Real-Time Load Forecasting by Artificial Neural Networks

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Abstract: The application of artificial neural networks (ANNs) to the real-time load forecasting (RTLF) problem is presented. The term RTLF is used for the prediction of the power system load over an interval ranging from one hour to several hours. This issue is becoming increasingly important with the approach of the open access market with the scheduling of buy/sell transactions as short as half an hour in advance.

Separate ANNs are utilized for load forecasting of one hour to four hours ahead. The load forecast of these networks are compared with the of one day ahead load forecast results. Based on simulation results, by utilizing ANN, two objectives are obtained: 1) a more accurate hourly load is predicted, and 2) any near-term buy/sell transactions are fitted in the optimal MW dispatch scheduling. Our approach are demonstrated by detailed study of New Brunswick Power data.

Keywords: Short-term load forecast, Real-time load forecast, Artificial neural networks, Open access market.

1 INTRODUCTION

The term short-term load forecasting (STLF) is used for the prediction of the power system load over an interval ranging from one hour to one week. The term real-time load forecast (RTLF) is a subset of STLF ranging from one hour to several hours. The first application of STLF/RTLF is to drive the scheduling functions that determine the most economic commitment of generation sources. This scheduling applies to purely hydro systems, purely thermal systems, and mixed hydro/thermal systems. The second application of STLF/RTLF is the scheduling of buy/sell transactions. Depending on the load forecast and the available generation, power utilities should decide about their purchase/sell transactions as soon as possible, to maximize profit.

In general terms, computer programs for STLF/RTLF involve tuning, adapting or training a mathematical model to fit historical data with minimal error, then using that model with forecast weather data, etc., to predict the future load level. STLF/RTLF models can be divided into four main categories: a) conventional methods, including time series or regression models, b) fuzzy logic models, c) artificial neural network models, and d) expert system load forecasters. Within each category there are different approaches, architectures and algorithms that may substantially impact performance.

Artificial neural networks (ANNs) have shown superior performance in recent studies [1]-[10]. Different types of ANNs including supervised and unsupervised networks are proposed in the literature. Supervised networks including recurrent [1], and feed-forward [2-10] networks have attracted more attention than unsupervised networks [2,3]. In most cases, the STLF problem has been emphasized [1-6], [8-10], and where RTLF is considered [4, 5], the lead-time is limited to only one hour. In this paper, a novel feed-forward neural network (FNN) for the RTLF applications is introduced. Based on the NB Power preferences, the range of RTLF is limited to four hours. Four separate networks are used to predict the load of the next four hours. For each network, a comprehensive set of input variables was tested, and the inputs with the best performance index were selected. The range of the training data was also adjusted to obtain the best results. A new performance index based on the daily energy forecast error for mixed hydro/thermal units is also introduced.

The organization of the paper is as follows: in Section 2, the motivation of RTLF is considered. In Section 3, the basic concepts related to feed-forward neural networks are described, and the architecture of input, hidden, and output layers are discussed. In Section 4, the prediction performance of the neural network is evaluated. In Section 5, the simulation results of the FNN for RTLF are presented, and concluding remarks are given in Section 6.

2 PROBLEM DESCRIPTION

Many utilities are going through major changes, due to the approaching open access market. After deregulation, customers will have the option of selecting their energy supplier among the available companies. Therefore, energy companies will try to supply the electric energy to the market as cheaply as possible. In an open access environment with an established spot market [6], RTLF becomes more and more important. In this market, the effective energy unit price can be set as short as half an hour in advance [6]. In these situations, an accurate forecast of the very near future situation can produce major benefits. Based on current experience and proposals for deregulated environments, it is obvious that the need for RTLF will certainly increase [5].

The New Brunswick (NB) Power Company, which has been purchasing/selling power to/from the neighboring companies during the last few decades, is also following the changes related to deregulation. For better energy pricing in open access market, NB Power is separating generation and transmission into two independent companies. RTLF is a crucial issue for these companies in a deregulated environment. At present, NB Power is doing a daily load forecast at 8:30 am by using a STLF package. This forecast utilizes the most recent available data. The historical data are used up to the day before the forecast day. The program also needs the weather variables for the forecast day. These data are generally the forecast values obtained at 4 am of the same day or one day before. The weather variables, specifically temperature, can move far off from the predicted value during the day. These weather forecast errors can impact the load forecast significantly. For this reason, load forecast should be executed very frequently, say hourly, with the most recent data.

This paper presents the results of designing an artificial neural network for RTLF applications. Based on company policy, the range of RTLF is limited to four hours ahead. The RTLF program has been designed to fulfill the following objectives:

1. Improving the accuracy of control room operations.
2. Predicting the next-hour load forecast for use in an economic dispatch program. The latter program is used to determine costs for the one hour ahead sales and optimal MW dispatch; external sales are committed both in terms of price and quantity before the hour begins.
3. Accounting for the cost of ancillary services, such as load following, regulation and reserves. These requirements are dependent on load, and need an accurate RTLF.
4. Revising the load forecast whenever the weather conditions change unexpectedly.

The architecture of feedforward neural networks (FNN) which are used for RTLF purposes are discussed in the following sections. Separate FNNs for the load forecast of one, two, three, and four hours ahead have been designed.

3 NEURAL NETWORK ARCHITECTURE

A multi-layer feed-forward neural network (FNN) can be used for RTLF purposes. The FNN is trained to approximate the nonlinear function $F(\cdot)$ between the hourly load and the input variables. The FNN comprises a layer of input units, one or more hidden layer(s) and a layer of output units. An FNN with one hidden layer is shown in

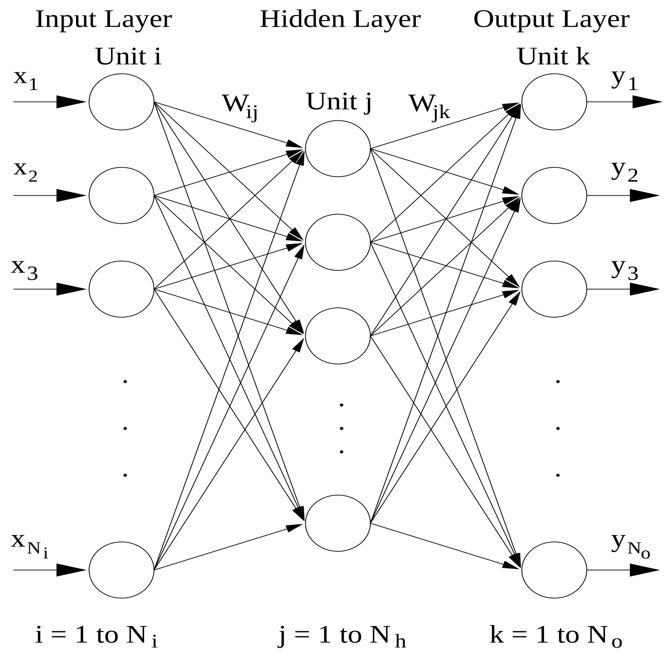

Fig. 1: A feedforward neural network with one hidden layer

Fig. 1. The model of unit j (neuron j) in the hidden layer is shown in Fig. 2.

The structure of the FNN output layer is similar to the hidden layer with the exception that the inputs of the output layer are the outputs of the hidden layer.

The number of inputs, hidden layers, neurons in the hidden layers, and outputs usually defines the FNN architecture. The load forecast of one to four hours ahead are performed by separate networks. The input variables of these networks have some similarity, but are not exactly the same.

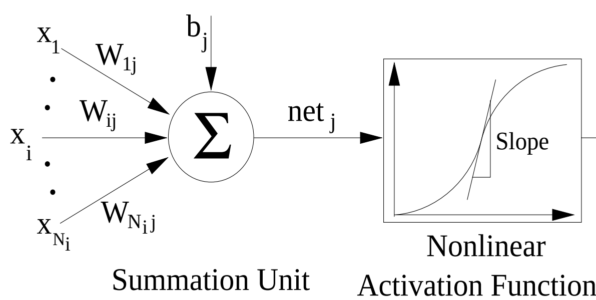

Fig. 2: The model of neuron j in hidden layer

For one hour ahead load forecasting, one network is used for each hour of a day - one network for hour one, one for hour two, and so on. The 24 FNNs are implemented in MetrixND, a neural network package [7]. A similar procedure has been performed for the two to four hours ahead networks. Many of the inputs of these networks are similar, and can be divided into three main categories: a) calendar variables, b) load variables, and c) weather variables. These inputs, and the architecture of hidden and output layers are explained in the following sections.

3.1 Inputs related to calendar variables

The Calendar variables which have the most impact on the load demand are described below.

a) The day of the week: The day of the week is shown by seven different binary variables instead of one integer variable varying from one to seven [1].

b) Holidays: One binary variable is used for specifying the holidays. If a given day is a regular weekday or weekend, this variable is zero; otherwise it gets assigned the value of one, which represents a holiday.

c) Days near holidays: One continuous variable between zero and one is selected for representing the days near holidays such as the days around Christmas.

d) Season: Four continuous variables between zero and one are dedicated for the four seasons of the year.

e) Daylight duration: The time difference between sunset and sunrise, which gives the daylight duration, is used as one continuous input variable.

f) Daylight saving: One binary variable is used for daylight saving. This value is 0 for days with standard time and 1 for days with daylight saving time.

g) The day of the year: One continuous input variable between 0 and 1 is dedicated to the day of the year.

3.2 Inputs related to historical load data

These data consist of actual hourly loads before the forecast hour. The load of the forecast hour are most highly correlated to the load of previous hours of the same day and the load of the same hour at one, two, seven, and eight days before [8]. The selected hourly load data are discussed below. It should be noted that not all of the following variables are used in all the networks. The best selection of the variables depends on the specific hour and the lead-time for load forecast. The appropriate inputs for each network are selected based on the minimum load forecast error after extensive simulations, as follows:

a) The load data of one to two hours before: If the actual load data of these hours are not available, the load forecast of that hour may be used.

b) The load data of three to five hours before: The actual load data of these hours are only used if they are available. In most cases, the load data of more than five hours before did not have any major effect.

c) The load of one day before at the same hour: The load of one day before at the same hour is used as an input variable regardless of the type of the previous day (weekday, weekend, or holiday).

d) The load of one day before at one hour before the forecast hour

e) The load of two days before at the same hour

f) The load of seven days before at the same hour

g) One load data point in the morning of the same day and/or one day before : One hourly historical load data in the morning (some time between 7 to 10 am) of the same day (if available) and one from one day before are selected as other input variables.

h) One load data point in the afternoon of the same day and/or one day before: One hourly historical load data in the afternoon (some time between 16 to 24) of the same day (if available) and one from one day before are selected as other inputs.

3.3 Inputs related to weather variables

The available historical weather data for the NB Power network, which are used as input variables, are described below.

a) Dry bulb temperature: Several dry bulb temperatures are used as input variables. These temperatures are related to: 1) the forecast hour, 2) one to five hours before the forecast hour, 3) the forecast hour of one, two and seven days before, 4) one hour before the forecast hour of one day before, 5) one hour in the morning of the same day (if available) and one from one day before, 6) one hour in the afternoon of the same day (if available) and one from one day before, 7) the minimum and maximum temperature of the forecast day, and 8) the minimum and maximum temperature of one and two days before the forecast day. It should be noted that the variables related to items 2 to 6 will be selected if the historical load data at the same hour is chosen.

b) Humidity: Only one humidity value of the forecast hour is selected as the input. The effect of the humidity of other hours is negligible.

c) Wind speed: One input is dedicated to the predicted wind speed of the forecast hour.

d) Opacity or cloud coverage: One variable related to the predicted opacity of the forecast hour is selected as the input of the neural network.

3.4 Architecture of the hidden layer

Each FNN has only one hidden layer. The number of neurons in this layer is equal to four. Other numbers of neurons, e.g., 3, 5, and 6 did not significantly impact the load forecast accuracy. Two types of activation functions, sigmoid and semi-linear, were tested. The sigmoid activation function was selected due to its better performance.

3.5 Architecture of the output layer

Each FNN has only one output neuron. This output is related to the load forecast of one, two, three, or four hours ahead. Separate FNNs are also designed for each hour of the day. This means that for each hour k; $k = 1, 2, \cdots, 24$; four separate FNNs predict the next four hours loads. For example, the four FNNs which are used at hour 6 are not the same as those at hour seven. In another words, for one hour ahead load forecast, the FNN which predicts the load of hour 7 at 6 o'clock is different from the network which predicts the load of hour 8 at 7 o'clock. In this way, 24 FNNs are designed for load forecast of one hour ahead, 24 networks for two hours ahead, and so on.

4 EVALUATION OF PREDICTION PERFORMANCE

An important step in the design procedure of the neural network is the evaluation of forecasting performance. In general, the performance index is a measure of the load prediction error on an independent data set. The load forecast error should be in an acceptable range if the training data set is representative of the forecasting period. The selection of appropriate training data sets and performance indices are discussed in the following sections.

4.1 Selection of training data sets

In the training procedure, the parameters of the neural network are optimized based on available data. The accuracy of a subsequent load forecast is strongly dependent on the closeness of the training data and the selected time period for the load forecast. For this reason, several approaches for the selection of training data set have been proposed in the literature. In [9], three years of historical data are selected for training the neural network, to obtain good generalization. The load pattern in each year is strongly dependent on the weather conditions during that year. We had a total range of twenty and a half months of historical data. In order to obtain good generalization, the windows for training data and test data were adjusted to 16 and $4\frac{1}{2}$ months, respectively. After the selection of training data set, the neural network can be trained weekly or even monthly.

4.2 Performance indices

Several measures of forecast accuracy have been proposed as the performance index [10]. In this study, the two most commonly adopted for load forecast evaluation were used: 1) variance, σ^2 ; and 2) mean absolute percentage error (MAPE); which can be formulated as follows:

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(L_F^n - L_A^n)^2 \tag{1}$$

where L_F is the forecast load, L_A is the actual load, n is the index of a data point in the data set, and N is the total number of data points. The mean absolute percentage error, ϵ, can be formulated as:

$$\epsilon = \frac{1}{N}\sum_{n=1}^{N}\frac{|L_F^n - L_A^n|}{L_A^n} * 100 \tag{2}$$

Another index, which has practical importance in mixed hydro/thermal systems, is the daily energy forecast error. In general, for hourly generation scheduling of hydro/thermal units, the total generation cost is minimized. This minimization is based on the load forecast of the next hour and the available energy from hydro units. In many cases, the available energy from a hydro unit is specified for the whole day, and hourly energy generation is not important as long as the daily energy generation meets the scheduled value. As a result, hydro unit generation can compensate for some part of the hourly load forecast error. The uncompensated part is related to the energy forecast error, which can be formulated as:

$$\epsilon_d = \sum_{n=1}^{24} L_F^n - L_A^n \tag{3}$$

where ϵ_d is the daily energy forecast error. The daily energy forecast percentage error, ϵ_{dp}, can also be used as an index for prediction performance, and formulated as:

$$\epsilon_{dp} = \frac{\sum_{n=1}^{24} L_F^n - L_A^n}{\sum_{n=1}^{24} L_A^n} * 100 \tag{4}$$

5 SIMULATION RESULTS

NB Power network is connected to its neighboring companies via 15 tie lines. NB Power has a peak load of 2800 MW during the Winter. As mentioned before, the neural network was trained with sixteen months of historical data. The training data set covers the period of September 1997 through December 1998. After training, the FNN is used for a load forecast study of 136 days from January 1st to May 16th 1999. Load forecast results of the 96 RTLF FNNs are compared with the load forecast results of a one day ahead STLF load forecasting routine. In both cases, the actual weather variables are used instead of forecast weather parameters, since the latter were not retained. It should be noted that the performance of STLF will be degraded much more than RTLF if the forecast weather data are used. That is because STLF uses the weather forecast data of the next 24 hours while RTLF utilizes the weather forecast data of the next one to four hours, and the latter are much more accurate.

Load forecast results of the two approaches for the specified 136-day study period are shown in Table 1. In column one, the hour number of the day is shown. The MAPE of load forecast for one to four hours ahead are given in columns two to five, respectively. The MAPE of the load forecast for the entire 24-hour period is given in column six. Based on these results, the MAPE of the load forecast is the lowest for one hour ahead, and become larger and larger when the lead-time of forecast increases. The one hour ahead load forecast can reduce the mean absolute percentage error of one day ahead load forecast by 68%. This reduction for two to four hours ahead load forecast comes to 50%, 38%, and 30%; respectively. The obtained RTLF results are also comparable with those reported in the literature. For one hour ahead, the MAPE of load forecast, 0.88%, is lower than that from [4], 0.9%.

Table 1: The study results of RTLF of neural network approach

Hour No.	Load forecast mean absolute percentage error				
	one hour ahead	two hours ahead	three hours ahead	four hours ahead	24 hours ahead
1	1.33	1.33	1.33	1.33	1.33
2	0.92	1.42	1.42	1.42	1.42
3	0.63	1.07	1.47	1.47	1.47
4	0.58	0.88	1.33	1.58	1.58
5	0.64	0.8	1.05	1.49	2.13
6	0.56	0.92	1.16	1.35	2.31
7	1.00	1.26	1.52	1.61	2.59
8	1.05	2.03	2.28	2.31	2.71
9	1.25	1.7	2.02	2.1	2.8
10	1.14	2.13	2.15	2.25	2.79
11	0.77	1.53	2.3	2.35	2.8
12	0.79	1.38	2.02	2.55	3.07
13	0.71	1.20	1.69	2.21	2.89
14	0.84	1.20	1.70	2.01	3.22
15	0.85	1.32	1.64	2.05	3.39
16	0.88	1.41	1.79	2.04	3.46
17	0.98	1.42	1.78	2.06	3.49
18	1.02	1.66	1.92	2.15	3.54
19	1.01	1.50	2.00	2.06	3.33
20	0.85	1.58	1.96	2.21	3.02
21	0.78	1.10	1.64	1.75	2.79
22	0.77	1.14	1.23	1.52	2.79
23	0.79	1.22	1.48	1.53	2.88
24	0.91	1.33	1.60	1.70	2.96
mean	0.88	1.36	1.69	1.88	2.7

The simulation results of the RTLF and STLF approaches are also presented in Fig. 3. The MAPEs related to one to four hours and one day ahead load forecast are shown in this figure. These MAPEs are based on all 136 days. A more detailed study of the MAPE of one hour ahead load forecast for different days of the week is depicted in Fig. 4. In Fig. 4-a, the mean of actual load over two weekdays (Mondays and Thursdays) and one weekend day (Saturdays); and in Fig. 4-b, the MAPE of load forecast for the same days are compared.

Energy forecast errors for the study period were also analyzed. The MAPE of energy forecast is obtained as follows: 1) first by using (4), the percentage energy error for each day is computed, and 2) the absolute values of these errors are averaged over each day of the week. The daily energy forecast results of one hour ahead load forecast for two weekdays (Monday and Wednesday) and one weekend day (Saturday) are presented in Fig. 5. By comparing the MAPE of energy forecast of one hour ahead (0.24%) with

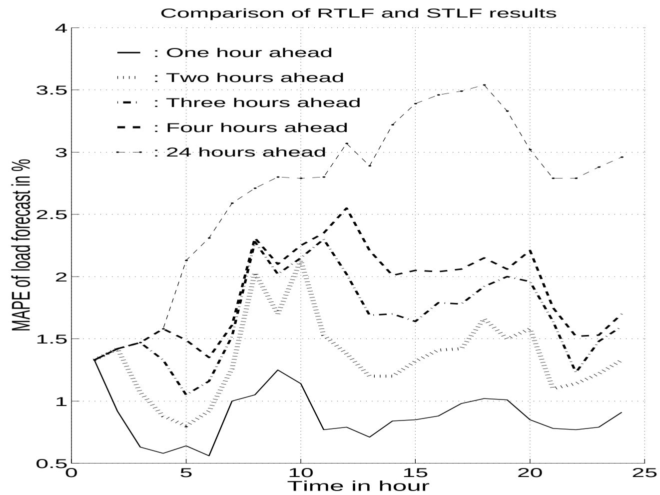

Fig. 3: Comparison of RTLF and STLF results

the MAPE of energy forecast of one day ahead (1.93%), it can be seen that the energy forecast error results have been reduced by nearly 88%.

6 CONCLUSION

A set of 96 feed-forward neural networks is proposed to reduce the hourly load forecast error of the upcoming hours. In this method, independent networks are utilized to predict the load of each hour during a day. The input variables of the FNNs are selected from three important categories: a) calendar variables, 2) load data variables, and 3) weather variables. A new performance index based on the daily energy forecast error for mixed hydro/thermal units is introduced. The range of training data set is adjusted to obtain the best performance indices. The hourly load of one to four hours and one day ahead by using the actual weather data is predicted. Totally 136 days were simulated. The load and energy forecast results of the RTLF and STLF approaches are compared.

Based on simulation results, the RTLF approach has reduced the MAPE of hourly load forecast substantially as compared with a 24-hour ahead STLF run. The one hour ahead RTLF results show a reduction of 68% in the MAPE of 24-hour ahead STLF. Similar reduction for two, three, and four hours ahead RTLF comes to 50%, 38%, and 30%; respectively. The reduction of the MAPE of daily energy forecast using one hour ahead RTLF is even much more significant in comparison with the one day ahead forecast. A reduction of up to 88% on the MAPE of one day ahead energy forecast is obtained when the load is predicted one hour ahead.

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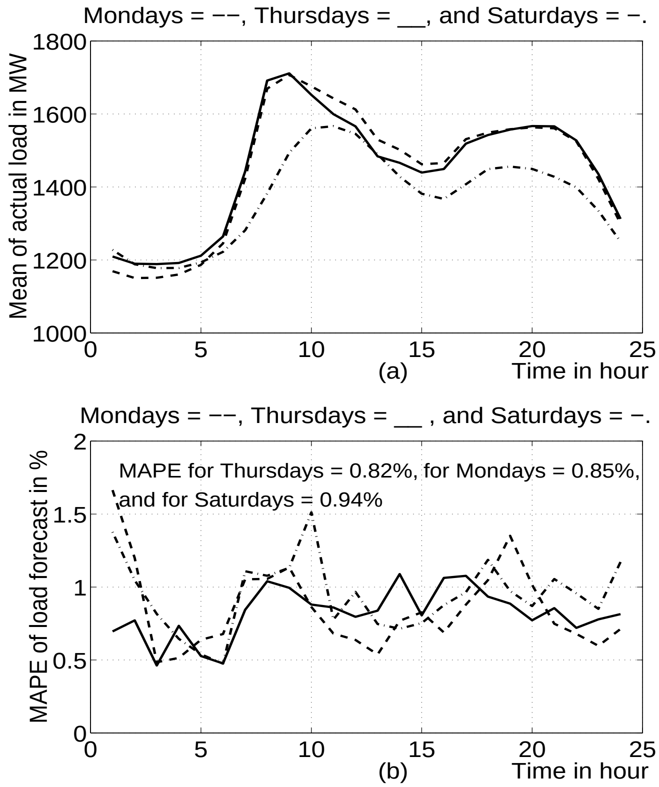

Fig. 4: a) Mean of actual load, b) MAPE of one hour ahead load forecast for two weekdays (Mondays and Thursdays) and Saturdays

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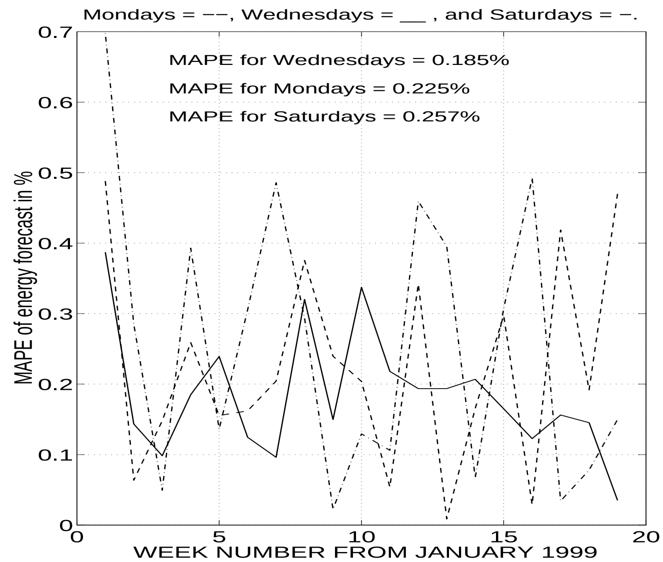

Fig. 5: MAPE of one hour ahead energy forecast for two weekdays (Mondays and Wednesdays) and Saturdays

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9 BIOGRAPHIES

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