

# HOURLY THERMAL LOAD PREDICTION FOR THE NEXT 24 HOURS BY ARIMA, EWMA, LR, AND AN ARTIFICIAL NEURAL NETWORK

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## ABSTRACT

*Predicting the thermal load for the next 24 hours is essential for optimal control of heating, ventilating, and air-conditioning (HVAC) systems that use thermal cool storage. It can be useful in minimizing costs and energy in nonstorage systems. A cooperative research project between a U.S. university and a Japanese corporation investigated four generally used prediction methods to examine the basic models with variations and to compare the accuracy of each model. A cooling and heating seasonal data set with known next-day weather was used to evaluate the accuracy of each prediction method. The results indicate that an artificial neural network (ANN) model produces the most accurate thermal load predictions.*

*After the initial comparisons with a computer-generated data set, the ANN model was applied to two measured building loads from another research project. These sets included typical measurement noise related to continuous field monitoring. The predictions of the next-day cooling load using the ANN prediction model were close to the actual data, even when the next-day weather was forecast. This confirms that the ANN model has sufficient accuracy and is the correct method for practical utilization in HVAC system control, thermal storage optimal control, and load/demand management.*

## INTRODUCTION

Accurate prediction allows us to engineer intelligently in many fields. In HVAC design, accurate prediction of the dynamic thermal behavior of cooling loads in a building is a key for successful design. Examples where accurate prediction is useful in HVAC operations include adjusting the starting time of cooling to meet start-up loads, minimizing or limiting the electric on-peak demand, thermal load prediction to optimize costs and energy use for cool storage systems, and related energy and cost optimization needs in other HVAC systems (i.e., cogeneration, dual paths, and dehumidification).

The objective of this research project was to determine the optimal thermal load prediction method for a thermal cool storage HVAC system. The prediction can then be used for optimal control to minimize operating costs and energy use throughout the year. Although storage systems have the potential to reduce operating costs by shifting chiller operation to off-peak periods, many existing systems do not minimize energy use and costs. One reason for this is that they do not adequately predict loads or use predictive methods to control the chiller or manage energy in and out of storage. If the hourly thermal loads for the next 24 hours can be predicted, operation decisions can be made to allow the proper amount of energy to be stored in the tank during off-peak hours. Subsequently, energy use during on-peak hours can be managed to minimize operating costs.

Several prediction techniques that can be used for on-line adaptive control have been previously investigated. Forrester and Wepfer (1984) presented a method based on an extensive multiple linear regression technique that predicts electrical demand up to four hours in advance. MacArthur et al. (1989) and Spethmann (1989) developed a prediction method and applied it to an optimal cold storage controller. It was based on the autoregressive integrated moving average model with exogenous inputs (ARIMAX time series model) adopted with a clockwise recursive regression technique. Seem and Braun (1991) examined a cerebellar model articulation controller (CMAC model) using an exponential weighted moving average model (EWMA) to determine its exponential smoothing constant. Ferrano and Wong (1990) described an artificial neural network (ANN) model to predict the next day's total thermal load. Kreider and Wang (1991) demonstrated an automated load predictor using the ANN. Anstett and Kreider (1993) examined the accuracy of the ANN for energy predictions. All of these works, as well as others, have been reported with varying degrees of success (Curtiss et al. 1993; Ding and Wong 1990; Kreider et al. 1991; Kreider and Wang 1992; Mistry and Nair 1993). However, there have been no clear performance comparisons between the various models.

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The first part of this paper presents a review of each model considered and a comparison of their accuracy in hourly load prediction for the next 24 hours. The models examined were four significantly different models, plus three modified models:

1. autoregressive integrated moving average (ARIMA) model,
2. exponential weighted moving average (EWMA) model,
3. modified EWMA model,
4. recursively modified EWMA model,
5. recursive linear regressive (LR) model,
6. artificial neural network (ANN) model, and
7. recursively modified ANN model.

In the second part of this paper, ANN models are examined using measured data sets to show the range of the prediction accuracy in actual buildings.

### CONDITIONS FOR COMPARISON

Common conditions for the comparison of the different models are as follows.

1. The hourly loads up to 24 hours in advance were predicted for three months of winter and summer using present and past hourly observed load and weather data.
2. The calculated load data set was prepared for the comparison by using a transfer-function-based dynamic thermal load calculation program with the TMY data of Tokyo in the situation where the office building was occupied from 8:00 a.m. to 6:00 p.m. on weekdays.
3. Since the thermal characteristics on Monday are different from those on other days, hourly predictions for Tuesday through Friday were used to compare the accuracy.
4. The accuracy of each model was evaluated using standard deviation ( $\sigma$ ), expected error percentage (EEP), coefficient of variation (CV), and mean bias error (MBE), defined by Equations 1 through 4, respectively:

$$\sigma = \sqrt{\frac{\sum_{t=1}^n (y_{pred,t} - y_{data,t})^2}{n}} \quad (1)$$

$$EEP = \frac{\sqrt{\frac{\sum_{t=1}^n (y_{pred,t} - y_{data,t})^2}{n}}}{|\bar{y}_{data,max}|} \times 100 \quad (2)$$

$$CV = \frac{\sqrt{\frac{\sum_{t=1}^n (y_{pred,t} - y_{data,t})^2}{n}}}{|\bar{y}_{data}|} \times 100 \quad (3)$$

and

$$MBE = \frac{\sum_{t=1}^n (y_{pred,t} - y_{data,t})}{|\bar{y}_{data}|} \times 100 \quad (4)$$

where

- $y_{data,t}$  = measured data at time  $t$ ,
- $y_{pred,t}$  = predicted data at time  $t$ ,
- $y_{data,max}$  = maximum measured data,
- $\bar{y}_{data}$  = mean value of the measured data, and
- $n$  = number of data.

### ARIMA MODEL

The autoregressive integrated moving average (ARIMA) model depends only on the previous time series data. The fundamental scheme of the model is shown by Equation 5. The  $p$ ,  $d$ , and  $q$  are order numbers of the processes for autoregressive, integrated, and moving average components, respectively. This means that the  $d$ th deviation of the time series data is expressed by the  $p$ th-order autoregressive term and the  $q$ th-order moving average term. If the data are also correlated with the previous data  $n$  steps before, Equation 5 can be rewritten as Equation 6. The  $P$ ,  $D$ , and  $Q$  refer to the same orders as  $p$ ,  $d$ , and  $q$  at  $n$ th previous time. The value 24 for  $n$  was chosen since the time series data have a 24-hour cycle, which means that the thermal loads at an hour are correlated with previous data a few hours before and one day before.

ARIMA( $p, d, q$ ):

$$\nabla^d y_t = \sum_{i=1}^p \phi_i \nabla^d y_{t-i} + a_t - \sum_{j=1}^q \theta_j a_{t-j} \quad (5)$$

where

- $y_t$  = time series data at time  $t$ ,
- $a_t$  = white noise at time  $t$  (expectation = 0.0),
- $\theta_j$  = coefficient of  $a_{t-j}$ ,
- $\phi_i$  = coefficient of  $y_{t-i}$ ,
- $\nabla^d y_t$  =  $d$ th difference of the  $y_t$  ( $\nabla^1 y_t = y_t - y_{t-1}$ ), and
- $p, d, q$  = order numbers of AR, I, and MA, respectively (0, 1, 2, ...).

ARIMA ( $p, d, q$ )  $\times$  ( $P, D, Q$ ) $_n$ :

$$\begin{aligned} \nabla^d \nabla^D y_t = & \sum_{i=1}^p \phi_i \nabla^d y_{t-i} + \sum_{k=1}^P \phi_k \nabla^D y_{t-k} \\ & + a_t - \sum_{j=1}^q \theta_j a_{t-j} - \sum_{l=1}^Q \theta_l a_{t-l} \end{aligned} \quad (6)$$

In this study, the coefficients  $\theta_p$ ,  $\theta_b$ ,  $\phi_i$ , and  $\phi_k$  were estimated using hourly loads for the first 10 days of data after the suitable order numbers ( $p$ ,  $d$ ,  $q$ ,  $P$ ,  $D$ ,  $Q$ ) were chosen empirically. Then, hourly thermal loads for the rest of the entire season were predicted. The order numbers were usually zero, one, or two. This model will be referred to as "ARIMA" in the following sections.

## EWMA MODEL

The exponential weighted moving average (EWMA) model is defined by Equation 7 or 8. The prediction of load also depends on previous load data only. The exponential smoothing constant,  $\lambda$ , ranging between zero and one, is the single parameter that needs to be identified for the model.

$$y'_t = \lambda y_{t-1} + \lambda(1-\lambda)y_{t-2} + \lambda(1-\lambda)^2 y_{t-3} + \dots \quad (7)$$

$$= \sum_{j=0}^{\infty} \lambda(1-\lambda)^j y_{t-(j+1)} \quad (8)$$

where

$y'_t$  = predicted data at time  $t$ ,  
 $\lambda$  = exponential smoothing constant, and  
 $y_{t-j}$  = observed data  $j$  times prior to time  $t$ .

For the thermal load data, the term  $t-1$  in Equation 7 can be replaced by  $t-24$  since the loads have a 24-hour cycle. If the previously predicted data are substituted for all the previously observed data except those 24 hours before, it can be denoted as Equation 9:

$$y'_t = y'_{t-24} + \lambda(y_{t-24} - y'_{t-24}) \quad (9)$$

where

$t$  = time of day,  
 $y'_t$  = predicted data at time  $t$ ,  
 $y_{t-24}$  = observed data at time  $t-24$ , and  
 $y'_{t-24}$  = predicted data at time  $t-24$ .

The previous ( $t-24$ ) thermal load data, both predicted and observed, always refer to the data when the building is occupied. The EWMA model is equal to an ARIMA model that can be abbreviated as ARIMA(0,0,0)  $\times$  (0,1,1)<sub>24</sub>.

In this study, the exponential smoothing constant ( $\lambda$ ) was estimated by using hourly data for the first 10 days of load data. Then, the hourly loads for the rest of the season were predicted. The value 0.3 for  $\lambda$  was used. This model is identified as "EWMA simple" in the following sections.

Two modified EWMA models were examined to improve the accuracy of the prediction. The first modified model was assumed to have the next day's total load. Since there is usually a strong correlation between maximum

ambient temperature and daily total load, the total load was computed by a regression equation. The hourly loads were predicted so that the daily total predicted load meets the daily total regressed load. This model is referred to as "EWMA modi" in the following sections. The second modified model is a recursively modified model of "EWMA modi." After the occupied hour has started, the difference between predicted and observed loads can be obtained. The hourly predicted loads were modified every hour by multiplying by the ratio of the total predicted load and the total observed load from the day's start time of occupancy to the current time. This recursive modification was examined since this adaptability is important for practical HVAC control. This model is referred to as "EWMA recur" in the following sections.

## LR MODEL

A linear system model that has  $n$  inputs ( $x_1, x_2, x_3, \dots, x_n$ ) and one output ( $y$ ) at time  $t$  can be described by Equation 10. The  $k_1, k_2, \dots, k_n$  are constant unknown parameters:

$$y = k_1 x_1 + k_2 x_2 + \dots + k_n x_n \quad (10)$$

The linear regression can be applied to the parameter identification process and is explained as follows. At time 1  $\sim m$ , the system is shown by Equation 11 using the vectors  $y$  and  $k$  and a matrix,  $X$ :

$$y = Xk \quad (11)$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}, \quad k = \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix},$$

and

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & \dots & \dots & \dots \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & \dots & \dots & x_{nm} \end{bmatrix}.$$

Then, the error vector,  $e$ , between observed and predicted data is as follows:

$$\mathbf{e} = \mathbf{y} - \mathbf{X}\mathbf{k}. \quad (12)$$

The square of the  $\mathbf{e}$  vector is denoted  $\mathbf{J}$ :

$$\mathbf{J} = \sum_{i=1}^m \mathbf{e}_i^2 = \mathbf{e}^T \mathbf{e} \quad (13)$$

$$= (\mathbf{y} - \mathbf{X}\mathbf{k})^T (\mathbf{y} - \mathbf{X}\mathbf{k}) \quad (14)$$

$$= \mathbf{y}^T \mathbf{y} - \mathbf{k}^T \mathbf{X}^T \mathbf{y} - \mathbf{y}^T \mathbf{X} \mathbf{k} + \mathbf{k}^T \mathbf{X}^T \mathbf{X} \mathbf{k}. \quad (15)$$

To determine the estimate  $\mathbf{k}$  that minimizes  $\mathbf{J}$ , the derivative of  $\mathbf{J}$  with respect to  $\mathbf{k}$  is set to 0:

$$\left. \frac{\partial \mathbf{J}}{\partial \mathbf{k}} \right|_{\mathbf{k}=\hat{\mathbf{k}}} = -2\mathbf{X}^T \mathbf{y} + 2\mathbf{X}^T \mathbf{X} \mathbf{k} = 0. \quad (16)$$

This yields

$$\mathbf{X}^T \mathbf{X} \mathbf{k} = \mathbf{X}^T \mathbf{y}. \quad (17)$$

$\mathbf{k}$  can be solved for

$$\hat{\mathbf{k}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}. \quad (18)$$

Then, prediction of  $\mathbf{y}$  at time  $m+1$  is

$$y_{m+1} = x_{1,m+1} k_1 + x_{2,m+1} k_2 + \dots + x_{n,m+1} k_n. \quad (19)$$

After obtaining new observed data at time  $t+1$ , further parameter estimation can be done by the recursive least-squares method. A forgetting (ignoring) factor,  $\lambda$  ( $0 \sim 1.0$ ), is introduced to weight recent data more than the previous data.

(See Appendix A.)

$\hat{\mathbf{k}}_{m+1}$  can be determined by the following equations:

$$\hat{\mathbf{k}}_{m+1} = \hat{\mathbf{k}}_m + \gamma_{m+1} \mathbf{P}_m \mathbf{x}_{m+1} [y_{m+1} - \mathbf{x}_{m+1}^T \hat{\mathbf{k}}_m], \quad (20)$$

$$\mathbf{P}_m = \frac{1}{\lambda} (\mathbf{X}_m^T \mathbf{X}_m)^{-1}, \quad (21)$$

and

$$\gamma_{m+1} = \frac{1}{[1 + \mathbf{x}_{m+1}^T \mathbf{P}_m \mathbf{x}_{m+1}]}. \quad (22)$$

$\mathbf{P}_{m+1}$  for the next recursive calculation is as follows:

$$\mathbf{P}_{m+1} = \frac{1}{\lambda} [\mathbf{P}_m - \gamma_{m+1} \mathbf{P}_m \mathbf{x}_{m+1} \mathbf{x}_{m+1}^T \mathbf{P}_m]. \quad (23)$$

In this study, the model was defined to have 15 inputs and one output. The inputs were the observed thermal load at  $t-24$  hours, seven ambient temperatures, and seven solar insolation data from six hours before to the current time. One output was the hourly thermal load. The initial parameters were calculated by using the hourly load and weather data for the first nine days, and then were used to predict the tenth-day loads. When the next 24 current observed data were obtained, the parameters were re-estimated by the recursive least-squares method. The hourly ambient temperatures and solar insolation for the next 24 hours are required to predict hourly loads for the next 24 hours. The recorded observed temperature and insolation data were used in this study. The thermal loads for the entire season were predicted using the recursive least-squares method. The predicted result is indicated as "LR" in the following sections.

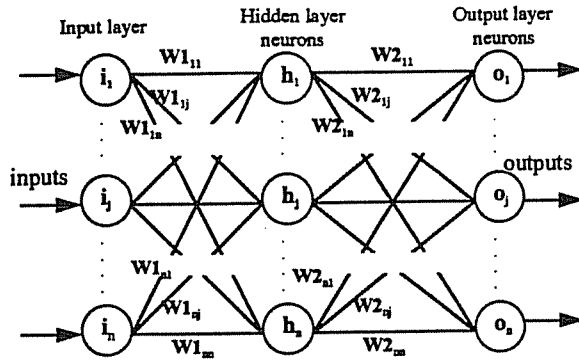
## ANN MODEL

An artificial neural network is one model used for non-linear systems. It has a topological structure that connects fundamental processing units called neurons. Each neuron receives several inputs through connections and determines the outgoing activation with a threshold function. The ANN could have several hidden layers to propagate its activations from the input to the output.

Backpropagation is the name of a supervised training algorithm. It requires a teacher's (known) outputs for particular inputs to train the network. During the training process, the synaptic weights are gradually adjusted to suitable values.

Figure 1 shows the fundamental model of the ANN with one hidden layer and two synaptic weighting matrices ( $\mathbf{W}_1$ ,  $\mathbf{W}_2$ ). The procedure of the ANN backpropagation algorithm is described as follows.

First, the output of the model ( $\mathbf{o}$ ) is computed by equations called the *forward path* (Equations 24 and 25) using initial weighting matrices and biases. Second, the error matrices ( $\mathbf{d}$ ,  $\mathbf{e}$ ) are computed using Equations 26 and 27. Third, the error ( $\mathbf{d}$ ) is propagated to the hidden layer. This is called the *backward path*. The weighting matrix and bias are



**Figure 1** Fundamental structure of an artificial neural network.

adjusted by Equations 28 through 30. Fourth, similar propagation and adjustment for the input layer are performed using Equations 31 through 33. These steps are repeated using all of the training data again and again until the sum of the squares error for the entire training data set becomes a minimum.

$$\mathbf{h} = F(\mathbf{i} \cdot \mathbf{W1} + \text{bias1}) \quad (24)$$

$$\mathbf{o} = F(\mathbf{h} \cdot \mathbf{W2} + \text{bias2}) \quad (25)$$

$$\mathbf{d} = \mathbf{o} (1 - \mathbf{o}) (\mathbf{o} - \mathbf{t}) \quad (26)$$

$$\mathbf{e} = \mathbf{h} (1 - \mathbf{h}) \mathbf{W2} \cdot \mathbf{d} \quad (27)$$

$$\mathbf{W2} = \mathbf{W2} + \Delta \mathbf{W2}_t \quad (28)$$

$$\Delta \mathbf{W2}_t = \alpha \mathbf{h} \mathbf{d} + \Theta \Delta \mathbf{W2}_{t-1} \quad (29)$$

$$\text{bias2} = \text{bias2} + \alpha \mathbf{d} \quad (30)$$

$$\mathbf{W1} = \mathbf{W1} + \Delta \mathbf{W1}_t \quad (31)$$

$$\Delta \mathbf{W1}_t = \alpha \mathbf{i} \mathbf{e} + \Theta \Delta \mathbf{W1}_{t-1} \quad (32)$$

$$\text{bias1} = \text{bias1} + \alpha \mathbf{e} \quad (33)$$

After the ANN has been sufficiently trained (the error is a minimum), it can estimate the outputs for the particular input data set using Equations 34 and 35:

$$\mathbf{h} = F(\mathbf{i} \cdot \mathbf{W1} + \text{bias1}) \quad (34)$$

$$\mathbf{o} = F(\mathbf{h} \cdot \mathbf{W2} + \text{bias2}) \quad (35)$$

where

$\mathbf{h}$  = hidden-layer neuron vector,

$\mathbf{i}$  = normalized input vector (values are from 0.0 to 1.0),

$\mathbf{o}$  = output vector,

$\mathbf{d}$  = output error vector,

$\mathbf{t}$  = teacher's output vector,

$\mathbf{e}$  = hidden-layer error vector,

$\mathbf{W1}$  = weighting matrix for the input layer,

$\mathbf{W2}$  = weighting matrix for the hidden layer,

$\text{bias1}$  = bias vector for the input layer,

$\text{bias2}$  = bias vector for the hidden layer,

$F(x)$  =  $1/(1 + e^{-x})$  (called the sigmoid function),

$\Delta \mathbf{W1}_t$  = changing value matrix for matrix  $\mathbf{W1}$  at time  $t$ ,

$\Delta \mathbf{W2}_t$  = changing value matrix for matrix  $\mathbf{W2}$  at time  $t$ ,

$\alpha$  = learning rate (value from 0.0 to 1.0), and

$\Theta$  = momentum factor (value from 0.0 to 1.0).

In this study, the learning rate ( $\alpha$ ) was gradually reduced by a "three-phase annealing procedure" during the training to accelerate the process. The three-phase annealing is described in detail in Kawashima (1994). Figure 2 shows the ANN model for the thermal load prediction. The 15 inputs and 1 output, which are the same as in the LR model, and the 31 hidden layer neurons were chosen for the ANN model. The network was trained using hourly data for the entire season. After the training, the hourly loads for the entire season were predicted using observed next-day weather data. This result is referred to as "ANN simple" in the following section.

One modified ANN model was examined to improve the accuracy of the prediction. This is a recursively modified model of the ANN simple model. The hourly predicted loads were updated every occupied hour by multiplying by the ratio of the total predicted load and the total observed load from the day's start time of occupancy to the current time. The recursive modification could improve the prediction accuracy. This adaptability is important for the practical HVAC controller. The modified ANN model is referred to as "ANN recur" in the following sections.

## COMPARISON OF THE SEVEN PREDICTIONS

Tables 1 and 2 show the accuracy criteria for the seven thermal load predictions during the summer and winter. The hourly-basis EEPs of the ANN simple model were 6.3% of the maximum load for the winter and 5.7% for the summer. Those of the "ANN recur" model were 5.3% and 4.7% for the winter and summer, respectively. These results show that the prediction accuracy of the ANN model is the best of all models and the recursive ANN is better than the simple

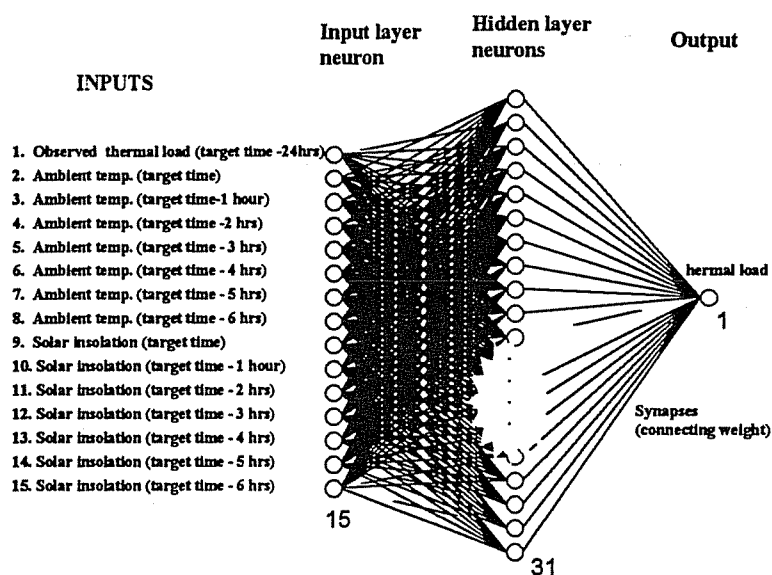


Figure 2 ANN model for the thermal load prediction.

TABLE 1  
Results of the Seven Thermal Load Predictions ( $\sigma$  and EEP)

Symbols	$\sigma$ (Kcal/hr)		EEP (%)			
	winter	summer	winter		summer	
	hourly basis	hourly basis	daily basis	hourly basis	daily basis	hourly basis
1. ARIMA	4592.8	7938.6	20.2	14.5	29.7	17.5
2. EWMA simple	3654.0	6016.1	18.1	11.5	23.9	13.2
3. EWMA modi.	2750.7	3195.2	10.6	8.7	10.4	7.0
4. EWMA recur.	2473.3	9733.8	8.7	7.8	9.3	21.4
5. LR	4614.3	4939.2	22.4	14.5	17.3	10.9
6. ANN simple	1861.1	2090.9	9.3	6.3	8.6	5.7
7. ANN recur.	1536.4	1562.9	5.8	5.3	4.4	4.7

TABLE 2  
Results of the Seven Thermal Load Predictions (CV and MBE)

Symbols	CV(%)		MBE(%)	
	winter	summer	winter	summer
	hourly basis	hourly basis	hourly basis	hourly basis
1. ARIMA	27.7	34.4	1.6	1.0
2. EWMA simple	22.0	26.0	1.8	3.3
3. EWMA modi.	16.6	13.8	1.8	0.3
4. EWMA recur.	14.9	42.1	0.5	-0.5
5. LR	27.8	21.4	-2.0	-1.3
6. ANN simple	11.2	9.1	-0.5	-0.2
7. ANN recur.	9.3	6.8	-0.5	-0.4

ANN. There are significant differences between results of the ANNs and the others.

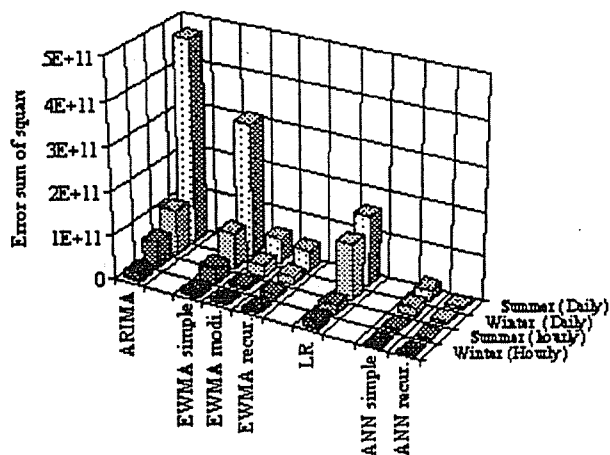
Figure 3 shows the error sum of squares on each model computed with data for the entire cooling and heating seasons. It clearly shows that both ANN models—simple and recursively modified—have better accuracy than the other models. Since ARIMA and EWMA depend on the previous series data, there is a limitation on tracing the swings of the load affected by the weather. The result of the LR shows that it is difficult to apply the linear regression process to a nonlinear system such as the thermal-load-determining mechanism. The ANN nonlinear model was satisfactory on the hourly thermal load prediction for the next 24 hours.

Figures 4 through 7 show examples of the results of the hourly thermal load predictions. The bars represent the observed loads and the lines represent the predicted loads. Figures 4 and 5 show the heating loads and Figures 6 and 7 show the cooling loads. Each figure shows the predictions by ARIMA, EWMA, LR, and ANN, in that order. The hourly load predictions by the ANN have good agreement even if the load profile for the day is different from the others in both the cooling and heating seasons.

## USING ANN MODEL WITH MEASURED DATA

Seven ANN prediction models were applied to two sets of building thermal loads that were measured in Seattle, Washington, and Phoenix, Arizona. The main objective of this analytical phase was to confirm the error range of the load prediction by the ANN on existing building loads that have noise and measurement errors. The results assess the performance of the ANN predictions in the nearly practical situation.

Both data sets used for analysis are the cooling loads from June 3 to October 13 (19 weeks) in 1991. Building S in Seattle is a 21-story office complex with stores. The HVAC



**Figure 3** Error sum of squares for seven load predictions.

system has static-type ice storage tanks, two chillers (107 and 243 tons), and is a 44°F cold air distribution system. Building P in Phoenix is an aerospace manufacturing factory with eutectic salt thermal storage. Measurements at both locations were taken with a computerized data-acquisition system at short time intervals (seconds). The measured data were summed and averaged for one hour for use in the prediction analysis.

There are several possibilities in defining the ANN model. For example, it could have multiple hidden layers, multiple outputs, etc. However, there is no approved modeling method to achieve the best accuracy on the prediction. The modeling of the ANN for this study followed a guideline listed in Kawashima (1994). It recommends that the ANN model have one output (thermal load) and one hidden layer that has  $2n+1$  neurons ( $n$  is the number of inputs). The three-phase annealing procedure for the learning rate was used during the training.

Figure 8 shows one of the models used for buildings S and P. The model has five or six inputs. The five inputs are observed load at  $t-24$ , ambient temperatures (at  $t$ ,  $t-1$ ,  $t-2$ ), and ambient relative humidity (at  $t$ ). After the five-input models were examined, the six-input models that had an occupancy indicator (0 or 1) were also examined to improve the prediction accuracy for building S. The solar insolation data should have been used as inputs. However, no solar insolation was available for either building. Both models with known (observed) weather data and predicted weather data (described below) were examined to determine the difference. The recursive modification, as described earlier, was also examined for building S. The conditions for the five models for building S and the two models for building P examined in this study are given in Table 3.

## WEATHER FORECAST FOR THE NEXT 24 HOURS

There are weather input items that have the time stamps  $t$ ,  $t-1$ , and  $t-2$  ( $t$  is the target time) in the ANN prediction model. This requires the predicted weather data for use in the next 24 hours in load prediction. The hourly ambient temperature and relative humidity must be estimated before the load prediction in an operating situation. Procedures used in this analysis assume that tomorrow's high and low temperatures can be obtained from a local weather station or reporting station. In this study, the high and low temperatures were obtained from recorded forecasts in old newspapers.

The hourly ambient temperatures were calculated using Equation 36. The  $\alpha_i$  are coefficients recommended by ASHRAE (1993):

$$T_t = T_H - \alpha_i \times (T_H - T_L) \quad (36)$$

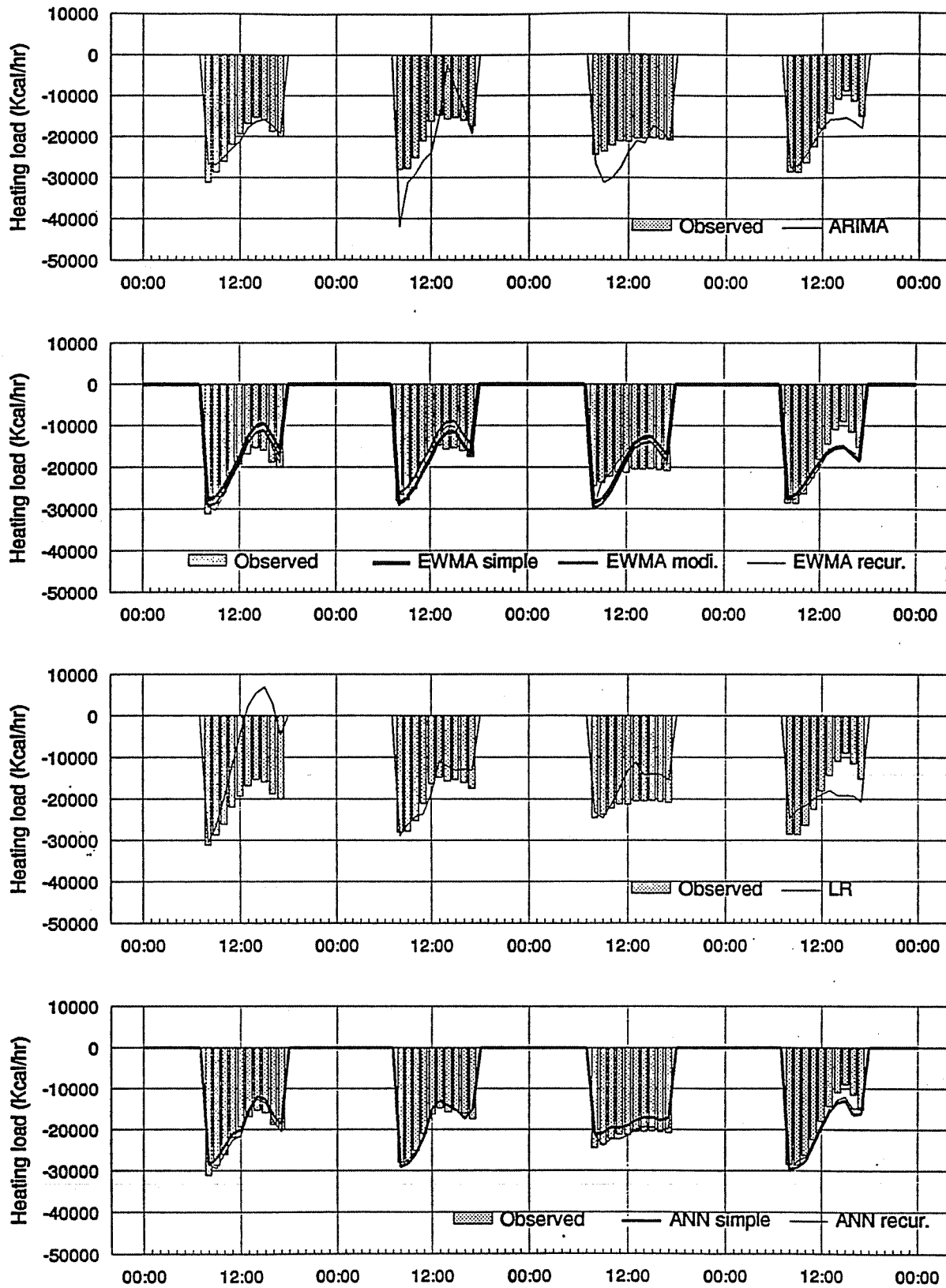


Figure 4 Thermal load prediction by ARIMA, EWMA, LR, and ANN (from January 31 to February 3).



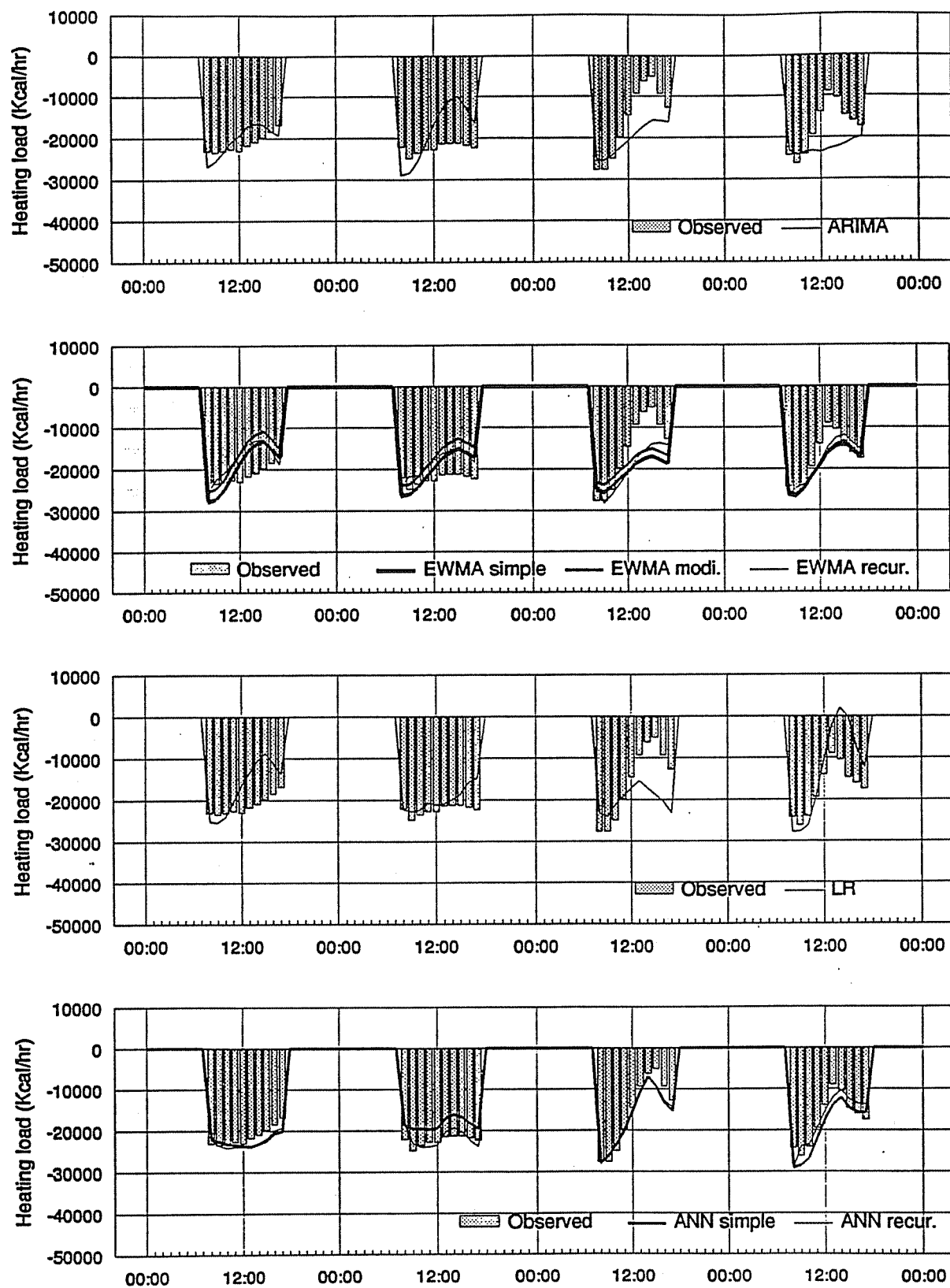


Figure 5 Thermal load prediction by ARIMA, EWMA, LR, and ANN (from February 7 to February 10).

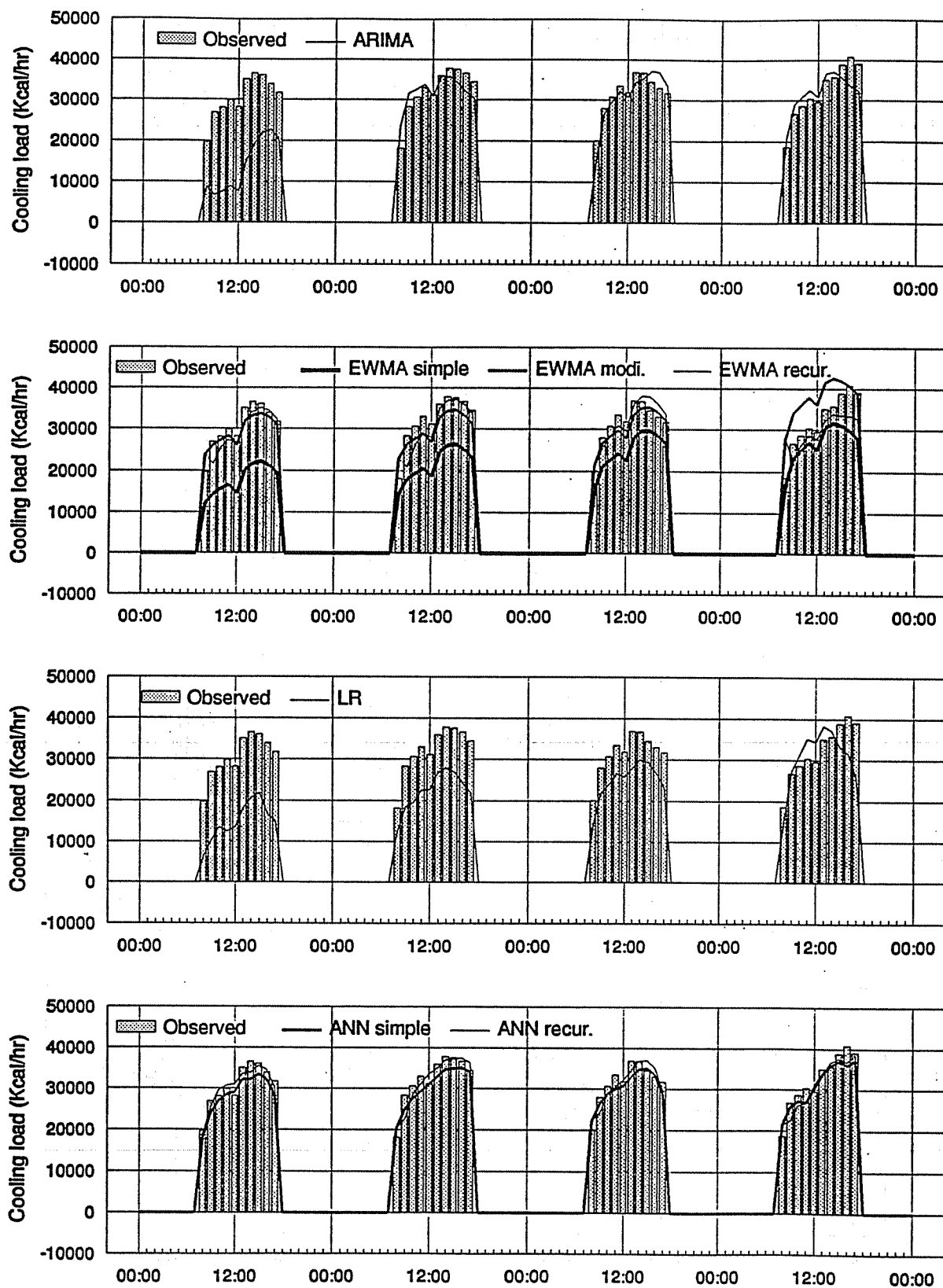


Figure 6 Thermal load prediction by ARIMA, EWMA, LR, and ANN (from August 1 to August 4).

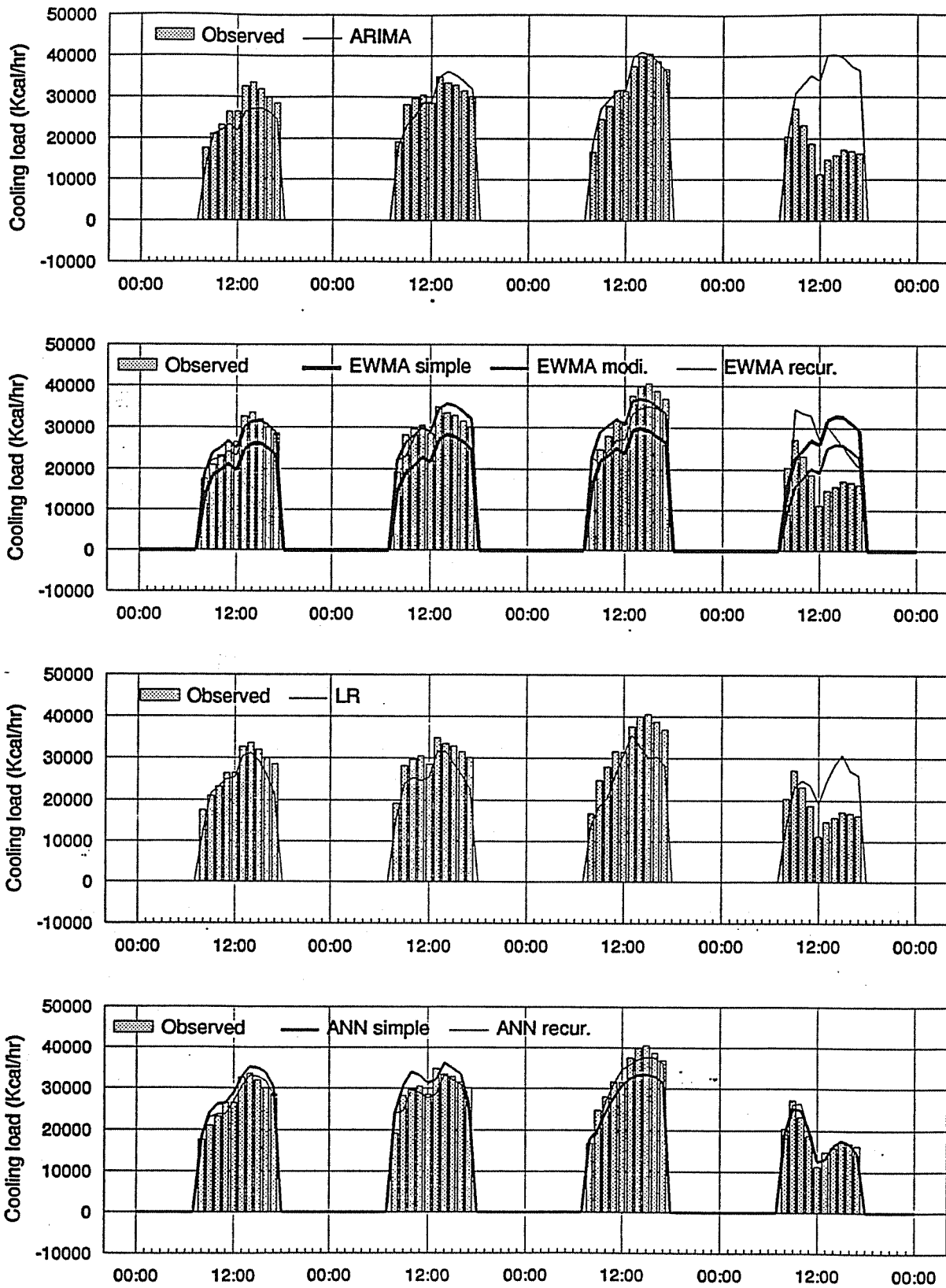
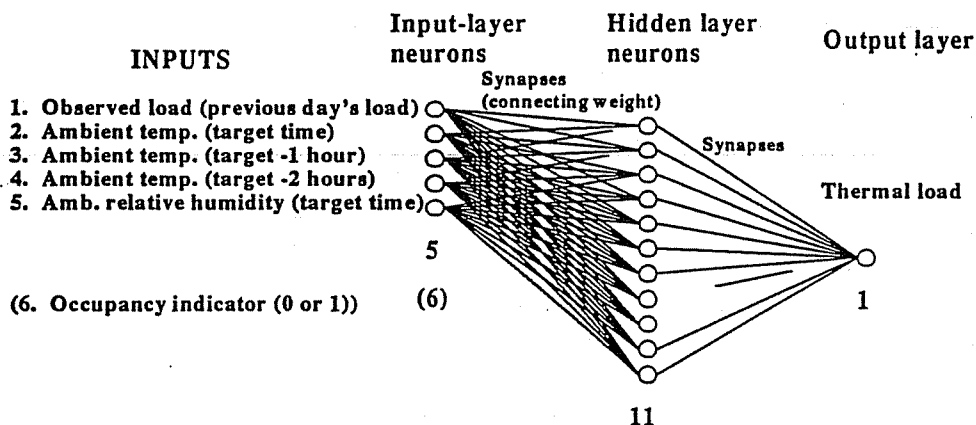


Figure 7 Thermal load prediction by ARIMA, EWMA, LR, and ANN (from September 5 to September 8).



**Figure 8** ANN model for hourly load prediction on an existing building.

**TABLE 3**  
**Conditions for the Seven ANN Models**

No.	Symbol	number of inputs	weather data	recursive modification
1	S-5-k-n	5	known	No
2	S-5-p-n	5	predicted	No
3	S-6-k-n	6	known	No
4	S-6-p-n	6	predicted	No
5	S-6-p-y	6	predicted	Yes
6	P-5-k-n	5	known	No
7	P-5-p-n	5	predicted	No

where

$T_t$  = predicted temperature at time  $t$ ,  
 $\alpha_t$  = coefficient at time  $t$ ,  
 $T_H$  = forecast high for the next day, and  
 $T_L$  = forecast low for the next day.

The hourly ambient relative humidity was calculated by the EWMA, as described earlier, using Equation 37:

$$H_t = H_{t-24} + \lambda (H_{t-24} - H_{t-24}) \quad (37)$$

where

$H_t$  = predicted humidity at time  $t$ ,  
 $H_{t-24}$  = predicted humidity at time  $t-24$ ,  
 $H_{t-24}$  = observed humidity at time  $t-24$ , and  
 $\lambda$  = exponential smoothing constant = 0.3.

The calculated (predicted) hourly ambient temperatures and humidity for up to the next 24 hours were used as inputs in the load predictions.

## RESULTS OF ANN PREDICTION WITH MEASURED DATA

Table 4 gives the performance of the seven load predictions for the measured data. With respect to building S, the prediction accuracy of the six-input models is better than that of the five-input models. It indicates that the more input information, the better the prediction accuracy. The expectation of error percentage of the maximum load (EEP) of all the models was less than 8.5% on an hourly basis and 10.3% on a daily basis. The best EEP (hourly basis) was 6.8% for "S-6-k-n." The EEPs on an hourly basis with the predicted weather data were 7.5% for "S-6-p-n" and 8.1% for "P-5-p-n." This means that prediction by the ANN has acceptable accuracy even with the predicted weather data. The prediction with the recursive modification has an EEP of 7.2% on an hourly basis. This is better than the nonmodified model (S-6-p-n), which has an EEP of 7.5%. The modification by observed load during the occupancy period improved the accuracy slightly. The improvement in the daily-basis value does not affect the system control since the value is modified after the overnight charge in the tank.

**TABLE 4**  
**Results of the Seven Thermal Load Predictions with Measured Data**

Symbol	$\sigma$ (Tons)	EEP (%)		CV(%)	MBE(%)
	hourly basis	daily basis	hourly basis	hourly basis	hourly basis
1. S-5-k-n	41.7	10.3	8.0	31.9	-12.9
2. S-5-p-n	43.9	10.2	8.5	33.6	-10.8
3. S-6-k-n	35.3	7.5	6.8	26.3	-7.3
4. S-6-p-n	38.7	8.1	7.5	28.9	-1.4
5. S-6-p-y	37.2	3.3	7.2	27.7	-0.4
6. P-5-k-n	269.3	6.5	7.7	16.8	-0.9
7. P-5-p-n	284.2	7.4	8.1	17.8	-3.7

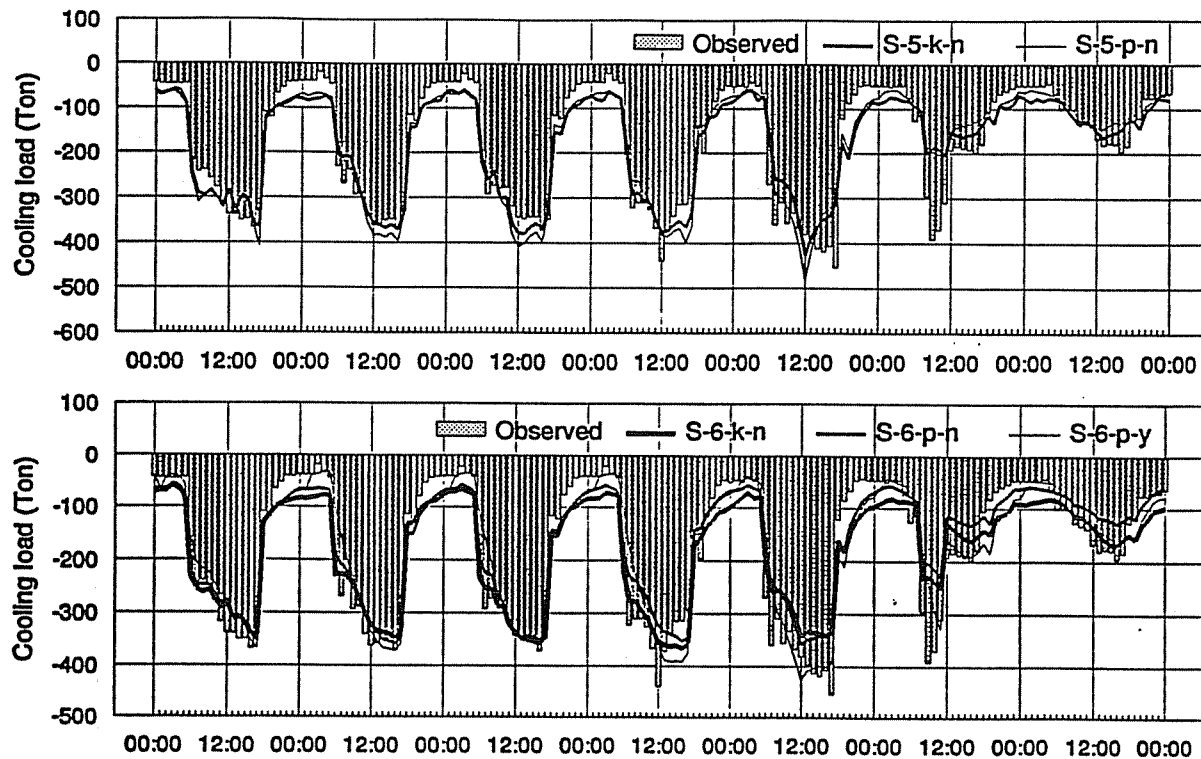
Figures 9 through 12 show examples of the hourly prediction for building S and P. The predicted loads for each ANN model have acceptable agreement with the observed loads.

### CONCLUSION

Four different models (ARIMA, EWMA, LR, and ANN) and three modified versions for the hourly thermal load prediction during the next 24 hours were examined using the same data set. According to a quantitative comparison, the artificial neural network model had the best accuracy of all the models. The expectation-of-error percentage of the maximum data (EEP) for the ANN models was less

than 6.3% for cooling and heating season data on an hourly basis. There was a significant improvement in the accuracy compared to that of the other models.

Next, seven ANN load prediction models were examined by using measured building data that included noise. The EEPs of all ANN models (including models with the predicted weather data) were between 6.8% and 8.5% on an hourly basis. These results show that the ANN model can predict the hourly loads accurately, even when using real operating data. This confirms that the ANN model has great potential for hourly thermal load prediction. The accuracy of the load prediction is sufficient for utilization in HVAC controllers.



**Figure 9** Hourly thermal load prediction for building S by ANN (from August 12 to August 18).

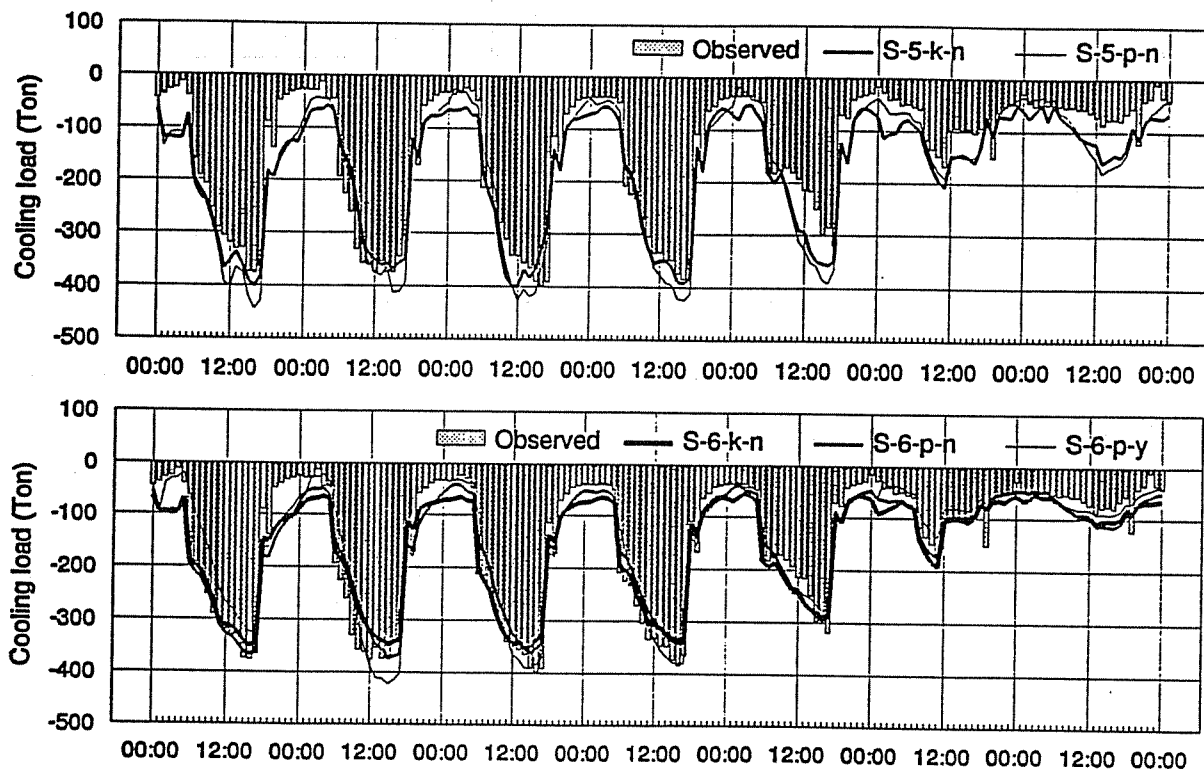


Figure 10 Hourly thermal load prediction for building S by ANN (from September 16 to September 22).

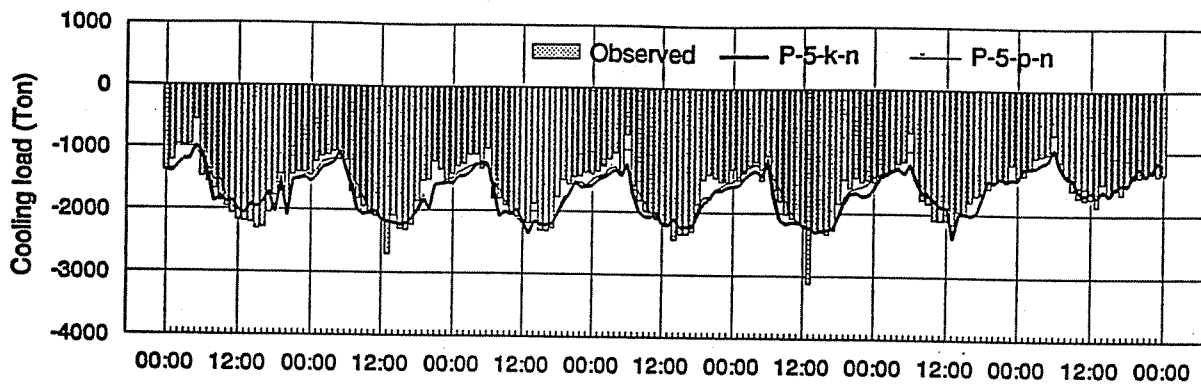


Figure 11 Hourly thermal load prediction for building P by ANN (from July 22 to July 28).

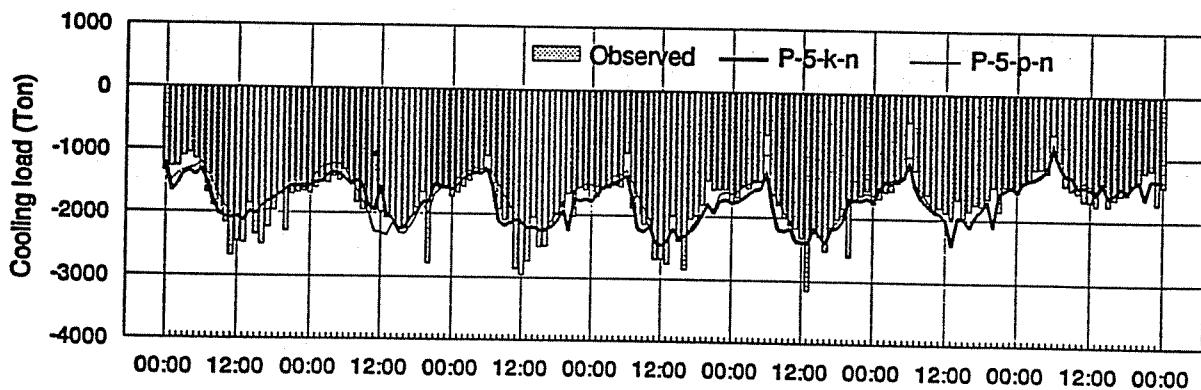


Figure 12 Hourly thermal load prediction for building P by ANN (from July 29 to August 4).

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## APPENDIX A

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \\ - \\ y_{m+1} \end{bmatrix}$$

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ x_{m1} & \cdot & \cdot & x_{mn} \\ - & - & - & - \\ x_{m+11} & \cdot & \cdot & x_{m+1n} \end{bmatrix} = \begin{bmatrix} \mathbf{X}_m \\ - \\ \mathbf{X}_{m+1}^T \end{bmatrix}$$

