Short-Term Hourly Load Forecasting Using Time-Series Modeling with Peak Load Estimation Capability

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***Abstract*—This paper presents a new time series modeling for short term load forecasting, which can model the valuable experiences of the expert operators. This approach can accurately forecast the hourly loads of weekdays, as well as, of weekends and public holidays. It is shown that the proposed method can provide more accurate results than the conventional techniques, such as artificial neural networks or Box–Jenkins models. In addition to hourly loads, daily peak load is an important problem for dispatching centers of a power network. Most of the common load forecasting approaches do not consider this problem. It is shown that the proposed method can exactly forecast the daily peak load of a power system. Obtained results from extensive testing on the Iran's power system network confirm the validity of the developed approach.**

***Index Terms*—Load forecasting, time series modeling.**

I. Introduction

SHORT term (24 hours ahead) prediction of future load demand is important for the economic and secure operation of power systems. Fundamental operational functions such as unit commitment, hydro-thermal coordination, interchange evaluation, scheduled maintenance and security assessment require a reliable short term load forecasting (STLF). Owing to the importance of the STLF, research in this area in the past 40 years has resulted in the development of numerous forecasting methods [1]–[4]. These methods are mainly classified into two categories: classical approaches and artificial intelligence (AI) based techniques. Classical STLF approaches are based on various statistical methods for processing the numerical information. These approaches forecast current value of a variable by using a mathematical combination of the previous values of that variable and previous or current values of other variables.

For instance, the time series model of ARMA forecasts the current value of a variable by means of a linear combination of previous values of the variable, previous values of noise and current value of noise [5]. Classical STLF approaches use, for example, regression [6], exponential smoothing [7], Box–Jenkins models [8] and Kalman filters [9]. A discussion of the these approaches can be found in [10].

Recently, AI based techniques have been applied to STLF. An innovative pattern recognition approach for hourly load forecasting has been developed in [11]. This approach, however, is applicable only when a clear weather-sensitive load pattern can be established. Expert system techniques, utilizing the knowledge and analogical reasoning of experienced human operators have been investigated [12]–[14]. In these, load forecasts are obtained based on the logical relationships between weather and load, and the prevailing load patterns. Also, forecasting for holidays can be simplified with the use of a knowledge based approach [12]. Application of fuzzy expert systems has also been proposed to include imprecise and probabilistic information in the input data [15]. Several research groups have studied the use of artificial neural networks (ANN) and fuzzy neural networks (FNN) for load forecasting [3], [4], [16]. The ANNs are trained to learn the relationship between various input variables (weather data, etc.) and historical load patterns. When presented with a novel input, these trained ANNs are then able to generalize among the training sets and produce a corresponding output. The FNNs, include a fuzzy knowledge base to constitute a framework for incorporating both quantitative and qualitative knowledge from human experts [4], [16]. On the contrary, the ANNs can use only quantitative knowledge in terms of input/output data. Thus, for STLF, FNNs can be more efficient than ANNs [3], [4].

In this paper, a novel approach for STLF is developed, which incorporates the time series modeling (Box–Jenkins) with the knowledge of experienced human operators. It is shown that the developed approach can produce more accurate results for the STLF than the conventional techniques (such as ANN and time series). In addition to hourly loads, daily peak load is an important problem for dispatching centers of a power system. For instance, operators of dispatching centers for scheduled maintenance or adequacy assessment require to daily peak load. Thus, forecasting of daily peak load must be considered in the STLF, but most of the common load forecasting approaches do not present any solution for this problem. It is shown that the developed approach can exactly forecast the daily peak load of a power system.

II. Description of the Proposed Approach

Various time series models, such as Box–Jenkins models, have been presented for STLF [5]. Here, the time series model of Auto Regressive Integrated Moving Average, ARIMA, has been used. The basic relation of the ARIMA is as follows:

$$A_{(q)}y_{(t)} + \sum_{i=1}^{n} B_{i(q)}U_{i(t)} = e_{(t)} \tag{1}$$

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where

$y(t)$ output;

$U_{i(t)}$ terms are inputs of ARIMA;

$e_{(t)}$ indicates noise term or error term;

n number of inputs.

In this relation, $A_{(q)}$ and $B_{i(q)}$s are delay polynomials, which are defined as:

$$A_{(q)} = 1 + a_1 q^{-1} + a_2 q^{-2} + \cdots + a_k q^{-k} \tag{2}$$

$$B_{i(q)} = b_{i0} + b_{i1} q^{-1} + b_{i2} q^{-2} + \cdots + b_{im} q^{-m} \quad (i = 1, 2, \ldots, n). \tag{3}$$

In these relations, k is order of the delay polynomial $A_{(q)}$ and m is order of the delay polynomial $B_{i(q)}$. $a_1, a_2, \ldots, a_k$ are coefficients of $A_{(q)}$ and $b_{io}, b_{i1}, b_{i2}, \ldots, b_{im}$ are coefficients of $B_{i(q)}$. q indicates delay operator or backshift operator. The delay operator of order j is defined as:

$$q^{-j} S_{(t)} = S_{(t-j)} \tag{4}$$

where $S_{(t)}$ is a time domain function. Thus:

$$A_{(q)} y_{(t)} = y_{(t)} + a_1 y_{(t-1)} + a_2 y_{(t-2)} + \cdots + a_k y_{(t-k)} \tag{5}$$

$$B_{i(q)} U_{i(t)} = b_{i0} U_{i(t)} + b_{i1} U_{i(t-1)} = b_{i2} U_{i(t-2)} + \cdots + b_{im} U_{i(t-m)}. \tag{6}$$

The purpose of this ARIMA model is forecasting the value of $y(t)$. Past values of this variable and all values of inputs up to time t are assumed to be known. Implementation of the ARIMA has two stages:

a) Parameter Tuning. In this phase, ARIMA calculates the coefficients of $A_{(q)}$ and the coefficients of $B_{i(q)}$s. For this purpose, ARIMA receives y and U_is for a number of known operating points of the related system. For instance, assume that the forecasting model has one output, $y_{(t)}$, and one input, $U_{1(t)}$. Also, assume that delay polynomials, $A_{(q)}$ and $B_{1(q)}$, are in the form of (5) and (6). Then, ARIMA receives samples of the related system in the following form:

Sample at time T (T is one of the known operating points of the related system): Input features and Target feature. Input features of the sample: $y_{(T-1)}, y_{(T-2)}, \ldots, y_{(T-k)}$ and $U_{1(T)}$, $U_{1(T-1)}$, $U_{1(T-2)}, \ldots, U_{1(T-m)}$. Target feature of the sample: $y_{(T)}$.

By using these samples, ARIMA calculates the coefficients of the delay polynomials so that the energy of the noise term, i.e., $e_{(t)}$ is minimized. This calculation is relatively similar to training phase of ANNs, but training of ANNs is done in successive iterations [19] and on the contrary parameter tuning of ARIMA is done in one step. Mathematical details of this calculation can be found in [17], [18]. Here, it is only noted that if sum of orders of all delay polynomials, $A_{(q)}$ and $B_{i(q)}$s, is less than number of parameter tuning samples, then ARIMA always converges and has one unique solution [17]. These are two important advantages of ARIMA for load forecasting. For instance, in many cases, ANNs and FNNs do not converge in the training phase or converge but trap in the local minimum [19], [20].

b) Forecasting. ARIMA forecasts the value of the output, i.e., $y_{(t)}$, for unknown operating points of the related system. In this phase, ARIMA employs (1), but assumes that the noise term or $e_{(t)}$ is equal to zero. Thus, $e_{(t)}$ will be the forecasting error of ARIMA. It can be shown that this enables ARIMA to provide some information about its forecasting error [5]. For instance, ARIMA can estimate variance or energy of its forecasting error [17].

In this paper, for modification the forecasting error of the ARIMA, the basic relation of this model, i.e., (1) has been changed as follows:

$$A_{(q)} y_{(t)} + \sum_{i=1}^{n+1} B_{i(q)} U_{i(t)} = e_{(t)}. \tag{7}$$

In this equation:

$$B_{n+1(q)} = b_{n+1} \tag{8}$$

(a delay polynomial of zero degree)

$$U_{n+1(t)} = y_{estim(t)} \tag{9}$$

where $y_{estim(t)}$ is an estimation of the output $y_{(t)}$. In other words, a multiple of the target estimation is aided to the basic relation of ARIMA to obtain the modified ARIMA. In the parameter tuning phase, the modified ARIMA treats $y_{estim(t)}$ as an input and calculates b_{n+1} along with the other coefficients of the delay polynomials so that the energy of the noise term is minimized. Then the modified ARIMA forecasts the output $y_{(t)}$ for the unknown operating points by using (7) instead of (1). From the mathematical point of view, since the estimation $y_{estim(t)}$ has a correlation with the output $y_{(t)}$, this term can increase the forecasting capability of the modified ARIMA in comparison with normal ARIMA. For the purpose of STLF, $y_{estim(t)}$ becomes the estimation of the experienced human operators for the feature hourly loads.

In addition to the hourly loads, the proposed approach can also forecast the daily peak load. For this purpose, a separate time series model has been developed for the daily peak load. This time series model is in the form of (7), i.e., the modified ARIMA. The parameter tuning and forecasting of the modified ARIMA model of daily peak load are similar to those of the modified ARIMA model of the hourly loads. The differences between these modified ARIMA models are in the inputs and delay polynomials. For instance, in the modified ARIMA model of the daily peak load, the $y_{estim(t)}$ becomes the estimation of the experienced human operators for the daily peak load. These items are explained in the following section.

III. Implementation of the Proposed Approach for the STLF

To implement the proposed approach, we statistically studied the load demand of the Iran's power network in the national dispatching center. This statistical study included hourly loads and daily peak load from 1991 to 1997 for the following reasons:

TABLE I
ANNUAL PEAK LOAD OF IRAN'S POWER NETWORK

Year	Annual Peak Load (MW)	Growth Rate (%)
1988	8112	3.89
1989	8497	4.75
1990	9504	11.85
1991	10230	7.64
1992	11009	7.61
1993	12162	10.47
1994	13043	7.24
1995	13876	6.39
1996	14562	4.94
1997	15844	8.80
1998	16835	6.25

1) In Table I, annual peak load of Iran's power network from 1988 to 1998 has been shown. Also, growth rate of annual peak load for each year has been shown in this Table. These growth rates indicate that the load demand varies rapidly because Iran is a developing country. From mathematical point of view, the correlation between load demand of different years decreases by increasing the distance between years. Thus, the loads before 1991 (with annual peak load less than 10 000 MW) have no significant value in the statistical study.
2) In 1988, the war between Iran and Iraq terminates. During war, the equipment of Iran's power network, such as power stations, damaged. For this reason, in the years after war (1988, 1989 and 1990) we have load curtailment in many hours of week. Thus, the actual load demands of these years are not available and recorded loads are estimated values. In 1991, by repairing damaged equipment, we could provide the load demand and load curtailment vanished. Thus, the load demand of 1991 and next years are actual values, which have been used in the statistical study.

From this statistical study, the following results have been obtained:

a) At first, it is noted that in Iran and other Islamic countries, weekend is Friday instead of Sunday for Christian countries. The shape of the load curve on all weekdays, i.e., Saturday to Wednesday is almost the same except for the morning load on Saturdays, which decreases due to its proximity to the weekend. The typical load curves for weekdays have been shown in the Fig. 1. In this figure, solid line indicates Saturday and dashed line indicates Sunday to Wednesday. As is seen from this figure, the decrease in the morning load of Saturdays approximately includes 1 am to 6 am, which has been shown by a vertical line. Therefore, the load demand of Saturdays is relatively different from the other weekdays.
b) The load curve on Thursdays (the day before the weekend), when most businesses are open for the first half of the day, is different from the rest of the days (Fig. 2). In this figure, solid line indicates Thursday and dashed line indicates the other weekdays (Sunday to Wednesday). As is seen from this figure, the load demand of Thursdays is less than the other weekdays, especially for the second half of the day (vertical line).
c) The load demand in the weekends and public holidays is generally less than weekdays. The typical load curves for Fridays and public holidays have been shown in the Fig. 3. In this figure, dotted line, solid line and dashed line indicate weekdays (Sunday to Wednesday), Fridays and public holidays, respectively. In some of the STLF references, weekends and public holidays have been treated in the same way [3], [21], and as is seen from this figure, these two load curves are similar. Thus, the same STLF model has been used for Fridays and public holidays in this paper.
d) The load curve of the hot days and cold days of the year is different. This is due to the domestic load [22], which constitutes a major part of the load demand. In Iran, the domestic load for cold days of year is less than hot days of year. Typical load curves for cold days and hot days of year have been shown in the Fig. 4. In this figure, solid

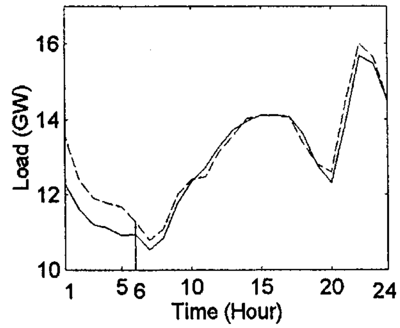

Fig. 1. Typical load curves for weekdays.

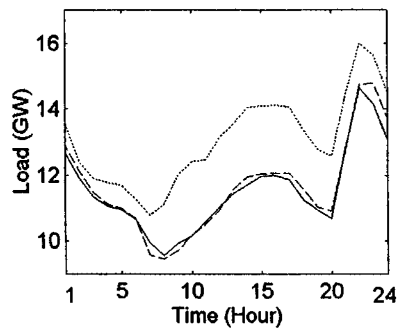

Fig. 2. Typical load curves for Thursdays.

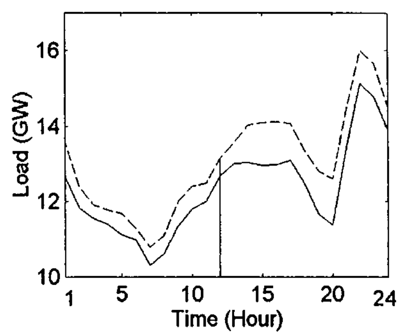

Fig. 3. Fridays and public holidays.

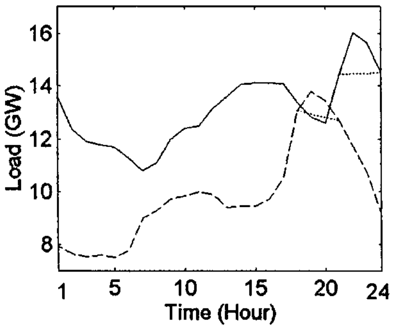

Fig. 4. Hot and cold days.

TABLE II
A HOT DAY AND A COLD DAY OF 1998

Day	Load (21) (MW)	Load (22) (MW)	Load (23) (MW)	Load (24) (MW)	Peak load (MW)	Peak time
hot	16145	16462	15435	14469	16835	21,22'
Day	Load (18)	Load (19)	Load (20)	Load (21)	Peak load	Peak time
cold	13100	13762	13077	12815	14094	18,50'

line and dashed line indicate hot and cold day, respectively. Statistical studies on the climate in the Iran and its relation with load demand have been indicated that for STLF, transition from hot days to cold days occurs in the beginning of autumn and transition from cold days to hot days occurs in the beginning of the spring. According to these studies, the following criterion for hot and cold days has been employed in this paper:

$$\begin{array}{ll} \text{If } T_{ave} > 23 & \text{Then hot day.} \\ \text{If } T_{ave} \leq 23 & \text{Then cold day.} \end{array} \tag{10}$$

(The unit of temperature is centigrade)

In this criterion, T_{ave} is the average temperature of the 24 hours of the related day.

e) The daily peak load for Iran's power network usually occurs among 19 to 22 (7 pm to 10 pm). From Fig. 4, it can be seen that in the winter, the time of daily peak load is about 19 and in the summer, this time shifts toward 22. As is seen from this figure, hourly loads between 18 and 21 for cold days and between 21 and 24 for hot days are in the range of the daily peak load (dotted lines). These hours have been selected for estimation of daily peak load. As an example, these hourly loads, daily peak load and time of occurrence of daily peak load for a cold day (Tuesday, December 8) and a hot day (Sunday, August 23) of 1998 have been represented in the Table II.

According to these results, four STLF models are required for hourly loads of Saturdays, Sunday to Wednesday, Thursdays and Fridays besides public holidays. These four STLF models must be separated for hot days and cold days of the year. Therefore, totally eight STLF models are required for hourly loads. All of these STLF models are in the form of the modified ARIMA, which has been selected as follows:

$$A_{(q)}L_{(t)} + B_{1(q)}T_{(t)} + B_{2(q)}L_{estim(t)} = e_{(t)} \tag{11}$$

TABLE III
ISOTHERMAL SECTIONS OF IRAN

Section	Type	Weighting (W_i)
Tehran	Mild	0.6
Ahvaz	Hot	0.3
Tabriz	Cold	0.1

where L is the load and T is the temperature. In (11), $B_{1(q)}$ and $B_{2(q)}$ are delay polynomials of zero order and $A_{(q)}$ is a delay polynomial of order 169. In other words, last 169 hourly loads, current temperature and estimation of the current load [$L_{estim(t)}$] have been used for forecasting of the current load or $L_{(t)}$. After forecasting the load of the first hour, its value [in the form of $L_{(t-1)}$] is used for forecasting of the second hour and forecasted values of the first and second hours [in the form of $L_{(t-2)}$ and $L_{(t-I)}$] have been used in the forecasting of the third hour and so on. This procedure continues until the load of the 24 hours ahead is forecasted.

Similarly, eight modified ARIMA models have been used for forecasting of daily peak load of Saturdays, Sunday to Wednesday, Thursdays and Fridays besides public holidays, in the hot and cold days of the year. These modified ARIMA models are as follows:

$$A_{(q)}L_{p(t)} + B_{1(q)}T_{(t)} + B_{2(q)}L_{pestim(t)} + B_{3(q)}L_{u(t)} = e_{(t)} \tag{12}$$

where, $L_{p(t)}$ and $L_{pestim(t)}$ are daily peak load and estimation of it, respectively. Also, $L_{u(t)}$ is the last hour, which is used for forecasting of the dairy peak load. It is 24 for the hot days and 21 for the cold days of the year. Here, $B_{1(q)}$, $B_{2(q)}$ and $T_{(t)}$ are as explained for (11). $A_{(q)}$ is also a delay polynomial of zero order, since daily peak load of a day has slight correlation with daily peak load of previous days. The order of delay polynomial $B_{3(q)}$ is 3. In other words, hourly loads among 21 and 24 for hot days and among 18 and 21 for cold days have been used for estimation of daily peak load.

IV. NUMERICAL RESULTS

As was explained, totally 16 modified ARIMA models are required for forecasting of hourly loads and daily peak load of Iran's power network. For parameter tuning of these models, the historical data of 1996 and 1997 have been used. Then these models have been tested using the data of 1998. The hourly loads and daily peak load of the Iran's power network have been obtained from the national dispatching center of Iran. Also, the estimations of the operators of this center for hourly loads and daily peak load in the last years have been reported, which have been used as $L_{estim(t)}$ and $L_{pestim(t)}$, respectively. In Iran, like many other vast countries, there are different types of climate. This causes large variation of temperature in different parts of Iran. Thus, a unique temperature, T, can not be defined. For solving this problem, we have used the climatology studies of Iran. According to these studies, Iran can be divided to three isothermal sections. Each isothermal section consists of areas with similar temperatures. Three isothermal sections of Iran have been indicated in Table III. To obtain the temperature

TABLE IV
OBTAINED RESULTS FOR HOURLY LOADS (1998)

Day Type	Day of Year(1)	MAPE (Modified ARIMA)	PAPE (Modified ARIMA)	MAPE (ARIMA)	PAPE (ARIMA)	MAPE (ANN)	PAPE (ANN)	MAPE (Operators)	PAPE (Operators)
Saturday	Hot	1.72%	4.95%	2.98%	7.61%	2.58%	6.56%	4.05%	9.1%
Sunday to Wednesday	Hot	1.48%	4.25%	2.21%	5.85%	2.24%	5.98%	2.78%	7.06%
Thursday	Hot	1.55%	4.48%	2.30%	6.20%	2.34%	6.10%	3.43%	7.33%
Friday and Public Holiday	Hot	1.98%	5.01%	4.18%	9.61%	4.68%	9.89%	4.86%	10.45%
Saturday	Cold	1.63%	4.70%	2.80%	7.10%	2.52%	6.41%	3.49%	7.85%
Sunday to Wednesday	Cold	1.45%	4.15%	2.18%	5.72%	2.22%	6.08%	2.70%	7.01%
Thursday	Cold	1.59%	4.61%	2.37%	6.09%	2.41%	6.21%	3.69%	7.71%
Friday and Public Holiday	Cold	1.99%	5.05%	4.29%	10.02%	4.62%	9.78%	5.05%	11.40%

(1): Hot and Cold days of Year have been separated according to (10)

of the power network, the temperature of these isothermal sections must be combined in an appropriate way. For this purpose, we have used the following equation:

$$T\sum_{i=1}^{n} W_iT_i \qquad (13)$$

where

T_i hourly temperature of the ith isothermal section;
n number of the isothermal sections;
T the hourly temperature of the power network.

W_is are weightings for combining the hourly temperatures of sections. Since the hourly temperature T is used for STLF, the W_i has been selected according to the proportion of the load demand of the ith section to the load demand of the power network. These weightings have been represented in the Table III. The hourly temperatures of the isothermal sections have been obtained from the Iranian meteorological organization and by using (13) the hourly temperatures of the power network have been calculated. The hourly temperatures of the power network have been used as $T_{(t)}$ for parameter tuning and testing of the 16 modified ARIMA models.

After parameter tuning of the modified ARIMA models by using the historical data, the following steps are followed in the forecast engine: 1) Take the last 169 hourly loads. 2) Take temperature forecast of the isothermal sections for future hours, which their loads should be forecasted. 3) Calculate temperature forecast of the power network from temperature forecast of isothermal sections by using (13). 4) Take estimation of operators for load forecast, i.e., $L_{estim(t)}$. 5) Calculate load forecast according to (11) by assuming that $e_{(t)}$ is zero [$e_{(t)}$ is the forecasting error]. 6) Select load forecast of future hours, which their loads are used in forecasting of daily peak load (for instance, hourly loads between 21 and 24 for hot days). 7) Take estimation of operators for daily peak load that is $L_{pestim(t)}$. 8) Calculate forecast of daily peak load according to (12) by assuming that $e_{(t)}$ is zero.

Obtained results from the modified ARIMA models for hourly loads have been represented in Table IV. In this Table, MAPE is Mean Absolute Percentage Error and PAPE is Peak

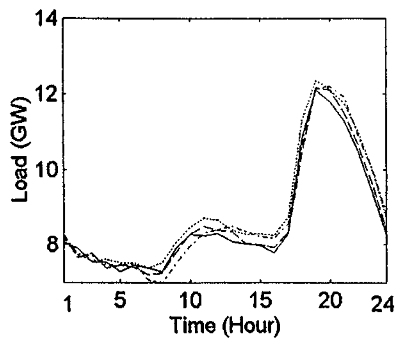

Fig. 5. Friday (November 6, 1998).

Absolute Percentage Error for 24 hours ahead, which have been averaged on 1998. For instance, MAPEs and PAPEs in the first row of Table IV are average values for all Saturdays of the hot days of 1998. In many of STLF references, only MAPE values have been presented [3], [4], [6], [7]. For planning purposes, this value may suffice, but for operational units of a power network this is insufficient. Dispatchers must be able to cope with the worst case. Thus, in addition to MAPE, the maximum error of STLF methods or PAPE has been presented in this paper, which gives a better insight for comparison of STLF methods.

In addition to the modified ARIMA, obtained results from ARIMA, ANN and operators for hourly loads of 1998 have been represented in Table IV. ARIMA results have been obtained from the commercial FOC package. This package is a product of the ABB corporation. ANN results have been obtained from the MATF package. This package has been produced by the research institute of EPRC. The ANNs employed in this package have multilayer perceptron (MLP) structure [19] and error backpropagation learning (EBPL) algorithm [22]. For parameter tuning of ARIMA, the FOC package, and training of ANN, the MATF package, we have used the historical data of 1996 and 1997, like the modified ARIMA model. In other words, all of these methods have been prepared with the same historical data. Sample results of these methods for a Friday and a public holiday are shown in Figs. 5 and 6, respectively. This

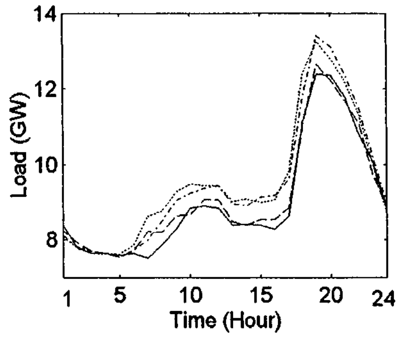

Fig. 6. Public holiday (November 3, 1998).

TABLE V
OBTAINED RESULTS FOR DAILY PEAK LOAD (1998)

Day Type	Day of Year	Average Error (Modified ARIMA)	Average Error (Operators)
Saturday	Hot	1.68%	3.69%
Sunday to Wednesday	Hot	1.05%	2.59%
Thursday	Hot	1.47%	3.42%
Friday and Public Holiday	Hot	1.95%	4.77%
Saturday	Cold	1.66%	3.51%
Sunday to Wednesday	Cold	1.01%	2.60%
Thursday	Cold	1.50%	3.74%
Friday and Public Holiday	Cold	1.97%	4.99%

public holiday is a religious holiday for Islamic countries. In these figures, solid line, dashed line, dashdot line and dotted line indicate actual, modified ARIMA, ARIMA and ANN load curves, respectively.

Obtained results from the modified ARIMA models and operators for daily peak load have been represented in Table V (the FOC and MATF packages have not this part). For instance, the first row of this table represents the average error for all Saturdays of the hot days of 1998. As is seen from Tables IV and V, accuracy of the modified ARIMA method is better than the other methods. Also, an interesting point, which can be seen from these tables is that although the modified ARIMA models use the operators estimation, but the accuracy of this method is much better than the operators. This is due to this fact that the modified ARIMA method combines the operators estimation with the temperature and load data. From the mathematical point of view, the modified ARIMA method employs the operators estimation as initial forecasting. Then it combines this initial forecasting with temperature and load data in a multivariable regression process, (7), to obtain a better forecasting. For this reason, the accuracy of the modified ARIMA method is better than the ARIMA, since the ARIMA has not this initial point. This also applies to ANNs and FNNs, since training of ANNs and FNNs begins with random initial weightings [19], [20].

TABLE VI
OBTAINED RESULTS FOR THREE KINDS OF OPERATORS

Average error (operator)	Average error (modified ARIMA)
4.05%	1.69%
4.77%	1.95%
4.97%	2.17%

TABLE VII
OFF-LINE PROCESSING TIMES (IRAN'S POWER NETWORK)

Applied Approach	Computation time	Number of Input Features
ARIMA	55' 47"	170
ANN	84' 45"	170
Modified ARIMA (Hourly Loads)	56' 11"	171
Modified ARIMA (Daily Peak Load)	1' 58"	6

Another important point of the modified ARIMA method is its dependency to the accuracy of the operators estimation. In Table VI, obtained results from the modified ARIMA for three kinds of operators have been represented. In this Table, average errors are due to daily peak load of Fridays and public holidays in hot days of 1998. Three kinds of operators in Table VI consist of operators of Tables IV and V (second row of Table VI), more proficient operators (first row) and less proficient operators (third row). As is seen from this Table, with better operator estimation, accuracy of the modified ARIMA method increases. In other words, with better initial forecasting, accuracy of the final forecasting increases. This feature can be attractive for the control centers of power networks, since in many cases there are expert operators in the control centers, which can enhance the efficiency of the modified ARIMA method.

The computation time of the parameter tuning phase or off-line processing time for ARIMA, the FOC package, and modified ARIMA, including hourly loads and daily peak load, have been represented in Table VII. Also, training time of ANN, the MATF package, has been shown in this Table. These computation times have been measured on a Pentium P233 personal computer. The CPU speed of this computer is 225 MHZ. The off-line processing time is dependent on type of approach (ARIMA, ANN, etc.) and number of input and target features. Here, all approaches have one target feature, which is hourly load or daily peak load. Number of input features for these approaches have been shown in Table VII. ARIMA and ANN have 170 input features, including last 169 hourly loads and one current temperature. Input features of the modified ARIMA for hourly loads and daily peak load have been determined in the previous section.

As is seen from Table VII, the off-line processing time of the modified ARIMA for hourly loads is approximately equal to ARIMA and less than ANN. The modified ARIMA has one input feature, operator's estimation, more than ARIMA, which slightly increases required computation time of the modified ARIMA method in comparison with ARIMA. Also, the modified ARIMA for daily peak load requires to short

TABLE VIII
AVERAGE FORECASTING ERROR (1998)

Power network	Hourly loads	Daily Peak load
Khorasan	1.54%	1.44%
Armenia	1.68%	1.56%

off-line processing time, since it has only 6 input features. The off-line process of ARIMA, modified ARIMA and ANN for STLF of Iran's power network in 1998 is performed once only.

In addition to Iran's power network, the modified ARIMA method has been examined on the two other power networks that are power networks of Khorasan and Armenia. Parameter tuning and testing of the modified ARIMA method for these power networks were similar to those of Iran's power network, i.e., parameter tuning of Khorasan and Armenia power networks was performed by using the historical data of 1996 and 1997. Then these power networks were tested by using the data of 1998.

Khorasan is the largest province of Iran and Armenia is a Christian country in the north of Iran. Before 1999, the power networks of Khorasan and Armenia were separate of Iran's power network, but in the beginning of this year these power networks were connected to Iran's power network. The annual peak load of Khorasan and Armenia power networks in 1998 were 1700 MW and 1400 MW, respectively. Due to space limitations, detailed results of the modified ARIMA method for these power networks are not presented. Only the average STLF error of the modified ARIMA method for hourly loads and daily peak load of Khorasan and Armenia power networks has been shown in Table VIII. For implementation of this method for Khorasan and Armenia power networks, the estimations of dispatching center operators of these power networks have been used in the modified ARIMA models as $L_{estim(t)}$ and $L_{pestim(t)}$. Also, we have used the results of statistical study of Iran's power network for power networks of Khorasan and Armenia, i.e., 16 modified ARIMA models (like Iran's power network) have been used for each of these power networks. As is seen from the obtained results, in spite of this shortcoming, the accuracy of the modified ARIMA method for these power networks is acceptable. Better STLF results can be obtained if modified ARIMA models are selected according to statistical study of these power networks. Thus, this method is not dependent on a special power system and can be used for any system.

All programs of the modified ARIMA method have been written in MATLAB and Borland C++ language. On the Pentium P233 personal computer, the response time of the modified ARIMA method for all testing cases, including hourly loads and daily peak load, is less than 0.2 second, which makes feasible the on-line application of the proposed approach for STLF.

V. CONCLUSION

In this paper, a novel approach for STLF has been developed, which incorporates the time series modeling of the ARIMA with the knowledge of experienced human operators. To implement this approach, named modified ARIMA, we statistically studied the load demand, including hourly loads and daily peak load, of the Iran's power network. It has been shown that the proposed method can provide more accurate results than the conventional techniques, such as ANN or ARIMA. In addition to the hourly loads, the proposed approach can accurately forecast the daily peak load.

The modified ARIMA method combines the operators estimation with the temperature and load data. From the mathematical point of view, this method employs the operators estimation as initial forecasting. Then it combines, this initial forecasting with temperature and load data in a multi-variable regression process to obtain a better forecasting. For this reason, the accuracy of the modified ARIMA method is better than ARIMA, since ARIMA has not this initial point. This also applies to ANNs and FNNs, since training of ANNs and FNNs begins with random initial weightings. Also, with better operator estimation, accuracy of the modified ARIMA method increases. In other words, with better initial forecasting, accuracy of the final forecasting increases. This feature can be attractive for the control centers of power networks, since in many cases there are expert operators in the control centers, which can enhance the efficiency of the modified ARIMA method.

Research work is under way in order to: 1) incorporate more weather data, such as humidity; 2) fuzzify the weather model; 3) determine a separate model for Islamic occasions; 4) forecast the time of daily peak load.

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