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REAL TIME MODELING TECHNIQUE FOR APPLICATION TO AUTOMATIC GENERATION CONTROL

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ABSTRACT

This paper presents a real time stochastic technique for modeling the load demand of a power system. The modeling approach discussed here is recursive and needs nominal core storage and computation time. The developed model is used for forecasting one-step-ahead demand of the system. Such forecasts are useful for real time control of generation and spinning reserve assessment.

In addition, a comparison is made between the current industry load modeling practice and the model developed by the technique discussed here. This comparison is made through modeling the real time load data of a utility company by using both methods.

INTRODUCTION

Under the current industry's automatic generation control practice, the assumption is usually made that the sampling rate is high enough to assume that the change in the system demand within one sampling period is negligible. Therefore, there have been no efforts made to estimate demand trends (one-step-ahead forecasts). However, in several on-line applications, it is becoming apparent that the sampling rate of economic dispatch is rather slow; and a model is needed for predicting the demand trend over the sampling period.

The technique that is to be discussed can also be used for longer term forecasting. The models do vary, however, in that the factors affecting the prediction differ, as well as the applications. For example, the weather information, which may be a dominant factor in short term hourly load forecasting, is not the important factor for predicting the system load in the next few minutes. Keeping in mind that the intended application of the model is for use in generation control and spinning reserve evaluation, this paper is concerned with sampling periods to up to fifteen minutes.

Previous contributors in the area of load modeling for use in generation control and reserve assessment are Farmer and Potton [1], Matthewman and Nicholson [2], and Brewer, et. al [3]. Farmer used a time series approach and represented the load by the sum of a long-term trend, a component varying with the day of the week, and with a component which fluctuates from day to day and hour to hour, and the residual component which is expressed in terms of correlation functions of the process. Farmer's model is based on several weeks of the past load demands. As he points out, due to the limitations in the storage capacity of the on-line process-control computer, it is necessary that part of the calculations be performed on a larger off-line computer, which is not desirable.

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The most recent attempt was made by the authors of this paper [4, 5]. Load demand processes were stochastically modeled with sampling rate of a few minutes. This paper takes another look at the problem and presents the improvements obtained over the previously reported results [4, 5].

This paper can be broken down as follows:

1) A background discussion describing the current industry's automatic generation control practice, and definition of the problem.

2) A qualitative presentation of the real time stochastic modeling technique of an observed sequence.

3) A mathematical description of the current load modeling practice used in generation control.

4) Presentation of a method for comparing optimal predictors obtained from different stochastic models.

5) Results of particular studies, conclusion and recommendations.

Current Industry's Automatic Generation Control Practice and Definition of the Problem [6, 7, 13, 14, 15, 16, 17]

Briefly, the functions and objectives of automatic generation control (AGC) are as follows:

1. Matching area generation to area load. That is, to match the tie-line interchanges with the schedules and to control the system frequency.

2. Distributing the changing loads among generators so as to minimize the operating costs subject to additional constraints such as might be introduced by security considerations.

The first objective is met by means of a supplementary controller in which the concept of tie-line bias is universally used. A small change in the system load produces proportional changes in the system frequency. That is, the Area Control Error (ACE $=\Delta P_{TL} - \beta\Delta f$) provides each area with approximate knowledge of the load change and directs the supplementary controller for the area to manipulate the turbine valves of the regulating units. In order to obtain a meaningful regulation (i.e., reducing the ACE to zero), the load demands of the system are sampled every few seconds.

The second objective is met by sampling the load every few minutes (5-10 minutes) and allocating the changing load among different units so as to minimize the operating costs. This preassumes the load demand remains constant during each period of economic dispatch.

To implement the above objectives, nearly all AGC software is based on unit control. For unit i, the desired generation at time instant K which is normally sampled every two or four seconds, is given by (1):

$$P_D^i(K) = P_E^i(K) + P_R^i(K) + P_{EA}^i(K), \quad (1)$$

where, $P_E^i(K)$, $P_R^i(K)$, and $P_{EA}^i(K)$ are the economic, regulating, and emergency assist components of desired generation for unit i at time instant K, respectively. These components of desired generation are calculated using equations (2), (3), and (4), respectively.

$$P_E^i(K) = EPF^i(KK) \times \Delta P_T(K) + P_{EB}^i(KK) \quad (2)$$

$$P_R^i(K) = G \times RF^i \times ACE(K) \quad (3)$$

$$P_{EA}^i(K) = AF^i \times ACE(K). \quad (4)$$

KK is the time instant, normally five-minute steps, at which the economic participation factors EPF^i, and economic basepoints P_{EB}^i are computed for unit i by the Economic Dispatch. The values of $EPF^i(KK)$ and $P_{EB}^i(KK)$ used in the calculation of P_E^i are those calculated by the most recent execution of the economic dispatch. In some installations, the calculation of economic basepoints and participation factors is performed every ten minutes and/or upon large load changes, and changes in unit status. AF^i, RF^i are the emergency assist factor and regulating factor per unit i, respectively, and G is the system regulating gain factor. AF, RF, and G are usually tuned in the field for proper unit control action.

In equation (2), $\Delta P_T(K)$ is the change in total unit economic desired generation since the most recent execution of the Economic Dispatch Calculation function at time instant KK. $\Delta P_T(K)$ is calculated using equation (5):

$$\Delta P_T(K) = \sum_{i=1}^{N} P_A^i(K) + ACE(K) - \sum_{i=1}^{N} P_{EB}^i(KK), \quad (5)$$

where, P_A^i is the actual generation of unit i at time instant K, ACE is the value of Area Control Error at time instant K, P_{EB}^i is the economic basepoint for unit i calculated by the most recent execution of the Economic Dispatch at time instant KK, and N is the number of units operating in the AUTOMATIC control mode. Figure 1 shows the block diagram representations of equations (1) through (5).

At this point, it should be noted that most of AGC packages have some kind of filter for removing the noise component of ACE which cannot be controlled. In addition, the desired generation of a unit is checked against the rate limit and regulating range of that unit. These aspects are discussed in references [6, 7, 13, 14, 15, 16].

It may be apparent that economic dispatch and tie-line bias control both have the task of matching the area generation to area load such that the net tie-line exchange and area frequency are at their scheduled values. Both of these control functions are achieved by pulsing governor motors to adjust the MW generated to the MW demand of the system. The high sampling rate of the area load provides an approximate direction of the changing load which allows the tie-line bias scheme to control the load's dynamics. But, the economic dispatch, with its low sampling rate, attempts to economize without concern for the direction of the changing load (i.e., load dynamics).

It is possible that under a rapid load rise, economic dispatch and tie-line bias control come up with potentially conflicting control commands. In such a case, the "Permissive" and "countdown" computer logic of the AGC attempts, but not always successfully, to cancel control action on any machine when the control commands have conflicts on sign.

Furthermore, it is the industry's practice to sacrifice economy (disabling economic dispatch) for the sake of regulation. That is, whenever the value of ACE exceeds a threshold value, for whatever the reasons are, the AGC's computer logic arrangements commit all units under its control to regulating action.

In order to further clarify this problem, let us rewrite the desired generation of unit i by substituting equations (2), (3) and (4) in (1):

$$P_D^i(K) = P_{EB}^i(KK) + EPF^i(KK)\Delta P_T(K) + (G \cdot RF^i + AF^i)\, ACE(K) \quad (6)$$

and

$$\Delta P_T(K) = \sum_{i=1}^{N} P_A^i(K) + ACE(K) - \Sigma P_{EB}^i(KK) \quad (7)$$

If, at time instant KK, (e.g., every five minutes), the total change in the desired generation, $\Delta P_T(\cdot)$, is small, then there is no need to recalculate a new set of economic participation factors. This is a typical operating condition during the night when the changes in the system load every five minutes are approximately less than .1 per cent.

On the other hand, when the system load is increasing or decreasing rapidly (like morning rise or evening drop), then the load changes during each economic dispatch period are usually significant. Under such conditions, for economical operation, a new set of economic participation factors is needed. But, the application of a new set of economic participation factors in equation (6) every five minutes means pulsing governor motors to adjust the base MW output of units under AGC control to their economical values when the generation in itself is changing quite rapidly to match the fast-changing load demand. That is exactly when AGC's tie-line bias control is rapidly pulsing the governor motors of units to reduce ACE. It is quite possible that some units are subjected to conflicting control commands, or, AGC may attempt to raise the base output of some units in one economic dispatch period and then lower them in the next period, which is not possible due to the relatively slow boiler response characteristics.

Note that this situation aggrevates the control problem and increases the ACE since a unit does not have a chance to settle on a new economic base loading. What normally happens is that due to the increase in ACE above its threshold value, AGC commits all units to regulation.

Note, also, that when the change in the system generation is significant, that is precisely the time when the economic reallocation is needed. But, unfortunately, when the system is at its most active state (i.e., fast-changing load), this reallocation will cause additional disturbances in the MW outputs which work against the regulating task.

From the analysis presented, it may be apparent that from the outset one should recognize the load changes are due to high frequency variations which are superimposed on low frequency variations. These low frequency variations can be modeled and controlled by an economic dispatch which correctly supplements through the load's dynamics (one-step-ahead forecast) the control actions of tie-line bias control. The result would be a reduction in ACE over the sampling periods of economic dispatch. This reduction of ACE will reduce the control actions by the AGC controller which in turn eliminates excessive pulsing of regulating units.

In this paper, a real-time stochastic technique is presented for modeling these low frequency variations of the load demand.

Modeling of An Observed Sequence Y(·) by Means of Stochastic Difference Equation

In the present study, we are interested in predicting the one-step-ahead power demand of the entire system as it is measured at the central dispatching office. For any given power system, the power demand is available at discrete intervals of time. Let $Y(\cdot)$ represent the power demand, as measured at the dispatching office. The problem of one-step-ahead load forecasting, given a set of past observations $(Y(1), Y(2), \ldots Y(K-1), Y(K)$ (where K is the instant of time), is to find the best estimate of the load at K+1; that is, to predict $\hat{Y}(K+1)$. Naturally, if we are interested in ℓ-step-ahead prediction, we must first determine one-step-ahead prediction; that is, $\hat{Y}(K+1)$, then two-step-ahead prediction, $\hat{Y}(K+2)$, ... $\hat{Y}(K+\ell-1)$, and finally $\hat{Y}(K+\ell)$ which is ℓ-step ahead prediction.

Let $\{Y(\cdot)\}$ represent the observations of the power demand, that is

$$Y(1),\ Y(2),\ \ldots\ Y(K-n),\ \ldots\ Y(K-2),\ Y(K-1),\ Y(K)$$

Let the given sequence $\{Y(\cdot)\}$ obey the following stochastic difference equation as expressed by equation (8):

$$Y(K) = a_1(K)Y(K-1) + a_2(K)Y(K-2) + \ldots + a_n(K)Y(K-n) + W(K) \qquad (8)$$

in which the disturbance W(K) cannot be directly observed. Alternatively, we can rewrite (8) in compact form as given by (9):

$$Y(K) = \sum_{j=1}^{n} a_j(K)Y(K-j) + W(K) \qquad (9)$$

A process which can be expressed as equation (9) is called an autoregressive process of order n or, in short, AR(n).

It can be shown that one-step-ahead prediction of the stochastic process $\{Y(\cdot)\}$, that is, $\hat{Y}(K+1)$, given the past observations $Y(1), Y(2), \ldots, Y(K-1), Y(K)$, is given by equation (10):

$$\hat{Y}(K+1) = \hat{a}_1(K)Y(K) + \hat{a}_2(K)Y(K-1) + \hat{a}_3(K)Y(K-2) + \ldots \qquad (10)$$

This can be written in compact form as

$$\hat{Y}(K+1) = \sum_{j=1}^{n} \hat{a}_j(K)Y(K-j+1)$$

where we have assumed that $E[W(K)] = 0$ and "$\hat{a}(K)$" is the estimate of "a(K)" based on the observations $[Y(j),\ j \leq K]$.

Once the observation Y(K+1) is available, the residue at instant K+1 can be calculated by equation (11):

$$W(K+1) = Y(K+1) - \hat{Y}(K+1) \qquad (11)$$

which is also the error at K+1 instant.

We may be able to use the past errors to improve our prediction of the future. Let us assume that the observations $\{Y(\cdot)\}$ and its past residues under certain estimation techniques are available to us. Then a better choice of a model for our process may be written as (12):

$$Y(K) = \sum_{j=1}^{n} a_j(K)Y(K-j) + \sum_{j=1}^{m} a_{n+j}(K)W(K-j) + W(K) \qquad (12)$$

This is called an autoregressive moving average of order n and m, or in short ARMA(n,m). The unknown parameters in equation (12) are a_j, j=1, ... n+m.

If there is reason to believe that our process has deterministic terms and/or harmonic components with period T, or observable inputs, we may choose the general model as given by (13):

$$Y(K) = \sum_{j=1}^{n} a_j(K)Y(K-j) + \sum_{j=1}^{m} a_{n+j}(K)W(K-j) + \sum_{j=1}^{\ell} a_{n+m+j}(K)\Phi_j(K) + W(K) \qquad (13)$$

where the integer ℓ is equal to all possible functions (deterministic or observable inputs) which we believe, for one reason or another, will improve the ability of our model to predict. For example, we may choose the following functions:

$\Phi_1 = 1$ $\qquad$ Φ_4 = some function of temperature

$\Phi_2 = \sin(\frac{2\pi k}{T})$ $\qquad$ $\Phi_5 = Y_K^2$

$\Phi_3 = \cos(\frac{2\pi k}{T})$ $\qquad$ $\Phi_6 = Y_K^3$, etc.

Finally, we can rewrite our general model in compact form as (14):

$$Y(K) = a^T(K)Z(K-1) + W(K) \qquad (14)$$

where

$$a^T(K) = (a_1(K),\ \ldots,\ a_{n+m}(K),\ \ldots,\ a_{n+m+\ell}(K))$$

$$Z^T(K) = [Z_1(K),\ \ldots,\ Z_n(K);\ Z_{n+1}(K),\ \ldots,\ Z_{n+m}(K);\ Z_{n+m+1}(K),\ \ldots,\ Z_{n+m+\ell}(K)]$$

$$= [Y(K-1),\ \ldots,\ Y(K-n);\ W(K),\ \ldots,\ W(K-m+1);\ \Phi_1,\ \ldots,\ \Phi_\ell]$$

Another important class of predictor is the multiplicative model [9] which has the following structure:

$$Y(K) = \prod_{j=1}^{n} (Y(K-j))^{a_j} \prod_{j=1}^{m} (W(K-j))^{a_{n+j}} \prod_{j=1}^{\ell} (\Phi_j(K-1))^{a_{n+m+j}} \qquad (15)$$

If we let $X(K) = \ell n(Y(K))$ where Y(K) is strictly positive, then the log transformed process will have the same form as the predictor described by equations (13) or (14).

Estimation of the Model's Parameters

There are a great number of methods for estimation of vector "a" in equation (14). Basically, the different techniques can be divided into two categories; namely, recursive or real-time algorithms, and non-recursive algorithms. Probably the most powerful non-recursive techniques are the statistically-based methods such as the maximum likelihood estimates [8, 10]. A heavy computational cost and storage requirement of maximum likelihood estimators make them the least desired approach.

In reference [11], an excellent comparative study of different real-time algorithms are made. Notable among these are the methods that only demand limited types of statistical behavior, such as instrument variable methods [10]. The simplest real time algorithm is an ad hoc or numerical analysis method, such as the extended least square. This method will be used in this study, and it is discussed extensively in reference [5].

Mathematical Description of Current Load Modeling Practice

As was pointed out, the load model currently used in economic dispatch algorithms assumes that the load demand remains constant during the sampling intervals. Such a load model can be called "piecewise constant". Mathematically, piecewise constant models can be written as:

$$\hat{Y}(K) = 1.0\ Y(K-1) \qquad \text{for all } K$$

where

$Y(\cdot)$ the observed load

$\hat{Y}(\cdot)$ the estimated (forecasted) load

Note that this is the simplest load model one can assume in which the only coefficient of the model is chosen a priori to be equal to unity.

In the study presented, the prediction performance of this model will be compared with the stochastic models discussed here.

The Choice of Model

In generation control and reserve calculation, the important consideration is that the maximum one-step-ahead forecast errors as well as the number of times this maximum errors occurs be as small as possible. In the case of generation control, the maximum error is a measure of on-line regulating generation needed for secure operation.

Due to the above considerations, the prediction ability of a model will be measured based on the number of times the absolute per cent error is greater than a prespecified number (say 2.5 percent). Mathematically, this criterion can be written as:

$$E_{NT,N} = \text{Number of Times}\left[\ \frac{Y(K)-\hat{Y}(K)}{Y(K)} \times 100 \cdot | > 2.5\right]$$

where

$Y(K)$: actual load at time instant K

$\hat{Y}(K)$: predicted load at time instant K

$E_{NT,N}$: number of times absolute per cent error is greater than 2.5 percent at N.

N : number of observations after the initial transient (normally 50 observations)

By choosing different integers n,m and different functions $\Phi_j(\cdot)$, we will have a class of different models. We will choose that model which yields the smallest value of $E_{NT,N}$. Naturally, the best predictor chosen this way should have smaller values of $E_{NT,N}$ than the model based on the current industry's practice (i.e., piecewise constant modeling).

In addition, in order to give a measure of actual errors in MW, the assumption is made that the resulting errors are normal, and the 99% confidence region is computed:

$$Pr\{-3\hat{\sigma}_e \leq e \leq 3\hat{\sigma}_e\} = .99$$

where

Pr: probability of { }

e: actual error in MW $(e(K) = Y(K) - \hat{Y}(K))$

$\hat{\sigma}_e$: estimate of standard deviation of actual error e

Results of Particular Studies

The theory discussed in the earlier sections was applied to the load demand sequence of Public Service Indiana. The first sequence studied was sampled every five minutes, and the second sequence was sampled every ten minutes.

A number of models were considered for prediction, among which a few are listed here. The models are made up of the various combinations of autoregressive and moving average terms. Some of the models are the function of the change of the latest observation and moving average terms. Some others have sinusoidal terms (forward signals) which are observed in the sequence.

A consistent notation is used in the nomenclature of coefficients; that is, $\hat{a}_1(K)$ is always the coefficient of $Y(K-1)$, $\hat{a}_6(K)$ is that of $W(K-3)$, etc.

The models are as follows:

S - models:

$$\begin{aligned}\hat{Y}(K|K-1) = {} & \hat{a}_0(K) + \hat{a}_1(K)Y(K-1) + \hat{a}_2(K)Y(K-2) + \\ & \hat{a}_3(K)Y(K-3) + \hat{a}_4(K)\bar{W}(K-1) + \hat{a}_5(K)\bar{W}(K-2) + \\ & \hat{a}_6(K)\bar{W}(K-3) \\ & + \hat{a}_7(K)\sin(\tfrac{2\pi k}{72}) + \hat{a}_8(K)\cos(\tfrac{2\pi k}{72}) \\ & + \hat{a}_9(K)\sin(\tfrac{2\pi k}{144}) + \hat{a}_{10}(K)\cos(\tfrac{2\pi k}{144}) \\ & + \hat{a}_{11}(K)\sin(\tfrac{2\pi k}{288}) + \hat{a}_{12}(K)\cos(\tfrac{2\pi k}{288}) \\ & + \hat{a}_{13}(K)\sin(\tfrac{2\pi k}{576}) + \hat{a}_{14}(K)\cos(\tfrac{2\pi k}{576})\end{aligned}$$

SC models:

$$\begin{aligned}\hat{Y}(K|K-1) = {} & \hat{a}_0(K) + \hat{a}_1(K)Y(K-1) + \hat{a}_2(K)[Y(K-1)-Y(K-2)] \\ & + \hat{a}_3(K)[Y(K-1)-Y(K-3)] + \hat{a}_4(K)\bar{W}(K-1) \\ & + \hat{a}_5(K)\bar{W}(K-2) + \hat{a}_6\bar{W}(K-3)\end{aligned}$$

$$+ \hat{a}_7(K)\sin(\frac{2\pi k}{72}) + \hat{a}_8(K)\cos(\frac{2\pi k}{72})$$

$$+ \hat{a}_9(K)\sin(\frac{2\pi k}{144}) + \hat{a}_{10}(K)\cos(\frac{2\pi k}{144})$$

$$+ \hat{a}_{11}(K)\sin(\frac{2\pi k}{288}) + \hat{a}_{12}(K)\cos(\frac{2\pi k}{288})$$

L - models:

$$\hat{Y}(K|K-1) = \hat{a}_0(K)Y(K-1)^{\hat{a}_1(K)}\, Y(K-2)^{\hat{a}_2(K)}$$

$$Y(K-3)^{\hat{a}_3(K)}\, \bar{W}(K-1)^{\hat{a}_4(K)}\, \bar{W}(K-2)^{\hat{a}_5(K)}$$

$$\bar{W}(K-3)^{\hat{a}_6(K)}\, \sin(\frac{2\pi k}{72})^{\hat{a}_7(K)}\, \cos(\frac{2\pi k}{72})^{\hat{a}_8(K)}$$

$$\sin(\frac{2\pi k}{144})^{\hat{a}_9(K)}\, \cos(\frac{2\pi k}{144})^{\hat{a}_{10}(K)}$$

$$\sin(\frac{2\pi k}{288})^{\hat{a}_{11}(K)}\, \cos(\frac{2\pi k}{288})^{\hat{a}_{12}(K)}$$

LC models:

$$\hat{Y}(K|K-1) = a_0(K)Y(K-1)^{\hat{a}_1(K)}\, [Y(K-1)-Y(K-2)]^{\hat{a}_2(K)}$$

$$[Y(K-1)-Y(K-3)]^{\hat{a}_3(K)}\, \bar{W}(K-1)^{\hat{a}_4(K)}\, \bar{W}(K-2)^{\hat{a}_5(K)}$$

$$\bar{W}(K-3)^{\hat{a}_6(K)}\, \sin(\frac{2\pi k}{72})^{\hat{a}_7(K)}\, \cos(\frac{2\pi k}{72})^{\hat{a}_8(K)}$$

$$\sin(\frac{2\pi k}{144})^{\hat{a}_9(K)}\, \cos(\frac{2\pi k}{144})^{\hat{a}_{10}(K)}$$

$$\sin(\frac{2\pi k}{288})^{\hat{a}_{11}(K)}\, \cos(\frac{2\pi k}{288})^{\hat{a}_{12}(K)}$$

Tables 1 and 2 give the final coefficients, the number of times per cent error is greater than 2.5 per cent, and the 99% confidence region on the resulting errors for the five minute load sequence and the ten minute load sequence, respectively. Note that "S 3" represents a model of type "S" which has three parameters, and similarly, "L 5" is a model of type L which has five parameters, etc. Figure 2 shows the plot of actual loads, forecasted loads, and per unit errors of a sampled portion of ten minute loads.

The results of different models for five minute loads, which is given in Table 1, indicate that the piecewise constant model (current industry practice) has the highest MW error ($\pm$ 189 MW) over the simulated data. It is interesting to note that the stochastic model, SC12, not only reduces $E_{NT,N}$ (i.e., number of times percent one-step-ahead forecast error is greater than 2.5 per cent) from 59 to 30, but it also reduces the one-step-ahead prediction error from $\pm$ 189 MW to $\pm$ 57 MW. A similar observation can be made from Table 2 for the ten minutes load sequence.

CONCLUSION AND RECOMMENDATIONS

The problem of on-line load modeling for use in the automatic generation control is studied. The simplicity of the model obtained, and the ease of implementation for real-time control are quite encouraging. The costs of implementation are nominal, and it only consists of the addition of the model to the existing software package of the economic dispatch.

The question that has to be answered is "How much money can be saved?" This question can be answered in the following manner:

In some power companies, the economic dispatch algorithm which calculates the unit participation factor is suspended during the rapid load fluctuation. Clearly, not operating economically means a higher operating cost. This may be avoided by computing the unit economic participation factor based on the load dynamics (i.e., one-step-ahead predicted load). With today's high price of fossil fuels (oil, gas and coal), even if the operating cost is reduced by small fractions, we will have a noticeable saving in overall cost.

Also, as was pointed out, neglecting the dynamics of the changing load (low frequency variations) would result in over-manipulating the turbine valves. Over-manipulation generates a large fluctuation in the turbine metal temperatures over the load range. This temperature change is caused by the throttling temperature difference. This results in large thermally generated stress levels in the turbine components, which is the primary cause of equipment life reduction. This is something to be avoided if possible. This is another aspect which must be considered in the overall savings made possible by incorporating the model of the load in the economic dispatch algorithm.

Principle observations and recommendations are as follows:

1) A proposed method for inclusion of one-step-ahead load forecasting in the Automatic Generation Control function is depicted in Figure 3. In this method one-step-ahead load forecasting is applied to the summation of the actual generation of the units operating in the AUTOMATIC control mode at time instant KK, $\Sigma P_A^i(KK)$, to obtain the total generation to be dispatched at time instant KK+1, $P_{FT}(KK+1)$, which is five to ten minutes in the future. An economic dispatch is then performed to obtain economic basepoint of unit i for time instant KK+1, $P_{ED}^i(KK+1)$. For units to be used for regulating purposes only, the regulation component, $P_R^j(K)$ of desired generation at time instant K for unit j are calculated in the same manner as conventional AGC schemes.

The projected economic basepoints, (MW targets) and the summation of the regulation and emergency assist components of desired generation are then transmitted to the respective plant computers where unit control signals are developed taking into account the dynamic response characteristics of each unit. In this way the control of a unit toward its MW target may be included as an integral part of the control system of the unit. That is, each unit would be allowed to track its MW target in terms of that unit dynamics. Also, the acquisition of information related to the dynamic response of a unit, as well as the transmission of control signals can be more easily and economically implemented by use of on-site plant computers. Note that this mode of unit operation would allow the generation control to benefit from the recent advancement made in optimization of dynamic costs [12, 5]. This mode of generation control should be investigated on a realistic power system model.

2) It is universally agreed that AGC is a vital and important function for secure operation of a power system. This fact alone dictates that first, a realistic model of a power system and its load should be simulated which could duplicate the actual control of the generation in the field with some degree of certainty. This model then should be used for testing any new control philosophy.

3) The load dynamics and the response of the units participating in generation control should carefully be studied. The sampling rate for economic dispatch should be determined based on the dynamic response of the units participating in the economic dispatch. This would allow the regulation and economic dispatch complement each other's tasks through the load dynamics.

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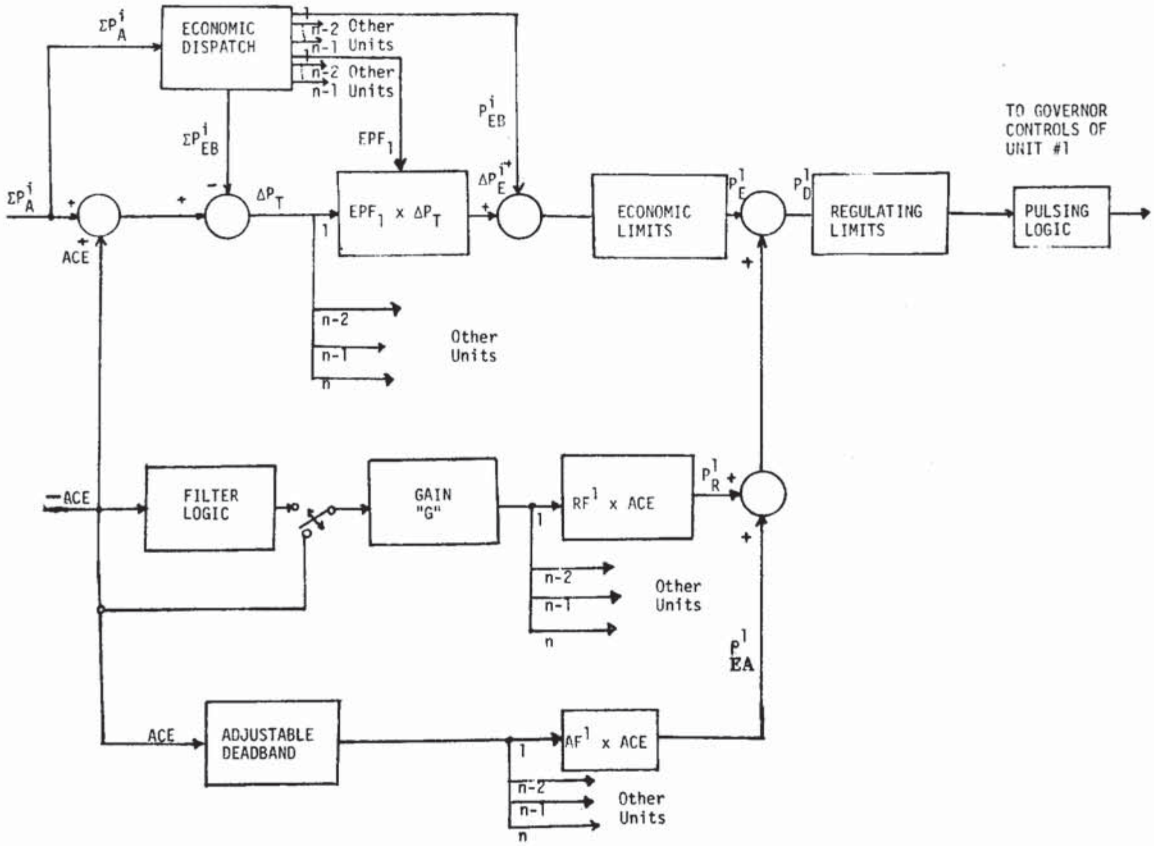

Figure 1. - Generalized Block Diagram Representation of The Automatic Generation Control Function

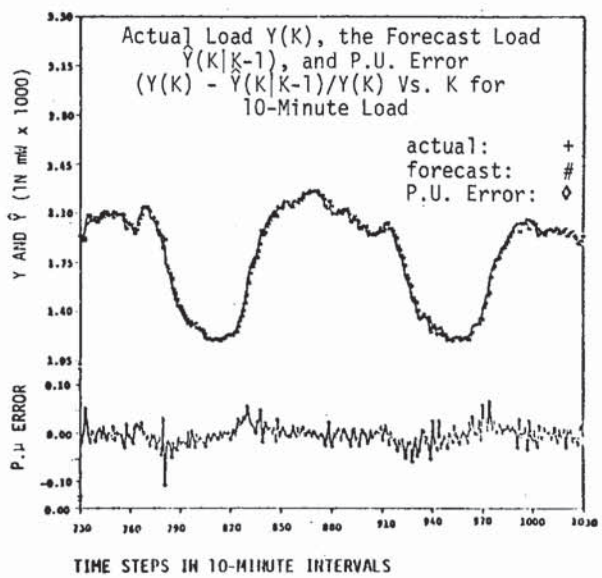

Figure 2. - 10-Minute Load

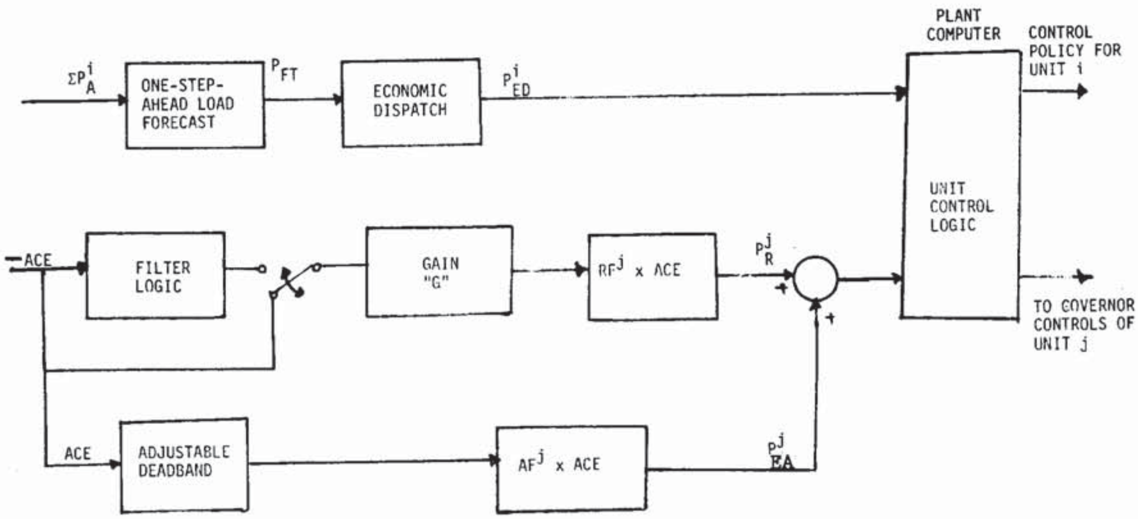

Figure 3. - Block Diagram of Proposed Automatic Generation Control Function

Table 1. - The Final Coefficients and Errors for Various Models of Five Minutes Load (N = 1200)

Models	$\hat{a}_0(N)$	$\hat{a}_1(N)$	$\hat{a}_2(N)$	$\hat{a}_3(N)$	$\hat{a}_4(N)$	$\hat{a}_5(N)$	$\hat{a}_6(N)$	$\hat{a}_7(N)$	$\hat{a}_8(N)$	$\hat{a}_9(N)$	$\hat{a}_{10}(N)$	$\hat{a}_{11}(N)$	$\hat{a}_{12}(N)$	$\hat{a}_{13}(N)$	$\hat{a}_{14}(N)$	$E_{NT,N}$	99% MW Error Confidence Region $Pr\{-3\hat{\sigma}_e \le e \le 3\hat{\sigma}_e\} = .99\%$
Piecewise Constant		1.0														59	-186.55, 189.44
L3	$9x10^{-4}$	.99	.09													58	-75.01, 72.48
S3	$3x10^{-3}$	.99	.07													61	-76.7, 74.1
L13		.54	.26	.19	.23	.03		$1.1x10^{-3}$	$-4x10^{-3}$	$-3x10^{-3}$	$8x10^{-3}$	$1.1x10^{-3}$	$-9x10^{-3}$	$1x10^{-3}$	$3x10^{-4}$	54	-72.9, 68.7
S13		.62	.23	.14	.24	$2x10^{-3}$		$2x10^{-3}$	$-7x10^{-3}$	$-4x10^{-3}$	$1.1x10^{-2}$	$1x10^{-3}$	$-1x10^{-2}$	$1x10^{-3}$	$5x10^{-4}$	53	-72.1, 67.3
LC10		1.1			.03	.03	.034	$7.7x10^{-4}$	$-2.6x10^{-3}$	$-2.0x10^{-3}$	$5.1x10^{-3}$	$4.6x10^{-4}$	$-6.6x10^{-3}$			33	-57.7, 56.8
SC10-1		1.01			.05	.05	.07	$2x10^{-3}$	$-5.1x10^{-3}$	$-3.5x10^{-3}$	$8.3x10^{-3}$	$7.7x10^{-4}$	$-1x10^{-2}$			32	-57.1, 56.4
SC10-2		1.01	.06	.07	.05			$2x10^{-3}$	$-5.1x10^{-3}$	$-3.5x10^{-3}$	$8.3x10^{-3}$	$7.7x10^{-4}$	$-1.2x10^{-2}$			32	-57.1, 56.4
SC11	$-1.2x10^{-4}$	1.02			.056			$1.7x10^{-3}$	$-4.8x10^{-3}$	$-3.2x10^{-3}$	$7.7x10^{-3}$	$6.5x10^{-4}$	$-1.1x10^{-2}$	$-6x10^{-5}$	$5.0x10^{-4}$	34	-58.2, 56.7
SC12		1.01	.06	.07	.05			$1.9x10^{-2}$	$-5.1x10^{-3}$	$-3.5x10^{-3}$	$8.2x10^{-3}$	$7.5x10^{-4}$	$-1.2x10^{-2}$	$-7x10^{-3}$	$5.8x10^{-4}$	30	-57.2, 56.8

Table 2. - The Final Coefficients and Errors for Various Models of Ten Minutes Load (N = 1200)

Models	$\hat{a}_0(N)$	$\hat{a}_1(N)$	$\hat{a}_2(N)$	$\hat{a}_3(N)$	$\hat{a}_4(N)$	$\hat{a}_5(N)$	$\hat{a}_6(N)$	$\hat{a}_7(N)$	$\hat{a}_8(N)$	$\hat{a}_9(N)$	$\hat{a}_{10}(N)$	$\hat{a}_{11}(N)$	$\hat{a}_{12}(N)$	$\hat{a}_{13}(N)$	$\hat{a}_{14}(N)$	$E_{NT,N}$	99% MW Error Confidence Region $PR\{-3\hat{\sigma}_e \leq e \leq 3\hat{\sigma}_e\} = .99\%$
Piecewise Constant		1.0														103	-264.3, 270.2
SC10-1		1.01	.04	-.04	.041			-6×10^{-3}	1.4×10^{-2}	1.2×10^{-3}	-2×10^{-2}	-3.3×10^{-4}	1×10^{-3}			60	-79.5, 79.13
LC9		1.03	.025		.026			-4.1×10^{-3}	9.7×10^{-3}	9.1×10^{-4}	-1.3×10^{-2}	-2.4×10^{-4}	4.9×10^{-4}			59	-80.2, 78.6
SC10-2		1.02			.041	.043	-0.44	-6.5×10^{-3}	1.4×10^{-2}	1.2×10^{-3}	-2.0×10^{-2}	-3.3×10^{-4}	1.0×10^{-3}			60	-79.5, 78.4
SC12		.991	.058	-.04	-.09	.05	0.03	-5.3×10^{-3}	1.27×10^{-2}	7.1×10^{-4}	-1.8×10^{-2}	-3.2×10^{-4}	8.9×10^{-4}			53	-78.6, 77.6
S9		.66	.33		.23			-8.4×10^{-3}	1.9×10^{-2}	3.1×10^{-3}	-2.5×10^{-2}	2.1×10^{-3}	1.3×10^{-3}			74	-96.9, 90.47
LC10		1.05	.03	-.04	.03			-4×10^{-3}	9.5×10^{-3}	8.6×10^{-4}	-1.2×10^{-2}	-2.3×10^{-4}	4.8×10^{-4}			56	-79.96, 78.35
LC4		1.0	-.07	-.18	-.12											86	-85.9, 85.02
S3		.70	.30		.36											119	-109.6, 100.4