ON-LINE WEATHER-SENSITIVE AND INDUSTRIAL GROUP BUS LOAD FORECASTING FOR MICROPROCESSOR-BASED APPLICATIONS

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Abstract--Algorithms are presented for on-line development of a nominal non-weather-sensitive load sequence and a pure weather-sensitive load sequence constructed from a composite residential and commercial weather-sensitive load sequence. These algorithms are intended for microprocessor-based applications, and they obey the realistic requirements of microprocessors.

The paper also presents the problems associated with industrial bus load and residential and commercial bus load modeling and forecasting through analysis of the American Electric Power's Canton Area Load Sequence.

1. INTRODUCTION

An on-line bus load forecasting algorithm is an essential part of a modern energy control center. Using such an algorithm, bus load demand can be forecasted from 15 minutes to a few hours in advance so that realistic contingencies can be formulated for security evaluation studies. Detection of vulnerable situations well ahead of time allows for the calculation and possible execution of corrective strategies.

A bibliography [1] prepared by the Load Forecasting Working Group, Power System Engineering Committee gives a comprehensive list of papers published on the system hourly load modeling and forecasting problems. As can be seen from this survey paper and other papers published on this subject [2,3,4,5,6,7,8, 9] the application of rigorous probability and stochastic theory to the problem of system load forecasting has been studied by many investigators. However, the literature survey does not show any investigation of the bus load forecasting problem. Some of the reasons that the bus load forecasting problem has not been studied are:

1. An average power system may have 500 buses. The memory requirements, computational complexities and associated cost have ruled out the use of control center computers for this purpose.
2. Bus loads do not have consistent patterns compared to system loads. This is primarily due to the switching operation in the system which normally transfers the load from one transformer to some other transformers within a load group.

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The recent advances of digital computer technology and the development of low-cost microprocessors should make it possible to develop cost-effective microprocessor-based group load modeling, and bus load forecasting. This paper presents some of the preliminary results of the investigations of this problem.

2. NOMENCLATURE

$\{Y(\cdot)\}$	Total area load sequence
$\{Y_I(\cdot)\}$	Industrial load sequence
$\{Y_R(\cdot)\}$	Residential and commercial weather-sensitive load sequence
$\{Y_N(\cdot)\}$	Residential and commercial non-weather-sensitive load sequence, or nominal load sequence
$\{Y_{PW}(\cdot)\}$	Pure weather load sequence
$\{T_M(\cdot)\}$	Temperature sequence
$W(\cdot)$	Unmeasurable disturbance sequence; white noise
$\overline{Y}$	Mean value of sequence $\{Y(\cdot)\}$
σ_Y^2	Variance of sequence $\{Y(\cdot)\}$
ARMA(n,m)	Autoregressive and moving average of order n and m
$\hat{Y}(K)$	Estimate of Y(K) based on observations Y(K-1), Y(K-2),...
E[]	Expected value
$\overline{Y}_{NB}$	Nominal bus load
Y_B	Actual weather-sensitive bus load
$\hat{DF}$	Estimated distribution factor
Y_{IB}	Actual industrial bus load.

3. STOCHASTIC MODELS

Definition and Basic Concepts

A sequence $\{Y(\cdot)\}$ is defined as weakly stationary [9] if it has constant mean and variance.

$$E[Y(K)] = \text{constant} = \overline{Y} \tag{1}$$

$$E[(Y(K)-\overline{Y})^2] = \text{constant} = \sigma_Y^2 \tag{2}$$

A sequence $\{Y(\cdot)\}$ is defined as non-stationary [9] if it has a time-varying mean and variance.

A stationary sequence $\{Y(\cdot)\}$ can be modeled by a stochastic difference equation of the form [9]:

$$Y(K) = \sum_{j=1}^{n} a_j Y(K-j) + \sum_{j=1}^{m} a_{n+j} W(K-j) + W(K) \tag{3}$$

where W(K-j) is the past residue at instant K-j, $\{W(\cdot)\}$ is a sequence of independent random variables with zero mean and unknown variance σ_W^2. The sequence $\{W(\cdot)\}$ by

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definition is called white noise. The model represented by Eq. 3 is called an autoregressive moving average model of order n and m, or in short ARMA(n,m). The unknown parameters in Eq. 3 are a_j, $j = 1,\ldots n+m$ and can be estimated using the recursive least square estimation technique. This algorithm is used in this paper and is given in [2,3,9].

4. BUS LOAD MODELING PROBLEM

Figure 1 shows the Canton area load of Ohio Power, an operating company of the American Electric Power Company.

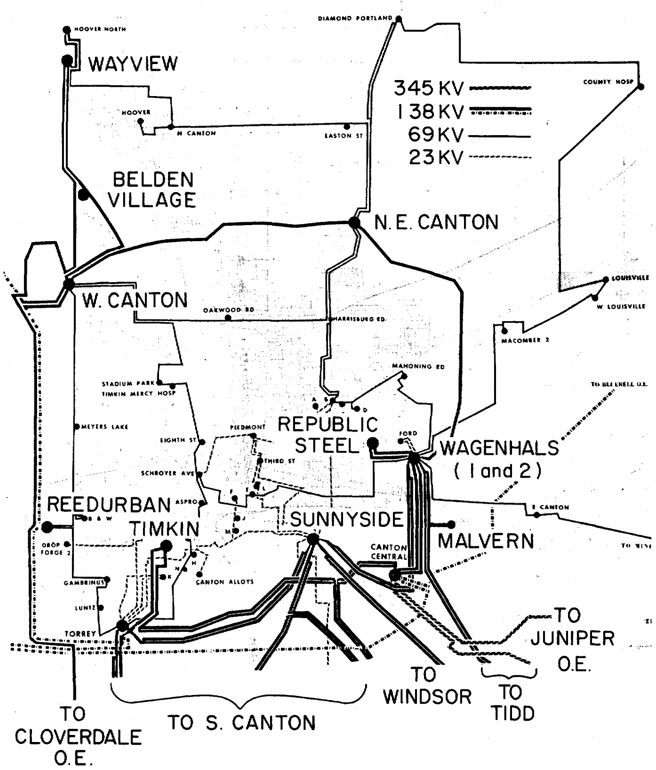


Fig. 1 Ohio Power Company -- Canton division 1980 system.

The power flow into this load area is essentially supplied by 345 kV and 138 kV transmission systems. The area load demands are satisfied by the secondary and tertiary windings of the following transformers: Malvern 138/69/12 kV, N.E. Canton 138/69/12 kV, Reedurban 138/69/12 kV, Belden Village 138/69/12 kV, Sunnyside 138/23/12 kV, Timkin 138/23 kV, Torrey 138/69/23 kV, Wagenhals 138/69/23 kV and 138/23 kV, West Canton 138/69/12 kV, Wayview 138/69/12 kV and Republic Steel 138/23 kV.

It may be reasonable to define a bus load as the power flowing into the primary windings of the transformers connected to that bus. This definition assumes that power flows from higher voltage systems to lower voltage systems, which is generally a correct assumption. Therefore, the problem of bus load predictions may be defined as the determination of 138 kV and/or 345 kV transformer loads which will be defined as bus loads. For the above area load, there are twelve 138 kV bus loads which need to be modeled and forecasted.

Three methods may be proposed to solve this problem. These methods are:

Method 1. -- To develop a separate model for each bus load based on past observations and weather conditions.

Method 2. -- To develop an area load model based on the combined past observations and weather conditions, and then assign part of the area load to each bus based on a set of predefined distribution factors.

Method 3. --Based on the physical characteristics of each load group, develop the similar group load sequences. That is, develop a group load sequence for the same recognizable cyclical load patterns. For example, group all of the industrial loads of the same type together. Similarly, group the residential loads and commercial loads together. Model each group load sequence based on past observations and weather conditions, and then assign part of the group load prediction to each bus of the group based on a set of predefined distribution factors.

Preliminary results of these methods are presented in this paper.

5. REQUIREMENTS OF A MICROPROCESSOR-BASED BUS LOAD MODELING ALGORITHM

The realistic requirements of microprocessor-based bus load modeling algorithms may be stated as follows:

1) the algorithms should be completely automatic in modeling and forecasting the bus loads from 15 minutes to a few hours in advance;

2) the algorithms should be able to recognize the historical load observations corrupted by communication noise during the transmission of data, outages on distribution systems, and load changes resulting from unpredictable events;

3) the algorithms should be feasible for modeling the regular weather-sensitive residential and commercial, and industrial loads;

4) the on-line microprocessor implementation of the models must not require much computing time and storage space. The storage requirement is a function of the number of parameters used in the models, the required past history for updating the coefficients, and the different types of models employed. This restriction requires that during any time instant K, only a finite, prespecified number of real numbers be stored in the microprocessor, ruling out the possibility of storing the entire past history at that instant. In addition, the amount of computations, such as the number of additions, multiplications, etc. needed to obtain the parameters of the model recursively shall be prespecified and independent of K.

In the following sections, algorithms are presented which obey these requirements.

6. MODELING OF CANTON AREA LOAD SEQUENCE

Proposed Sequences Based on Physical Aspects

A composite hourly load sequence was generated by the addition of the twelve 138 kV hourly bus load data of the Canton area. The late Spring and Summer load data for the period of May 5 through August 31, 1980 were used in this analysis. This sequence is designated as $\{Y(\cdot)\}$. The recursive mean and variance of $\{Y(\cdot)\}$ can be computed based on the following equations:

$$\bar{Y}(K+1) = \bar{Y}(K) + \frac{Y(K+1) - \bar{Y}(K)}{K+1} \tag{4}$$

$$\sigma_y^2(K+1) = \frac{K}{K+1}\sigma_y^2(K) + \frac{[Y(K+1) - \bar{Y}(K+1)]^2}{K} \tag{5}$$

Fig. 2 shows the mean and variance of the load sequence. Also shown in Fig. 2 is the weekly mean of

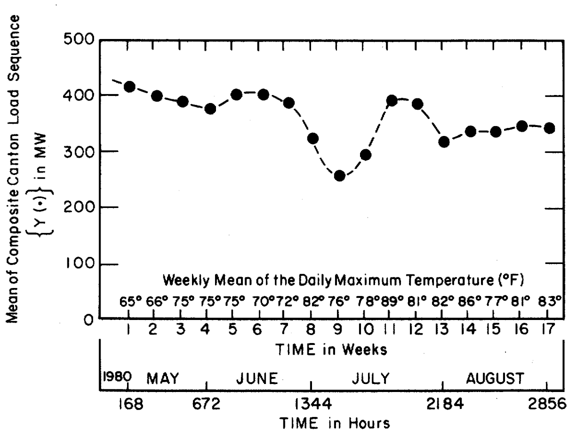


Fig. 2 (a)

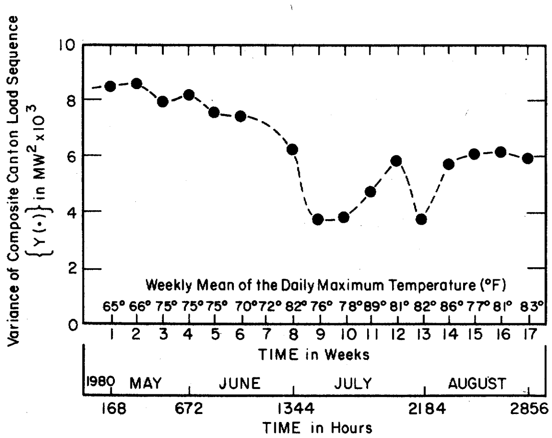


Fig. 2 (b)

Fig. 2: a) Plot of mean and b) variance of the sequence $\{Y(\cdot)\}$.

the daily maximum temperature for the months of May, June, July, and August of 1980. The following observations may be made from Figure 2: 1) the mean and variance are time-varying, and therefore, the sequence is non-stationary; 2) during the late spring when the mean of the maximum temperature was approximately 72° (F), the mean load was about 400 MW; however, during late July and early August when the mean of the maximum temperature was approximately 82° (F), the mean load was about 314 MW. These observations point out that the non-stationary behavior of the $\{Y(\cdot)\}$ sequence is primarily due to industrial loads, since higher temperature cannot result in lower loads.

The demands on the Republic Steel, Timkin, and Wagenhals transformers were known to be from industrial-type loads. These loads are combined into an industrial load sequence and this combined sequence is designated as $\{Y_I(\cdot)\}$. Now the Canton area load sequence has been divided into two load sequences, namely; the industrial load sequence, $\{Y_I(\cdot)\}$ and the residential and commercial weather-sensitive load sequence, $\{Y_R(\cdot)\}$. The sequence $\{Y_R(\cdot)\}$ is the difference between the sequence $\{Y(\cdot)\}$ and the sequence $\{Y_I(\cdot)\}$. Figures 3 and 4 show the mean and variance of these sequences.

Figures 3 and 4 show that the industrial load sequence, $\{Y_I(\cdot)\}$ and the residential and commercial weather-sensitive load sequence, $\{Y_R(\cdot)\}$ are both non-stationary. The non-stationary behavior of $\{Y_I(\cdot)\}$ sequence may be due to large industrial loads with random on and off operation cycles, strikes, and plant shut-downs due to temporary problems. The non-stationary behavior of $\{Y_R(\cdot)\}$ sequence is primarily due to the effect of weather conditions on the load.

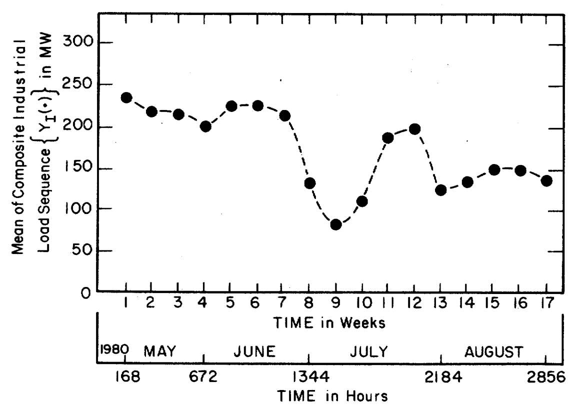


Fig. 3 (a)

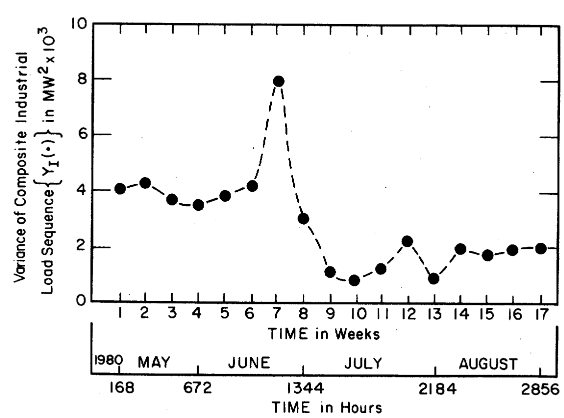


Fig. 3 (b)

Fig. 3: a) Plot of mean and b) variance of the sequence $\{Y_I(\cdot)\}$.

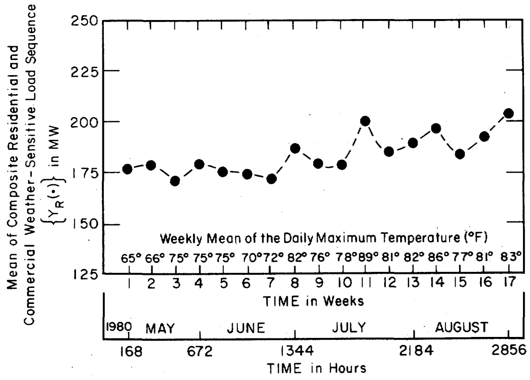


Fig. 4 (a)

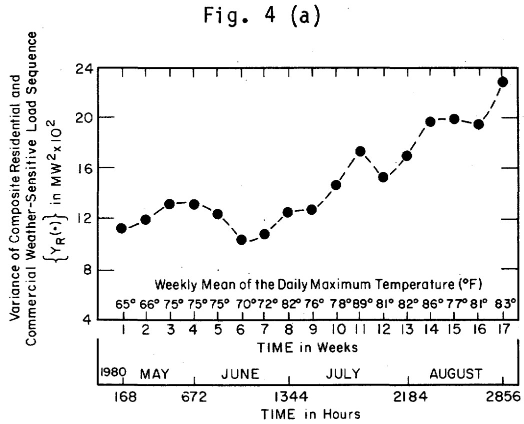


Fig. 4 (b)

Fig. 4: a) Plot of mean and b) variance of the sequence $\{Y_R(\cdot)\}$

Other conditions which can contribute to non-stationary behavior are as follows: 1) the outages on the 69 kV and lower voltage transmission systems which have resulted in load drops; 2) unusually high demand during a popular television program or low load demand due to the occurence of a holiday or a special event on a working day.

To detect these conditions in the Canton area load sequence, the load for the week of May 5 through May 11, 1980 is chosen as a nominal reference load and designated as Week 1. This first week load profile is plotted along with the future weekly load profiles in Fig. 5. Fig. 5(a) and (b) show that for the late spring with approximately the same maximum daily temperature, the weekly load profiles are essentially the same. Fig. 5(c) shows that on Monday of Week 4, loads were dropped due to some outages on the distribution system, which contributed to the non-stationary behavior of the sequence $\{Y(\cdot)\}$. The weekly load profiles for Weeks 5, 6, 7, and 8 were essentially the same as the first week and are not shown in Fig. 5. Fig. 5(d), (e), and (f) show the weekly load profiles for the second, third, and fourth weeks of the summer. Lower load demand for the second and third weeks of the summer as compared to Week 1 (late Spring) are due to lower economic activities and lower industrial loads. Fig. 5(d) shows the effect of a holiday on a working day which also causes non-stationary behavior. Fig. 5(f) shows the effect of a week of high temperature on the weekly load profile, which also contributes to the non-stationary behavior of this load sequence.

In the preceding analysis, it has been pointed out that the non-stationary behavior of $\{Y(\cdot)\}$ sequence is due to industrial loads, the weather effect on the

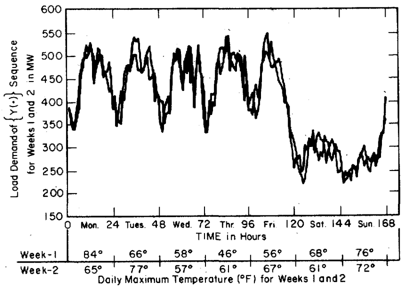


Fig. 5 (a)

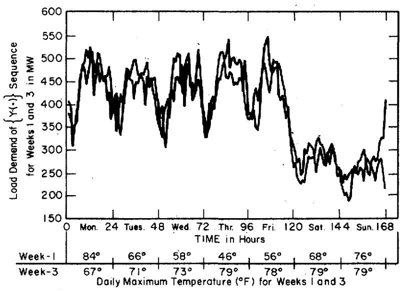


Fig. 5 (b)

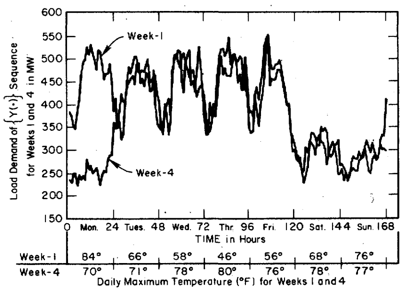


Fig. 5 (c)

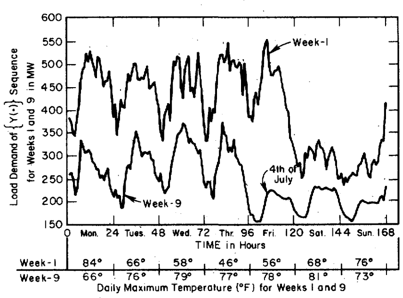


Fig. 5 (d)

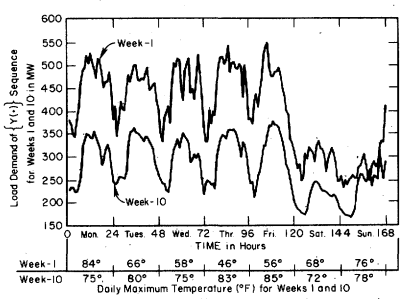


Fig. 5 (e)

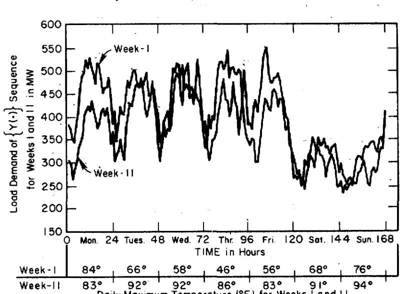


Fig. 5 (f)

Fig. 5: Plots of $\{Y(\cdot)\}$ for Week 1 vs. Weeks 2, 3, 4, 9, 10 and 11.

load sequence, holidays and unforeseen conditions which cause the load demand sequence to be higher or lower than a given nominal load profile sequence.

In the next sections, a method is proposed for on-line construction of a stationary nominal load sequence and a pure weather load sequence. The methods proposed are intended for microprocessor-based applications and take their computational limitations as stated in this paper into account.

The On-Line Construction of a Stationary Nominal Load Sequence from the Weather-Sensitive Load Sequence $\{Y_R(\cdot)\}$.

The proposed method is based on removing the non-stationary component of $\{Y_R(\cdot)\}$ due to the weather effect, sudden load changes related to outages and special events; and generating a new sequence designated as the nominal load sequence $\{Y_N(\cdot)\}$. The effect of weather conditions on the load depends on temperature, humidity, wind speed and illumination. But only the weighted average, maximum and minimum temperatures were recorded, and therefore the effect of weather conditions on the load is expressed in terms of temperature. That is, it is assumed that a weather-sensitive load is present when the daily temperature, T, is outside of the comfort range of $T_{min} < T < T_{max}$ where T_{min} and T_{max} are the lower and upper limits of the comfort range. This suggests that the nominal load sequence $\{Y_N(\cdot)\}$ can be assumed to be equal to the sequence $\{Y_R(\cdot)\}$ when the temperature is within the comfort range, and sudden load changes due to outages or special events have not occurred. The algorithm steps for construction of the sequence $\{Y_N(\cdot)\}$ are as follows:

Step 1: Pick a few weeks of the $\{Y_R(\cdot)\}$ sequence in the Spring when the load has been normal and the temperature T is within the comfort range and it is reasonable to believe no special events have occurred. Calculate the mean and variance for each hour of the week, i.e., $[\bar{Y}_N(\cdot)]_{K=1}^{168}$ and $[\sigma_N^2(K)]_{K=1}^{168}$.

Step 2: Check to see if $Y_R(K)$ at instant K is a normal, non-weather-sensitive load demand observation. To do this, the following conditions are checked: Condition 1 --$Y_R(K)$ is a non-weather-sensitive load demand observation if the temperature, T, is within the comfort range, that is, $T_{min} < T < T_{max}$ where T_{min} and T_{max} can be specified based on the knowledge of the buildings' thermal inertia and extensive testing. Condition 2 --Check $Y_R(K)$ for unusually high or low demand based on the following equations:

$$\sigma^2_{N(max)} = \text{max. of } [\sigma^2_{N(1)}, \sigma^2_{N(2)}, \ldots, \sigma^2_{N(168)}] \quad (6)$$

$$\sigma_{test} = \alpha \cdot \sigma_{N(max)} \quad (7)$$

The observation $Y_R(K)$ at instant K is normal if $|Y_R(K) - \bar{Y}_N(K)| < \sigma_{test}$. Otherwise $Y_R(K)$ is not normal and should be disregarded as a normal nominal load demand for $\{Y_N(\cdot)\}$ sequence. In this case, $\bar{Y}_N(K)$ is used as a normal load for that instant. α is a tolerance factor of reasonable load variation and can be specified by testing. In our study, α of 1.1 was used.

Step 3: Generate the sequences $\{Y_N(\cdot)\}$ and $\{\sigma_N^2(\cdot)\}$ using the following equations

$$\bar{Y}_N(K+168) = \bar{Y}_N(K) + \frac{Y_R(K) - \bar{Y}_N(K)}{N} \quad (8)$$

$$\hat{\sigma}_N^2(K+168) = \frac{N-1}{N}\,\hat{\sigma}_N^2(K) + \frac{[Y_R(K) - \bar{Y}_N(K+168)]^2}{N-1} \quad (9)$$

where N is the number of weeks and can be re-initialized on a yearly basis. $Y_R(K)$ in Eq 8 and 9 must satisfy the conditions of Step 2.

Fig. 6(a),(b),(c), and (d) show the plots of $\{Y_R(\cdot)\}$ and $\{Y_N(\cdot)\}$ sequences for weeks 10, 11, 12 and 13 of the Canton area load. It can be seen that the general weekly profile of weather-sensitive load sequence $\{Y_R(\cdot)\}$ and nominal load (non-weather-sensitive) sequence $\{Y_N(\cdot)\}$ are essentially the same when the daily temperature is normal. However, when the daily temperature is high, a weather-induced load is superimposed on the $\{Y_N(\cdot)\}$ sequence.

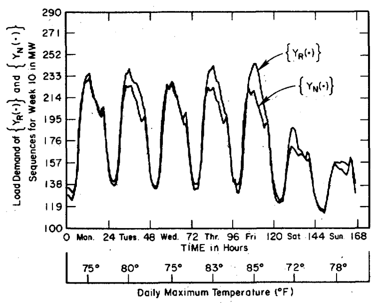
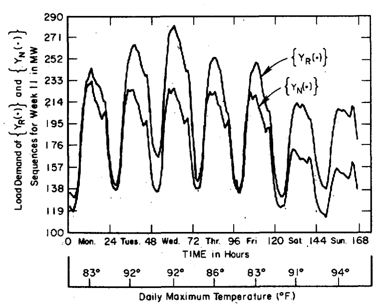


Fig. 6 (a)



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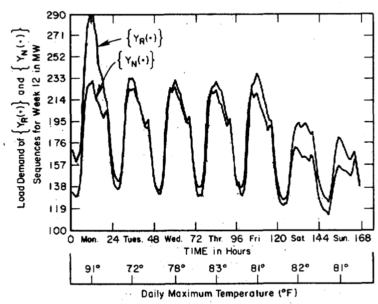

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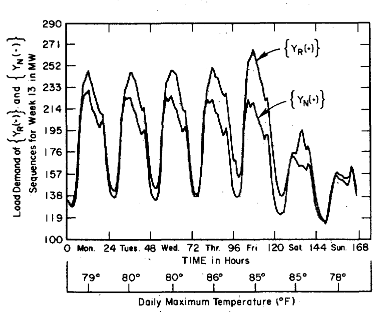

Fig. 6 (d)

Fig. 6: Plot of $\{Y_R(\cdot)\}$ and $\{Y_N(\cdot)\}$ for Weeks 10, 11, 12 and 13.

Figure 7 (a) and (b) show that the mean and variance for sequence $\{Y_N(\cdot)\}$ are constant; therefore, this sequence is stationary. Thus, this sequence can be modeled by the stochastic representation of Eq. 3.

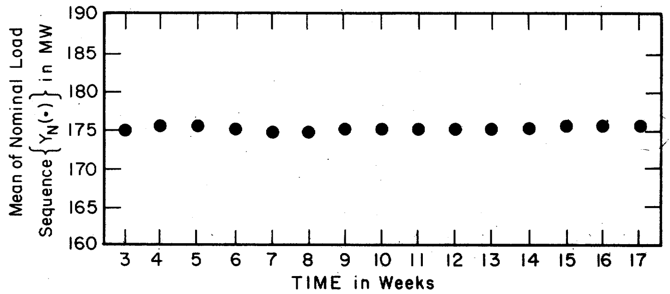

Fig. 7 (a)

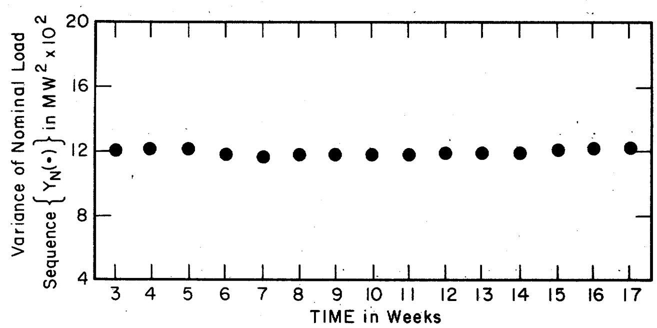

Fig. 7 (b)

Fig. 7: a) Plot of mean value and b) variance of sequence $\{Y_N(\cdot)\}$.

<u>The On-Line Modeling and Prediction of Pure Weather-Sensitive Load</u>

The procedure is based on computing an average relationship between the temperature and the pure weather-induced component of the load, which is designated as Y_{PW}. That is, a sequence $\{Y_{PW}(\cdot)\}$ is generated where each member of $\{Y_{PW}(\cdot)\}$ is a mean value of the pure weather-sensitive component of the load at a given temperature. The algorithm steps are as follows:

Step 1: Compute the pure weather-induced load sequence by taking the difference between $\{Y_R(\cdot)\}$ and $\{Y_N(\cdot)\}$.

Step 2: Compute the mean values of Y_{PW}'s corresponding to the same temperature and generate a sequence $\{Y_{PW}(\cdot)\}$ and a temperature sequence $\{T_M(\cdot)\}$ where there is a one-to-one correspondence between the two sequences. That is, a given temperature, T, in the sequence $\{T_M(\cdot)\}$, has a corresponding pure weather-induced load, $\bar{Y}_{PW}$ in $\{Y_{PW}(\cdot)\}$.

Step 3: For forecasting the pure weather induced component of the load, locate the desired temperature in $\{T_M(\cdot)\}$ and its corresponding load in $\{Y_{PW}(\cdot)\}$.

Step 4: At any instant K, use the difference between actual $Y_R(K)$ and $\bar{Y}_N(K)$ to update the sequence $\{Y_{PW}(.)\}$ in a recursive manner.

Figure 8 shows the mean and standard deviation ($\pm 2\sigma_{PW}$) of the pure weather-induced component of the load at different temperatures for the Canton area load.

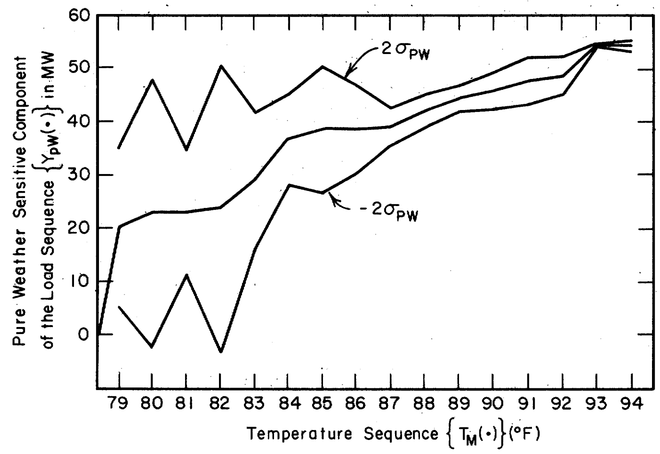

Fig. 8: Mean and standard deviation of pure weather-sensitive load vs. temperature .

As can be seen from Fig. 8, the pure weather-sensitive component of the load is non-linear, and it has saturated at 80°-82°, 84°-87° and above 93° Fahrenheit.

7. PRELIMINARY RESULTS

In Section 4, it was pointed out that three methods may be used to model bus loads or group bus loads, based on the stochastic representation discussed previously. Due to limited space, only the preliminary results of methods 2 and 3 will be presented here. The results of method 1 are given in reference [11].

Method 2 was based on modeling the composite load sequence $\{Y(\cdot)\}$. Table 1 shows the coefficients of a few stochastic models, the mean error, the absolute mean error and RMS error as a percentage of daily peak load.

In the third method, $\{Y_R(\cdot)\}$ and $\{Y_I(\cdot)\}$ sequences were modeled separately. Table 2 shows the same results as Table 1 for a few stochastic models of the industrial load sequence $\{Y_I(\cdot)\}$.

For the sequence $\{Y_R(\cdot)\}$, in addition to a few stochastic models, the following special models were also simulated:

$$A1: \quad \hat{Y}_R(K) = \bar{Y}_N(K-168) + \hat{Y}_{PW}(T(K-2)) \tag{10}$$

$$A2: \quad \hat{Y}_R(K) = \bar{Y}_N(K-168) + \hat{Y}_{PW}(T(K-2)) + \hat{a}_1(K)Y_R(K-1) + \hat{a}_2(K)Y_R(K-2) \tag{11}$$

$$A3: \quad \hat{Y}_R(K) = Y_N(K-168) + \hat{Y}_{PW}(T(K-2)) + a1(K)\hat{W}(K-1) \tag{12}$$

$$A4: \hat{Y}_R(K) = \bar{Y}_N(K-168) + \hat{Y}_{PW}(T(K-2)) + \hat{a}_1(K)W(K-1) + \hat{a}_2(K)W(K-2) \quad (13)$$

Table 1: Final coefficients and errors for the various models of the sequence $\{Y(\cdot)\}$. N = 2,184.

Model	Model Coefficients					Mean Error (MW)	Absolute Mean Error (MW)	RMS Error as percentage of daily peak load
	$a_1(N)$	$a_2(N)$	$a_3(N)$	$a_4(N)$	$a_5(N)$			
AR(1)	0.954					0.0707	17.4	3.16
AR(2)	0.301	0.649				0.2765	23.0	4.0
AR(3)	0.408	0.862	-0.343			0.1737	21.2	3.8
ARMA(1,1)	0.943			0.083		-0.0509	17.3	3.14
ARMA(2,1)	0.324	0.785		-0.188		-0.1543	22.4	3.9
ARMA(2,2)	0.396	0.461		0.247	0.600	0.0097	23.4	4.2
ARMA(3,1)	0.376	0.870	-0.30	-0.023		-0.074	21.6	3.8
ARMA(3,2)	0.995	0.01	0.001	-0.007	-0.314	-1.647	18.68	3.3

Table 2: Final coefficients and errors for the various models of the sequence $\{Y_I(\cdot)\}$. N = 2,184.

Model	Model Coefficients					Mean Error (MW)	Absolute Mean Error (MW)	RMS Error as percentage of daily peak load
	$a_1(N)$	$a_2(N)$	$a_3(N)$	$a_4(N)$	$a_5(N)$			
AR(1)	0.8896					-0.473	14.687	4.16
AR(2)	0.6850	0.2172				-0.1822	14.170	4.0
AR(3)	0.557	0.0.45	0.304			0.2065	14.377	4.0
ARMA(1,1)	0.721			0.291		0.098	14.599	4.14
ARMA(2,1)	0.471	0.467		0.278		-0.0031	15.07	4.4
ARMA(2,2)	0.4763	0.457		0.275	0.0192	0.0160	14.518	4.1

Table 3: Final coefficients and errors for the various models of the sequence $\{Y_R(\cdot)\}$. N = 2,184.

Model	Model Coefficients					Mean Error (MW)	Absolute Mean Error (MW)	RMS Error as percentage of daily peak load
	$a_1(N)$	$a_2(N)$	$a_3(N)$	$a_4(N)$	$a_5(N)$			
A1						0.071	4.81	2.5
A2	-0.002	0.0042				0.085	4.57	2.2
A3	0.518					0.059	4.37	2.0
A4	0.505	0.226				0.097	4.51	2.2
AR(1)	0.968					0.097	8.6	4.3
AR(2)	1.107	-0.166				0.099	7.6	3.7
AR(3)	1.1325	-0.078	-0.135			0.0954	6.6	3.3
ARMA(1,1)	0.761			0.344		-0.174	16.64	7.8
ARMA(2,1)	0.576	0.316		0.571		0.234	7.38	3.6
ARMA(3,1)	0.461	0.263	0.097	0.467		-0.165	8.20	4.0
ARMA(2,2)	0.555	0.317		0.55	0.171	-0.005	6.86	3.5
ARMA(3,2)	0.44	0.266	0.091	0.45	0.108	-0.06	8.06	3.4

From Table 2 it can be seen that, based on the models simulated, AR(2) has the best stochastic representation for the industrial load sequence $\{Y_I(\cdot)\}$. From Table 3, it can be seen that the model A3 has the best stochastic representation for the residential and commercial weather-sensitive load sequence $\{Y_R(\cdot)\}$. Using these two models, the composite load can be forecasted based on the following equation:

$$\hat{Y}(K) = \hat{Y}_R(K) + \hat{Y}_I(K) \quad (14)$$

Based on Eq. 14, the one-step-ahead forecasted errors are:

Mean Error in MW = -0.1232
Absolute Mean Error in MW = 14.8
RMS Error as a percentage of daily peak load = 2.5

Comparing these results with the results given in Table 1, it can be seen that the recognition of the structure of each load sequence improves the forecasting performance.

To obtain the forecasts for residential and commercial bus loads, we may proceed as follows:

Step 1: Generate a stationary nominal bus load sequence $Y_{NB}(\cdot)$. Use the same algorithm given for group load sequence $Y_N(\cdot)$.

Step 2: For each hour K, estimate the bus distribution factor (DF) and its variance according to the following equations:

$$DF(K) = \frac{\bar{Y}_{NB}(K)}{\Sigma \bar{Y}_{NB}(K)} \quad (15)$$

where $\Sigma \bar{Y}_{BN}(K) = \bar{Y}_{NB1} + \bar{Y}_{NB2} + \ldots$

$$\hat{DF}(K) = \hat{DF}(K-168) + \frac{DF(K) - \hat{DF}(K-168)}{N} \quad (16)$$

$$\hat{\sigma}^2_{DF}(K) = \frac{N-1}{N}\hat{\sigma}^2_{DF}(K-168) + \frac{[DF(K) - \hat{DF}(K)]^2}{N-1} \quad (17)$$

where N is the number of weeks.

Step 3: Obtain the forecast of the bus load for hour K, $Y_B(K)$, from the predicted value of the group load, $Y_R(K)$, using the following equation:

$$\hat{Y}_B(K) = \hat{DF}(K) \times \hat{Y}_R(K) \quad (18)$$

where $\hat{\sigma}_{DF}(K)$ represents the measure of uncertainty in the forecast.

To forecast industrial bus loads, skip Step 1 and use actual, rather than nominal, predictions in Eq. 15; $\hat{Y}_I(K)$ would replace $\hat{Y}_R(K)$ in Eq. 18.

8. IMPLEMENTATION

Figure 9 shows a processing scheme for an on-line implementation of the proposed bus load forecasting algorithms. The analog data (temperature and transformer load) are sampled, multiplexed, and converted to digital data, and stored in the RAM for access by the microprocessor. The operation of the single-board processor is under the control of the PROM, where the developed algorithms are stored. The PROMS are programmed using a microcomputer development laboratory system in the following manner: a) The blank PROM is inserted into the appropriate socket in

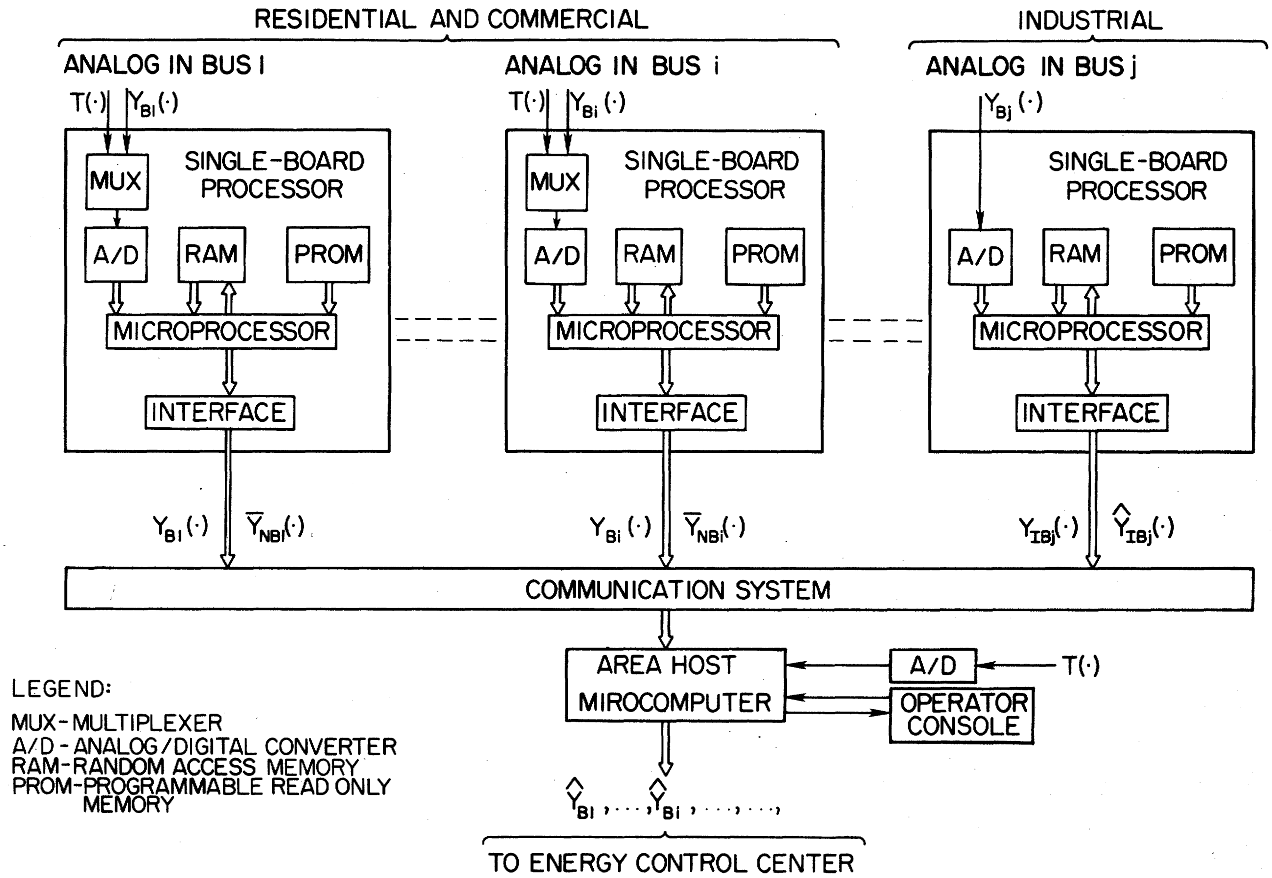

Fig. 9 Processing scheme for an on-line implementation of bus load forecasting.

the development system; b) the algorithms are programmed in a high level language, debugged, and tested in the development system, and then compiled into the appropriate machine language; c) the developed machine language program is now literally burned into the blank PROM; e) the programmed PROM is then ready for control in the single-board processor at the substations. The use of the PROM has the further advantage that any future modification of the algorithms can be easily accommodated by simply reprogramming and changing the PROM.

Under the control of the PROM, the nominal bus load, $\bar{Y}_{NB}(\cdot)$, and the forecasted industrial bus load, $\hat{Y}_{IB}(\cdot)$, are computed. The host microcomputer scans the area single-board processors and collects the data $Y_B(\cdot)$, $\bar{Y}_{NB}(\cdot)$, $Y_{IB}(\cdot)$ and $\hat{Y}_{IB}(\cdot)$. Based on the received data, the host microcomputer calculates the bus load distribution factors, DF(·), pure weather load, $Y_{PW}(\cdot)$, area nominal load, $\bar{Y}_N(\cdot)$, weather-sensitive load, $Y_R(\cdot)$, and industrial load, $\hat{Y}_I(\cdot)$. The distribution factors are used for forecasting the bus load using Eq. 18. A research proposal is pending for actual implementation of the bus load forecasting scheme presented in this paper.

9. CONCLUSIONS AND COMMENTS

The paper presents two algorithms for on-line development of stationary nominal loads, pure weather-sensitive loads, and distribution factor sequences. In addition, the paper presents a microprocessor-based scheme for an on-line implementation of bus load forecasting using these algorithms [11].

Currently, work is in progress to develop bus load probability density function algorithm which can be stored in the PROM of a single-board processor. The bus load density function will give the probability of occurrence of a forecasted bus load.

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