

Short-Term Load Forecasting Via ARMA Model Identification Including Non-Gaussian Process Considerations

Shyh-Jier Huang, *Senior Member, IEEE*, and Kuang-Rong Shih

Abstract—In this paper, the short-term load forecast by use of autoregressive moving average (ARMA) model including non-Gaussian process considerations is proposed. In the proposed method, the concept of cumulant and bispectrum are embedded into the ARMA model in order to facilitate Gaussian and non-Gaussian process. With embodiment of a Gaussianity verification procedure, the forecasted model is identified more appropriately. Therefore, the performance of ARMA model is better ensured, improving the load forecast accuracy significantly. The proposed method has been applied on a practical system and the results are compared with other published techniques.

Index Terms—Bispectrum, cumulant, non-Gaussian process, short-term load forecast.

I. INTRODUCTION

SHORT-TERM load forecast is aimed at predicting system load over a short time interval. It plays an important role in the operation of power system, where several controls such as energy transactions, security analysis, economic dispatch, hydro-thermal coordination, load management, and generator maintenance scheduling have all benefited [1], [2]. Several methods for the load forecast modeling have been reported in the last decades [3]–[7]. These techniques can be largely classified into regression techniques [8]–[11] and time series approaches [12]–[16]. In regression techniques, linear or piecewise-linear representations are adopted as the primary forecasting functions, where functional relationships between weather variables and electric loads were prudently investigated. This method was tested feasible, but short of handling nonstationary temporal cases. In time series approach, one treated load demands as time series signals and predicted load demands using different time series analysis techniques. The results of using such approaches were satisfactory; however, inherent numerical instability may affect the computational performance.

Among different time series methods, one of most often used procedures is autoregressive moving average (ARMA) model [17]. In the implementation of such a model, the operation of difference is employed first such that the stationary time series can be formed. Then, by use of the autocorrelation

function (ACF) and partial autocorrelation function (PACF), the preliminary order identification of a model is confirmed. This can be followed by the application of maximum likelihood or weighted least-squares methods for parameter estimation [18]. It is also worth noting here that the formulation of the above model is based on Gaussian process, yet the short-term load forecast problem, in general, might not completely adhere to this Gaussianity assumption. This is attributed to several factors that may affect the load profiles, including seasonal variation, government policy, customer behavior, and natural disasters. Problems like how to distinguish Gaussianity or which method would be more suitable to formulate the load forecast under non-Gaussian situation are, therefore, worth further investigation.

Determination of Gaussianity in a random process has been deemed crucially important in several engineering applications [19], [20]. In non-Gaussian process identification, the computed cumulants can be used as important information. This is because cumulants are generally asymmetric functions of their arguments, as such carry phase information about the ARMA transfer function. Therefore, cumulant statistics are capable of determining the order of ARMA model [21], [22]. In addition, when the ARMA process is corrupted by Gaussian noise of unknown covariance function, they are also considered suitable for the order determination. Besides the cumulant information, the bispectrum is also useful for the analysis of time series data. The bispectrum is the Fourier transform of the cumulant. The calculated value of bispectrum serves as a useful index to validate the Gaussianity of time series [23], [24]. In other words, for load forecast applications, a sample bispectrum can be used to construct a statistics in order to test whether the bispectrum of load data equals nonzero. A rejection of the null hypothesis implies a rejection of the hypothesis that load data is Gaussian.

In this paper, after the input of historical data, the load data becomes stationary one through the difference operation. Then, the Gaussian test is performed. Based on the Gaussian features of the load, a method can be accordingly chosen to identify the ARMA model. By use of such a method, the related information could be effectively extracted from the load data in order to achieve a higher forecast accuracy. Features of the proposed approach are threefold:

- 1) The method provides the engineers a more reliable way of predicting the load demand of a power system.
- 2) The approach is feasible to apply under various scenarios. It can be also developed as a didactic tool to help students be more acquainted with power system planning.

Manuscript received September 5, 2002. This work was supported in part by the National Science Council of the Republic of China under Contract NSC88-2213-E-006-075 and in part by Taiwan Power Company under Contract NSC88-TPC-E-006-013.

The authors are with the Department of Electrical Engineering, National Cheng Kung University, Tainan, 70101, Taiwan, R.O.C.

Digital Object Identifier 10.1109/TPWRS.2003.811010

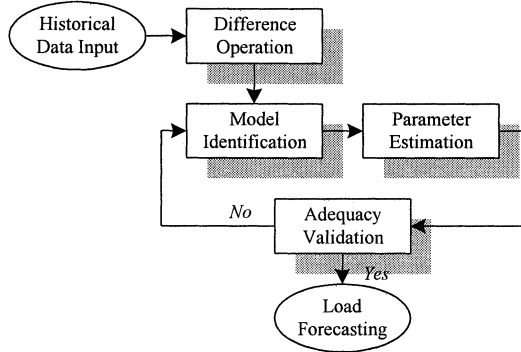


Fig. 1. Model identification process.

- 3) As the growth of load is increasingly significant in a developing country, the method may serve as a potential candidate and a useful reference to solve the load forecasting problems besides traditional approaches.

In this paper, Section II describes the paradigm of load forecast, Section III addresses the proposed method and computation procedures, Section IV gives the numerical study results, and Section V draws the conclusions.

II. PARADIGMS

For a stationary time series of load data, because the properties of historical and future data are mutually similar, the historical data can be used as the reference to formulate an adequate ARMA model. Then, if this stationary time series is Gaussian, it will be deemed a linear combination for autoregressive (AR) and moving average (MA) [17]. Fig. 1 depicts the identification process of this model, where the process can be largely divided into three steps, including system modeling, parameter estimation, and adequacy validation.

A. System Modeling

Consider a system load expressed as the following ARMA form:

$$\phi(B)y_t = \theta(B)a_t \quad (1)$$

where y_t is the observed time series of load at time t , a_t is the white noise at time t , and B is the back-shift operator such that $By_t = y_{t-1}$, $B^m y_t = y_{t-m}$. In the left-hand side of (1), $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$, where ϕ_1, \dots, ϕ_p are parameters of the AR part, and p is the AR order. For the right-hand side of (1), $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$, where $\theta_1, \dots, \theta_q$ are parameters of the MA part, and q is the MA order. In the study, the information on the sample autocorrelation function and the sample partial autocorrelation function are used as references to conjecture the appropriate model order. This process heavily depends on the experiences of the users, yet repeated trials of different combinations of model order would be helpful to relieve the computation burden.

B. Parameter Estimation

Following the model formulation, the related parameters are required to estimate. This work can be done with the aid of the

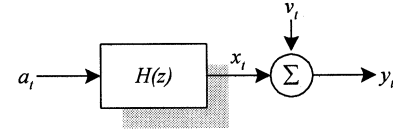


Fig. 2. Block diagram of a non-Gaussian model.

gradient-based method, where parameters are estimated in order to have zero gradient of mean squared sum of fitting errors to the historical load data. Note that the primary objective of this parameter estimation is to minimize the forecasting error; however, as the conventional process is only valid under the Gaussianity assumption, an investigation of another approach that is more suitable for non-Gaussian environment becomes indispensable.

C. Adequacy Validation

When the parameters of the model are well estimated, the adequacy of the model should be validated. Three items listed below are required to confirm in this procedure:

- 1) Estimated parameters are significantly different from zero.
- 2) Residuals are the realization of white noise process.
- 3) The fitted model is adequate.

After the confirmation of the above items, the formulated model is ready to perform the load forecast. Yet, if the model fails to pass these tests, then the aforementioned process should be repeated again until an adequate model is achieved.

III. PROPOSED METHOD

A. Non-Gaussian ARMA Model

Fig. 2 shows the block diagram of a non-Gaussian model. With a stationary and linear causal process x_t , the model can be described by the following difference equation:

$$\sum_{i=0}^p \phi_i x_{t-i} = \sum_{i=0}^q \theta_i a_{t-i} \quad (2)$$

where ϕ_i and θ_i are parameters, p and q are the order of model. By expressing the transfer function of the model in z domain while the model is assumed free of pole-zero cancellations and exponentially stable, it can be formulated as below

$$\begin{aligned} H(z) &= \sum_{i=0}^{\infty} h(i) z^{-i} \\ &= \frac{\left[\sum_{i=0}^q \theta_i z^{-i} \right]}{\left[1 + \sum_{i=1}^p \phi_i z^{-i} \right]} \\ &= \frac{\Theta(z)}{\Phi(z)} \end{aligned} \quad (3)$$

Now, for identifying the time series with non-Gaussian process, a driving noise sequence a_t is assumed to add in the ARMA model, which is a zero mean, stationary and

non-Gaussian independently identically distributed (i. i. d.) noise. The output signal y_t becomes

$$y_t = x_t + v_t \quad (4)$$

where v_t is a white Gaussian noise independent of input a_t , and hence, of output x_t . With this model, the cumulant and bispectrum used in the non-Gaussian process are described as follows.

Cumulant: The purpose of cumulant is to estimate the order and parameters of ARMA model. If a time series y_t is zero-mean random variables, then the second, the third, and the fourth order cumulant of time series y_t are individually defined as follows:

$$c_{2y}(m) = E\{y_t y_{t+m}\} \quad (5)$$

$$c_{3y}(m, n) = E\{y_t y_{t+m} y_{t+n}\} \quad (6)$$

$$\begin{aligned} c_{4y}(m, n, l) = & E\{y_t y_{t+m} y_{t+n} y_{t+l}\} - c_{2y}(m) c_{2y}(n-l) \\ & - c_{2y}(n) c_{2y}(l-m) \\ & - c_{2y}(l) c_{2y}(m-n). \end{aligned} \quad (7)$$

The second order cumulant is called the autocorrelation of y_t . As the cumulant of higher than second-order found in a Gaussian process is identical to zero, the following expression can be inferred:

$$c_{3y}(m, n) = c_{3x}(m, n). \quad (8)$$

In (8), it informs that the cumulant of the third, the fourth, or the higher order is insensitive to the additive Gaussian noise of unknown covariance function. This property can be thus used to distinguish the Gaussian process from the non-Gaussian one.

Bispectrum: The bispectrum $B_y(\omega_1, \omega_2)$ is a two-dimensional (2-D) Fourier transforms of the third-order cumulant obtained from the time series y_t [22], helping investigate the characteristic of time series. It can be defined as follows:

$$\begin{aligned} B_y(\omega_1, \omega_2) &= \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} c_{3y}(m, n) \exp[-i(\omega_1 m + \omega_2 n)] \end{aligned} \quad (9)$$

where $0 \leq \omega_1 \leq \pi$, $\omega_2 \leq \omega_1$, $2\omega_1 + \omega_2 \leq 2\pi$. One important property here is that the value of calculated bispectrum becomes identically zero whenever the stationary zero-mean time series is Gaussian.

B. Modeling Process

Fig. 3 presents the computation procedure of the proposed method, where two Gaussian tests are included. The first Gaussian test is employed before the identification of AR model, while the second one is used before the identification of MA model. Results of these Gaussian tests serve as the basis for the selection of a suitable method to identify the ARMA model. Important blocks of the algorithm are described as follows:

Step 1: Load Data Conversion: Historical load points are first collected to be the set of time series data. As this time series may not conform to the stationary features, the difference operation is first applied to remove the seasonal effect for obtaining a zero mean stationary time series.

Step 2: Gaussianity Test: The Gaussianity test is then performed for the formulated stationary time series. If this data

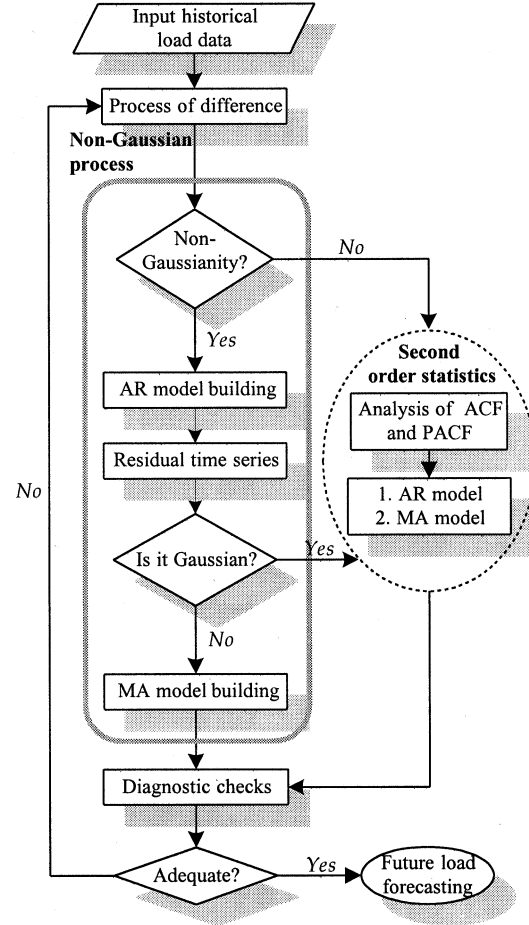


Fig. 3. Flowchart of the proposed method.

series follows a Gaussian process, then the second-order statistics shown in the block of Fig. 3 will be applied to estimate the ARMA model; otherwise, the AR model building block will be activated for the non-Gaussian process. This can be also inspected from the viewpoint of cumulant and bispectrum. It is known that with the Gaussian input a_t , it will result in the Gaussian output. However, once a_t is not a Gaussian signal, then the output y_t will become non-Gaussian with the third order nonzero cumulant $c_{3y}(m, n)$ existed for different values of m and n , implying that the value of bispectrum is nonzero [25].

To implement this step, the null hypothesis was assumed. The confidence level of the chi-square random variable of the indicated degrees of freedom is computed. If the confidence level value is larger than 0.05 (namely, it is risky to accept the alternative hypothesis), then the null hypothesis is accepted. Otherwise, the alternative hypothesis is accepted.

Step 3: AR Model Estimation: At this step, if the time series is reckoned as non-Gaussian through the above test, then the AR model estimation is performed [26]. First, by computing the third-order cumulant at both sides of (2) with the assumption of the maximum order of AR and MA to be \bar{p} and \bar{q} , a recursive form is expressed as follows:

$$c_{3y}(m, n) + \sum_{i=1}^{\bar{p}} \phi_i c_{3y}(m-i, n) = \begin{cases} = 0; & m > \bar{q} \\ \neq 0; & m \leq \bar{q}. \end{cases} \quad (10)$$

With the collection of the set of $\bar{p} + \bar{q} + 1$ slices that correspond to $m = \bar{q} + 1, \dots, \bar{q} + \bar{p}$, $n = -\bar{p}, \dots, \bar{q}$, the following matrix of the third-order cumulants is formulated:

$$\bar{C} = \begin{bmatrix} c_{3y}(\bar{q} + 1, -\bar{p}) & \cdots & c_{3y}(\bar{q} + \bar{p}, -\bar{p}) \\ \vdots & \vdots & \vdots \\ c_{3y}(\bar{q} + 1, \bar{q}) & \cdots & c_{3y}(\bar{q} + \bar{p}, \bar{q}) \\ \vdots & \vdots & \vdots \\ c_{3y}(\bar{q} + \bar{p}, -\bar{p}) & \cdots & c_{3y}(\bar{q} + 2\bar{p} - 1, -\bar{p}) \\ \vdots & \vdots & \vdots \\ c_{3y}(\bar{q} + \bar{p}, \bar{q}) & \cdots & c_{3y}(\bar{q} + 2\bar{p} - 1, \bar{q}) \end{bmatrix}. \quad (11)$$

Note that as the AR order equals the number of nonzero singular values of \bar{C} , the order of AR model is p . At this time, if we also collect the fixed set of $p + 1$ slices corresponding to $m = \bar{q} + 1, \dots, \bar{q} + p$, $n = \bar{q} - p, \dots, \bar{q}$, then the following matrix equation can be derived:

$$A_1 X_1 = -B_1 \quad (12)$$

where $X_1 = [\phi_p, \phi_{p-1}, \dots, \phi_1]^T$, $B_1 = [c_{3y}(\bar{q} + 1, \bar{q} - p), \dots, c_{3y}(\bar{q} + p, \bar{q})]^T$, and the structure of A_1 derived from (10) is shown below

$$A_1 = \begin{bmatrix} c_{3y}(q + 1 - p, q - p) & \cdots & c_{3y}(q, q - p) \\ \vdots & \vdots & \vdots \\ c_{3y}(q + 1 - p, q) & \cdots & c_{3y}(q, q) \\ \vdots & \vdots & \vdots \\ c_{3y}(q, q - p) & \cdots & c_{3y}(q + p - 1, q - p) \\ \vdots & \vdots & \vdots \\ c_{3y}(q, q) & \cdots & c_{3y}(q + p - 1, q) \end{bmatrix}. \quad (13)$$

The least-square solution of (12) yields the coefficients of AR as shown below

$$\hat{X}_1 = (A_1^T A_1)^{-1} A_1^T B_1. \quad (14)$$

Step 4: Formulation of Residual Time Series: At this step, the process of residual time series with the AR polynomial constructed from the estimated parameters is written as follows:

$$\bar{y}_t = y_t + \left(\sum_{i=1}^p \phi_i y_{t-i} \right) \quad (15)$$

where \bar{y}_t is the residual time series obtained without the AR part. The Gaussian test shown in step 2 can be employed to check the residual time series. If the residual time series is Gaussian, then the second order statistics can be applied to estimate the MA model; otherwise, the following step 5 will be activated.

Step 5: MA Model Estimation: In this step, the MA order determination is performed. When the model is purely MA and \bar{y}_t is just the output $y(i)$, then by denoting $c_{3\bar{y}}(m, n)$ the third-order cumulant of \bar{y}_t , the following equation can be obtained

$$c_{3\bar{y}}(q, 0) \neq 0, \quad c_{3\bar{y}}(q + 1, 0) = 0. \quad (16)$$

In (16), q can be identified as the lag of the last nonzero cumulant sample [27]–[29]. The merit of this cumulant-based order determination is its immunity of cumulants to additive Gaussian

noise of unknown covariance. Now, in the MA model approach, a closed form solution for the nonminimum θ_i phase form, $r(m)$ and $c(m)$ is also formulated

$$r(m) + \sum_{i=1}^q \theta_i^2 r(m - i) = \varepsilon \left[c(m) + \sum_{i=1}^q \theta_i c(m - i) \right] \quad (17)$$

where

$$r(m) = E\{\bar{y}_t \bar{y}_{t+m}\} \quad (18)$$

$$c(m) = E\{\bar{y}_t \bar{y}_{t+m}^2\}. \quad (19)$$

By substituting $m = -q, \dots, 0, \dots, q$ into (16) with the arrangement of (17), a matrix equation can be inferred

$$A_2 X_2 = B_2 \quad (20)$$

where

$$X_2 = [\varepsilon, \varepsilon\theta_1, \dots, \varepsilon\theta_q, \theta_1^2, \dots, \theta_q^2]^T, \\ B_2 = [r(q), r(q-1), \dots, r(1), r(0), r(1), \dots, \\ r(q), 0, \dots, 0]^T,$$

and the structure of A_2 is deduced from (16) as in AR case. The least-squared solution of this over-determined system of equations is therefore expressed as follows:

$$X_2 = (A_2^T A_2)^{-1} A_2^T B_2. \quad (21)$$

Step 6: Adequacy Validation: With the ARMA model formulated through collected load data, the adequacy validation methods can be applied to check the adequacy for the application considered. While the answer is yes, the future load can be therefore predicted; otherwise the aforementioned procedures will be repeated in order to find a better-fitted model.

IV. NUMERICAL STUDY

The performance of the proposed method has been validated on one-week ahead and one-day ahead load forecast through the load data provided by Taipower Company. The method was implemented by Microsoft Visual C++ language performed on a Pentium-IV 1.2-GHz computer. Fig. 4 illustrates the hourly load curves of March 15–27, 1999. In the figure, the load behavior of weekdays (Monday through Friday) is seen mutually similar, while that of Saturday and Sunday are significantly different. The reason for this pattern difference is that in year of 1999 in Taiwan, based on Government regulations, Saturdays are only off every two weeks; therefore, it caused the difference of load patterns between Saturdays and Sundays. In other words, the load patterns of Taipower can be categorized into three groups: weekdays, Saturdays, and Sundays.

In the study, three cases provided by Taipower are employed to investigate the performance of the proposed model. Case 1 is to forecast one-week ahead of weekdays, case 2 is to perform one-day ahead forecast of weekends including load singularity considerations, and case 3 is to investigate one-day ahead forecast among different load types. All cases use 1200 historical

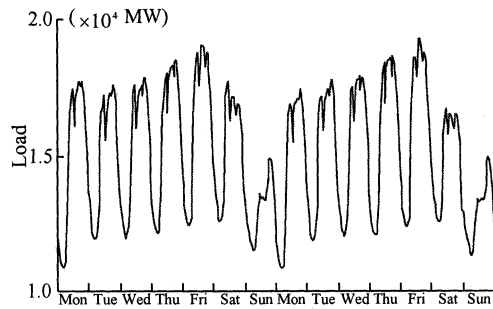


Fig. 4. Hourly load curve for two weeks.

TABLE I
RECORDED AND FORECAST PERIOD

Scenario	Recorded period	Forecast period
1	Nov. 5, 1998- Jan. 22 1999	Jan. 25-29, 1999 Monday-Friday
2	Nov. 16, 1998- Jan. 29, 1999	Feb.1-5, 1999 Monday-Friday

load data for the forecast work. Table I tabulates the recorded period and the predicted period, where two scenarios are included. All of the results are summarized and presented in terms of their average and maximum value of forecast errors.

Case 1: One-Week Ahead Forecast of Weekdays: In this case, the load data ranging from January 25 to January 29 is the primary concern in this forecast. Following the difference operation, the post-processed load data (from November 5, 1998 to January 22, 1999) was employed for the Gaussian test. The confidence level of the first Gaussian test is 0.01. As this value is smaller than 0.05, the null hypothesis was rejected. This also means that the time series exhibit non-Gaussian characters; hence, the non-Gaussian process would be applied to estimate the AR model, informing that the weekdays load data in Taiwan tends to be non-Gaussian.

Now, as the non-Gaussian process proceeds, the order of AR model is computed to be 1, and the coefficient is -0.934 . Following the removal of AR part, the residual time series is formulated. This is followed by a Gaussian test, where the resultant confidence level is found near one, indicating that the residual time series is Gaussian. The MA model of this time series can be estimated via the second order statistics, where the order of MA model is thus computed to be 24 and the corresponding coefficient is -0.755 .

Fig. 5 delineates the relative error obtained by the proposed approach and the traditional method. In the figure, the relative error is defined as below

$$\text{relative error(\%)} = \frac{|\text{Forecast Load}-\text{Actual Load}|}{\text{Actual Load}}. \quad (22)$$

For both scenarios in the figure, the proposed method exhibits a significantly improved forecast accuracy over the traditional ARMA model. For scenario 1 and 2, the averaged relative error of the proposed method are 1.37% and 1.57%, while that of the other method are 3.22% and 4.62%, respectively. The forecast of daily peak is also investigated in this study, where Tables II

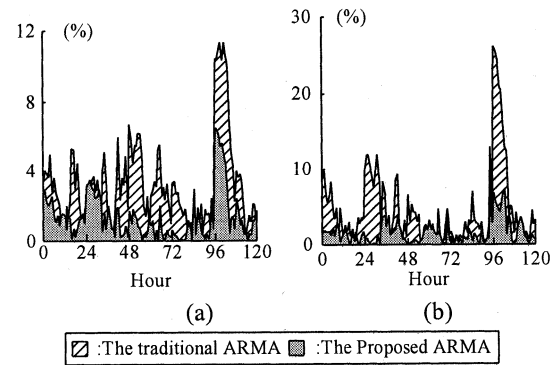


Fig. 5. Comparisons of relative errors at different scenarios (a) scenario 1. (b) Scenario 2.

TABLE II
PERCENTAGE PEAK ERROR OF SCENARIO 1

Day	Actual Peak (MW)	Forecasted Peak (MW)	Error (%)
Jan. 25 (Mon.)	17284.8	17243.6	0.24
Jan. 26 (Tue.)	17010.7	17340.3	1.94
Jan. 27 (Wed.)	17326.3	17378.8	0.30
Jan. 28 (Thu.)	17320.5	17293.9	0.15
Jan. 29 (Fri.)	17386.8	17388.5	0.01
Averaged predicted error: 0.53 %			

TABLE III
PERCENTAGE PEAK ERROR OF SCENARIO 2

Day	Actual Peak (MW)	Forecasted Peak (MW)	Error (%)
Feb. 1 (Mon.)	17220.8	17312.4	0.53
Feb. 2 (Tue.)	17873.1	17133.6	4.14
Feb. 3 (Wed.)	17406.2	17232.3	1.00
Feb. 4 (Thu.)	17272.7	17239.1	0.19
Feb. 5 (Fri.)	17342.7	16936.0	2.35
Averaged predicted error: 1.64 %			

and III summarize these results. By observing these tables, the largest percentage peak error of scenario 1 was seen happened on Tuesday, January 26, 1999, while that of scenario 2 was on February 2, 1999. The average peak error of scenario 1 and 2 are 0.53% and 1.64%, respectively.

Case 2: One-Day Ahead Forecast of Saturday and Sunday With Load Singularity Included: This case is to examine the influence of drastic load variations on the predicted model. Fig. 6 shows the set of 1200 hourly load data consisting of 600 historical and 24 forecasting hourly loads, ranging from September 2 to October 12 except holidays. During this time interval, there is an earthquake that took place on September 21, 1999. The U.S. Geological Survey's National Earthquake Information Center recorded this earthquake at the Richter scale of 7.6. The quake caused power outages almost island-wide. Since this event drastically changed the trend of load data, the performance of load forecast was largely affected.

Table IV shows the forecast results of four days using Gaussian test. It is found that the critical value of September 5 before the earthquake is 27.6134 as well as the confidence

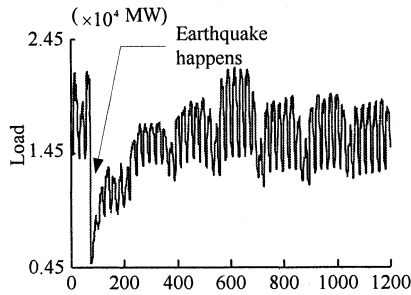


Fig. 6. Historical data recorded from September 18 to November 6, 1999.

TABLE IV
GAUSSIAN TEST OF CASE 2

Forecasting day	Critical value	Confidence level
September. 4 (Saturday)	59.0971	0.0176
September. 5 (Sunday)	27.6134	0.8409
October. 16 (Saturday)	517.891	Near 0
October. 17 (Sunday)	533.321	Near 0

TABLE V
ONE-DAY-AHEAD HOURLY FORECAST FROM THE PROPOSED METHOD AND OTHER METHODS (OCTOBER 17, 1999)

Hour	Actual (MW)	ARMA Method (MW)	Error (%)	ANN (MW)	Error (%)	Proposed Method (MW)	Error (%)
1	14258	15042	5.50	144710	1.49	14912	4.59
2	13709	13610	0.72	144600	5.49	13628	0.59
3	13276	13284	0.07	134020	0.96	13293	0.13
4	12913	12871	0.32	131220	1.62	12891	0.17
5	12719	12596	0.97	127910	0.56	12608	0.87
6	12689	12383	2.41	125760	0.87	12404	2.24
7	12411	12385	0.21	124390	0.24	12403	0.07
8	12424	12435	0.09	123880	0.30	12439	0.12
9	13044	12765	2.13	126880	2.72	12800	1.87
10	13667	13770	0.75	134940	1.27	13752	0.62
11	14183	14403	1.55	143420	1.12	14395	1.50
12	14295	14631	2.35	148800	4.09	14661	2.56
13	14036	14455	2.99	146310	4.24	14463	3.04
14	14138	14497	2.54	141590	0.15	14530	2.77
15	13955	14193	1.71	142600	2.18	14234	2.00
16	13910	13841	0.50	140240	0.82	13880	0.21
17	14237	13987	1.75	139330	2.14	14029	1.46
18	15278	14534	4.87	143870	5.83	14564	4.67
19	15796	16078	1.78	155620	1.47	16097	1.91
20	15536	15987	2.91	160620	3.39	15887	2.26
21	15256	15405	0.97	153460	0.60	15429	1.13
22	14832	14952	0.81	150250	1.30	15008	1.19
23	13936	14179	1.74	144690	3.81	14227	2.09
24	12682	12734	0.41	134700	6.21	12788	0.84

Averaged forecast error (%):

ARMA: 1.67, ANN: 2.20, Proposed method: 1.62

Maximum forecast error (%):

ARMA: 5.50, ANN: 6.21, Proposed method: 4.67

level is larger than 0.05; therefore, for this case the second order statistic is suitable. However, after the earthquake, the critical value of October 17 was seen to become 533.321 and the confidence level was near 0, indicating that the computation

TABLE VI
RELATIVE FORECAST ERROR OF ONE-DAY AHEAD IN SPRING

March		15	16	17	18	19	20	21
Traditional method	Ave.	3.93	2.09	2.29	1.90	2.27	3.81	0.99
	Max.	11.7	5.96	6.19	3.84	4.39	8.53	2.51
ANN	Ave.	4.08	1.88	2.81	2.36	2.49	2.33	1.86
	Max.	10.8	6.86	6.70	7.61	7.36	7.61	8.34
Proposed method	Ave.	2.58	1.76	2.03	1.20	1.53	2.28	0.99
	Max.	10.9	4.52	5.11	2.60	4.29	5.18	2.51

Remark: March 15, 1999, Monday

TABLE VII
RELATIVE FORECAST ERROR OF ONE-DAY AHEAD IN SUMMER

July		19	20	21	22	23	24	25
Traditional method	Ave.	2.59	2.28	2.40	1.81	1.64	3.27	2.36
	Max.	5.99	6.75	6.44	5.59	5.87	8.24	5.30
ANN	Ave.	3.35	2.32	2.38	2.41	2.17	3.89	2.61
	Max.	7.05	8.69	7.46	6.94	7.42	10.5	7.4
Proposed method	Ave.	1.91	2.17	0.99	1.69	1.61	2.43	2.36
	Max.	3.79	5.07	3.11	3.40	4.14	7.10	5.30

Remark: July 19, 1999, Monday

TABLE VIII
RELATIVE FORECAST ERROR OF ONE-DAY AHEAD IN AUTUMN

November		1	2	3	4	5	6	7
Traditional model	Ave.	2.42	2.14	1.49	0.84	1.49	2.39	2.48
	Max.	8.91	7.14	6.63	2.34	3.46	5.96	7.81
ANN	Ave.	2.99	1.94	2.88	1.62	1.45	2.22	2.34
	Max.	7.31	7.94	8.28	6.03	6.45	9.34	7.95
Proposed method	Ave.	2.35	1.79	1.43	0.81	1.43	2.08	2.27
	Max.	8.66	6.48	6.10	2.10	3.39	5.62	7.32

Remark: November 1, 1999, Monday

TABLE IX
RELATIVE FORECAST ERROR OF ONE-DAY AHEAD IN WINTER

February		8	9	10	11	12	13	14
Traditional method	Ave.	3.05	1.53	3.44	1.82	2.62	3.03	2.85
	Max.	10.4	4.19	8.93	7.16	5.77	8.93	5.19
ANN	Ave.	4.03	1.93	2.91	2.13	2.42	3.29	3.14
	Max.	10.4	5.48	5.13	5.35	5.87	8.14	7.04
Proposed method	Ave.	2.02	1.37	2.53	1.49	2.25	2.13	2.85
	Max.	9.89	3.62	6.86	4.19	5.59	7.55	5.19

Remark: February 8, 1999, Monday

of the order and parameters of ARMA model by using second order statistic was not adequate.

Table V shows the forecast result of October 17 obtained from ARMA, ANN, and the proposed model, where artificial neural network (ANN) approach consists of 20 hidden neurons, eight input neurons, and one output neuron. Judging from the magnitudes of averaged and maximum forecast error, the proposed method exhibited a better performance than other methods.

Case 3: One-Day Ahead Forecast in Different Load Type: In this case, three load patterns (including weekdays, Saturdays, and Sundays) are considered for one-day ahead forecast. The results were presented in four representative months within different seasons, by which the forecasted load of February (for

winter season), March (for spring season), July (for summer season), and November (or autumn season) are individually listed in Tables VI–IX. In these tables, numerical results confirmed that the proposed method achieved a highest accuracy among all forecasting periods. For the load forecast of Saturdays, because the load characteristics was non-Gaussian, the predicted error was seen larger such as November 6; however, the error value of using the proposed method was still the smallest one among different methods.

V. CONCLUSIONS

In this paper, an ARMA model identification approach for short-term load forecasting including non-Gaussian process considerations is proposed. This method utilized the bispectrum to justify the Gaussianity of the characteristics of load data, then the model identification and parameter estimation are accordingly employed to reach a better representative model. The approach was tested on a practical system through the utility data, and test results help solidify the effectiveness of the method. At present, the method is being extended to a utility project that includes environmental constraints in the software development.

ACKNOWLEDGMENT

The authors are greatly indebted to Taiwan Power Company for providing their valuable operating experience.

REFERENCES

- [1] W. Vandaele, *Applied Time Series and Box-Jenkins Model*. New York: Academic Press, 1983.
- [2] G. Gross and F. D. Galiana, "Short term load forecasting," *Proc. IEEE*, vol. 75, pp. 1558–1573, Dec. 1987.
- [3] K. G. Rajesh, "Expert systems: Their implications and applications for power systems," *IEEE Potentials*, vol. 16, no. 2, pp. 35–37, Apr./May 1997.
- [4] K. H. Kim, J. K. Park, K. J. Hwang, and S. H. Kim, "Implementation of hybrid short-term load forecasting system using artificial neural networks and fuzzy expert systems," *IEEE Trans. Power Syst.*, vol. 10, pp. 1534–1539, Aug. 1995.
- [5] D. Srinivasan, T. S. Swee, C. S. Cheng, and E. K. Chan, "Parallel neural network-fuzzy expert system strategy for short-term load forecasting: System implementation and performance evaluation," *IEEE Trans. Power Syst.*, vol. 14, pp. 1100–1106, Aug. 1999.
- [6] D. C. Park, M. A. El-Sharkawi, R. J. Marks II, L. E. Atlas, and M. J. Damborg, "Electric load forecasting using an artificial neural network," *IEEE Trans. Power Syst.*, vol. 6, pp. 442–449, May 1991.
- [7] S. J. Huang and C. L. Huang, "Genetic-Based multi-layered perceptrons for taiwan power system short-term load forecasting," *Int. J. Elect. Power Syst. Res.*, vol. 38, no. 3, pp. 69–74, July 1996.
- [8] W. Charytoniuk, M. S. Chen, and P. Van Olinda, "Nonparametric regression based short-term load forecasting," *IEEE Trans. Power Syst.*, vol. 13, pp. 725–730, Aug. 1998.
- [9] H. Mori and K. Kosemura, "Optimal regression tree based rule discovery for short-term load forecasting," in *IEEE Power Eng. Soc. Winter Meeting*, Columbus, OH, Jan. 2001, pp. 421–426.
- [10] T. Haida and S. Muto, "Regression based peak load forecasting using a transformation technique," *IEEE Trans. Power Syst.*, vol. 9, pp. 1788–1794, Nov. 1994.
- [11] W. Charytoniuk, M. Chen, and P. Olinda, "Nonparametric regression based short-term load forecasting," *IEEE Trans. Power Syst.*, vol. 13, pp. 725–730, Aug. 1998.
- [12] A. A. El-Desouky and M. M. Elkateb, "Hybrid adaptive techniques for electric-load forecast using ANN and ARIMA," *Proc. Inst. Elect. Eng.—Gen., Transm., Dist.*, vol. 147, no. 4, pp. 213–217, July 2000.
- [13] P. K. Dash, G. Ramakrishna, A. C. Liew, and S. Rahman, "Fuzzy neural networks for time-series forecasting of electric load," *Proc. Inst. Elect. Eng.—Gen., Transm. Dist.*, vol. 142, pp. 535–544, Sept. 1995.
- [14] E. H. Barakat and J. M. Al-Qasem, "Methodology for weekly load forecasting," *IEEE Trans. Power Syst.*, vol. 13, pp. 1548–1555, Nov. 1998.
- [15] N. Amjady, "Short-Term hourly load forecasting using time-series modeling with peak load estimation capability," *IEEE Trans. Power Syst.*, vol. 16, pp. 798–805, Nov. 2001.
- [16] J. D. Cryer, *Time Series Analysis*. New York: Duxbury Press, 1986.
- [17] J. M. Mendel, "Tutorial on higher-order statistics in signal processing and system theory: Theoretical results and some applications," *Proc. IEEE*, vol. 79, pp. 278–305, Mar. 1991.
- [18] C. L. Nikias and J. M. Mendel, "Signal processing with higher-order spectra," *IEEE Signal Processing Mag.*, pp. 10–37, July 1991.
- [19] M. J. Hinch, "Testing for gaussianity and linearity of a stationary time series," *J. Time Series Analysis*, vol. 3, no. 3, pp. 169–176, 1982.
- [20] J. K. Tugnait, "Testing for linearity of noisy stationary signals," *IEEE Trans. Signal Processing*, vol. 42, pp. 2747–2748, July 1989.
- [21] G. B. Giannakis and J. M. Mendel, "Identification of nonminimum phase systems using higher order statistics," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 37, no. 3, pp. 360–377, Mar. 1989.
- [22] M. J. Hinch and G. R. Wilson, "Detection of nongaussian signals in nongaussian noise using the bispectrum," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 38, pp. 1126–1131, July 1989.
- [23] A. Swami and J. M. Mendel, "ARMA parameter estimation using only output cumulants," *IEEE Trans. Acoust., Speech, Signal Processing*, vol. 38, pp. 1257–1265, July 1990.
- [24] A. Al-Smadi and D. Mitchell Wilkes, "Robust and accurate ARX and ARMA model order estimation of nongaussian processes," *IEEE Trans. Signal Processing*, vol. 50, pp. 759–763, Mar. 2002.
- [25] A. M. Zoubir and D. R. Iskander, "A bispectrum based gaussianity test using the bootstrap," in *Proc. IEEE Int. Conf. Acoust., Speech, and Signal Processing*, Atlanta, GA, May 1996, pp. 3029–3032.
- [26] D. Aboutajdine, A. Adib, and A. Meziane, "Fast adaptive algorithm for AR parameters estimation using higher order statistics," *IEEE Signal Processing Magazine*, vol. 44, no. 8, pp. 1998–2009, August 1996.
- [27] X. D. Zhang and Y. S. Zhang, "Singular value decomposition-based MA order determination of nongaussian ARMA models," *IEEE Trans. Signal Processing*, vol. 41, pp. 2657–2664, Aug. 1993.
- [28] J. R. Dickie, "AR modeling of skewed signals using third-order cumulants," *Proc. Inst. Elect. Eng.—Visual Image Signal Processing*, vol. 142, no. 2, pp. 78–86, Apr. 1995.
- [29] S. A. Alshebeili, "Order determination of MA models using fourth-order cumulants," *IEEE Signal Processing Lett.*, vol. 2, pp. 120–122, June 1995.

Shyh-Jier Huang (M'95–SM'01) received the Ph.D. degree in electrical engineering from the University of Washington, Seattle.

Currently, he is Professor of Electrical Engineering at National Cheng Kung University, Tainan, Taiwan, R.O.C. He worked on projects at the Department of Electrical Engineering and Computer Science, University of California, Berkeley, from 1989 to 1991. His main areas of interests are power system analysis, power quality and signal-processing applications.

Dr. Huang received research awards from National Science Council, Taiwan, R.O.C., from 1996 to 2001. He is a Senior Member at IEEE.

Kuang-Rong Shih received the M.S. degree from the Department of Electrical Engineering, National Tsing Hua University, Taiwan, R.O.C., in 1987. He is currently pursuing the Ph.D. degree at National Cheng Kung University, Taiwan, R.O.C.

His major areas of interests are state estimation, load forecasting, and fuzzy system applications.