee of the Power System Engineering Committee.

Francisco D. Galiana (Senior Member, IEEE) was born in Alicante, Spain, in 1944, but is presently a Canadian citizen living in Montreal, Que., Canada. He received the undergraduate degree in electrical engineering (with Honors) from McGill University, Montreal, and the S.M. and Ph.D. degrees from the Massachusetts Institute of Technology, Cambridge, in 1968 and 1971, respectively, for work and research in the areas of automatic control and power systems.

From 1971 to 1974 he was with Brown Boveri Research Center, Baden, Switzerland, where he worked on power system automation. This was followed by a position as an Assistant Professor in the Department of Electrical and Computer Engineering at the University of Michigan, Ann Arbor, until 1977. Since then he has been with the Department of Electrical Engineering, McGill University, Montreal, where he is a Full Professor. His fields of interest are in the application of computational and control methods to power system operation and planning.

Dr. Galiana is a member of Sigma Xi. He was Technical Chairman of the IEEE 1987 Power Industry Computer Applications Conference held in Montreal.