Optimizing System Control with Load Prediction by Neural Networks for an Ice-Storage System

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ABSTRACT

This paper describes the performance of a partial ice storage system that has a controller that predicts the load by neural networks. To evaluate the performance, a comparison was carried out between the two control strategies—chiller priority control and predictive control—using simulation. Chiller priority is the most common control strategy for existing thermal storage systems. The predictive control proposed in this study uses an hourly thermal load prediction by neural networks. The predictive control is described in detail. The study indicates that the accuracy of the load prediction is a key for optimizing the system control. The predictive control can significantly reduce the operating cost without energy shortage.

INTRODUCTION

Heating, ventilating, and air-conditioning (HVAC) systems can be optimized in two stages. One is the design stage and the other is the operating stage. A system will not work efficiently without proper control even if it is designed correctly. This paper deals with the optimization in the operating stage and on the assumption that the partial storage system is designed correctly.

In thermal storage systems, the capacity is specified for chillers and storage tanks to meet the design loads. The system should work as expected on the design day; however, how does it work on off-design days? There are many days that have a medium amount of load. Rooms should be kept comfortable by the system and, at the same time, the operating cost should be minimized by reducing the electricity consumed during on-peak hours. It is generally thought that there is no problem if energy remains in the tank at the end of the occupied hours because the energy could be used on the next day. However, this is not correct. The fact that there is a significant amount of energy remaining at the end of the occupied hours means that there was unnecessary chiller operation during on-peak hours when the energy charge is much more expensive than during off-peak hours. On the other hand, if the system uses the stored energy first and is completely discharged, there will be an energy shortage in the afternoon because the system normally does not have a large enough chiller to meet the peak loads alone. Therefore, the discharge of the storage must be properly controlled to minimize costs and maintain comfort.

METHODOLOGY OF CONTROL

There are two design concepts for thermal storage systems as shown in Figure 1—partial storage and full storage. The full-storage design means that all thermal loads are met solely by the stored energy. The partial-storage design means the loads are met by a combination of storage and chillers. The control of the full-storage system is simple—build ice every night until the tanks are full and melt as much as needed to cool the building during on-peak hours. However, in a full-storage system a lot of energy remains in the tank at the end of the occupancy if the load is small. In contrast, the partial-storage system is popular because there is a lower initial cost than for the full-storage system. However, in the control of the partial-storage system it is difficult to maintain comfort in the occu-

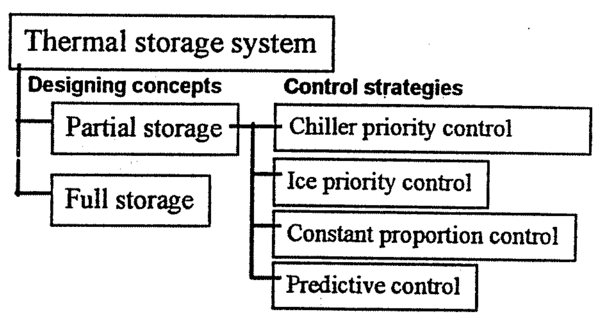

Figure 1 *Classification of thermal storage system.*

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pied room and minimize operating costs simultaneously. Control strategies of the partial-storage system are classified in Figure 1. Rawlings (1985) and Braun (1992) presented similar classifications.

The three conventional control strategies for partial storage are chiller-priority, ice-priority, and constant proportion. In this paper there is a newly suggested strategy, predictive control. All of these control strategies are reviewed as follows. In the chiller-priority control, the thermal load is first met by the chiller that is operated by a scheduled timer. During the chiller operation, the ice only is melted if the thermal load exceeds the chiller capacity. Because the control is simple, this is the most popular control strategy for the partial-storage system. The drawback is that the stored ice may not be fully utilized. This means that there is unnecessary chiller operation during on-peak hours.

The ice-priority control operates the chiller as little as possible during the occupied hours. The chiller is operated at desired capacity only if the load exceeds the tank-output capacity. Generally, the chiller operation is triggered when the tank outlet temperature exceeds a predetermined setting point. Ideally, this control strategy could minimize the running cost and demand charge; however, there are some difficulties in practice. First, it is difficult (sometimes it also is expensive) to control the chiller capacity to be the desired amount at any level. More important, the strategy might not meet the peak load on a hot day because the ice might melt completely in the early stage of the occupancy. The peak load usually is larger than the full capacity of the chiller and so comfort would not be maintained.

In the constant proportion control, the chiller and the ice tank, respectively, handle a certain percentage of the building load in every occupied hour. It also is difficult (and usually expensive) to control the chiller capacity in a desired amount in practice. This strategy has the advantage of meeting the peak load using both energy from the chiller and the ice tank. This means a lower demand charge than the chiller priority control; however, ice may remain or an energy shortage may occur as a result of daily load fluctuations. This control method has been discussed by Rawlings (1985). A similar control method, named "load-limiting," was described by Braun (1992). The percentage of chiller operation during on-peak hours can be optimized to fully discharge the tank at the end of the occupied hours if a load prediction is available.

The last control is a proposed strategy called "predictive control" in this study. Studies on control associated with prediction, for example, have been done by Shapiro et al. (1988) and Braun (1990) to use the massive building structure as a thermal storage. Ferrano and Wong (1990) discussed prediction of the next-day cooling load for overnight chiller operation. The main purpose of predictive control in this study is to minimize the operating cost for the entire season in situations where the off-peak electric charge is much less than the on-peak charge. (The energy charge of on-peak is roughly four to five times the off-peak charge in Japan.) The strategy controls chiller operation based on the predicted hourly loads for the next 24 hours. The prediction is computed at the beginning of the off-peak hour (22:00 in Japan). During off-peak hours, as much ice as the building needs for the next day is built. During on-peak hours, the strategy compares the remaining energy in the tank and the total predicted load from now to the end of the occupancy. Then, if the remaining energy is less than the total predicted load, the chiller operates. This comparison is made every 30 minutes. In this strategy, ice is saved and used for the afternoon peak loads. As a result, the ice melts completely by the end of the occupancy.

After the start of air-conditioning, the predicted loads are recursively modified at every hour by multiplying the load by a coefficient that is the ratio of the total predicted load and the total measured loads from start to current time. This modification improves the accuracy of the prediction. The load prediction is made with a neural network that needs to be trained previously using the measured data. In this study, measured weather data for three months and computed thermal loads were used for the training.

NEURAL NETWORK MODEL FOR LOAD PREDICTION

The load prediction methods discussed here are applicable to real thermal energy storage (TES) systems. It is possible to use physical-based modeling methods that are popularly used in the design process. However, the physical-based modeling is not suitable for real systems because it requires considerable effort to adapt it to practical situations. There are several methods suitable for the real-time load prediction, such as the time series model, the regression model, and the artificial neural network model. Ferrano and Wong (1990), Kreider and Wang (1991, 1992), and Anstett and Kreider (1993) examined the artificial neural network (ANN) model for load prediction. Kawashima (1995) compared the accuracy of the prediction with several methods including ANN by employing exactly the same data. The results showed that an ANN model had the best accuracy among the methods examined.

The ANN is one of the modeling methods for nonlinear systems. It has self-training capability but needs an input and output data set from the target system for supervised training. The biggest concern in this study is the accuracy of the prediction and the applicability to a practical controller. Therefore, it does not matter if the model's coefficients do not have physical meanings.

An abstract model of a neuron that is the processing unit of ANN is shown in Figure 2. The neuron receives several inputs through synapses. The incoming activations are multiplied by the weight of synapses and summed up. The outgoing activation is computed by applying a threshold function to the summation. The neuron has only one outgoing activation value, although it might have several connections to other neurons. The typical threshold function, called a sigmoid function, is shown in Figure 3.

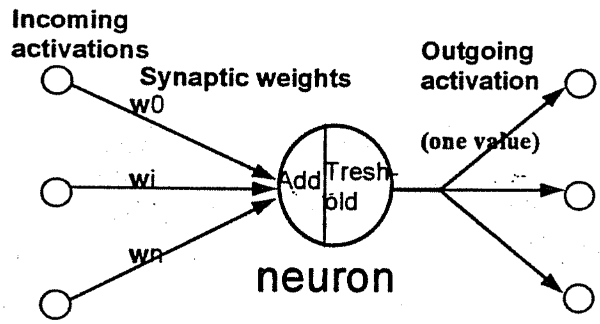

Figure 2 *Model of an abstract neuron.*

$$F(x)=\frac{1}{1+e^{-x}}$$

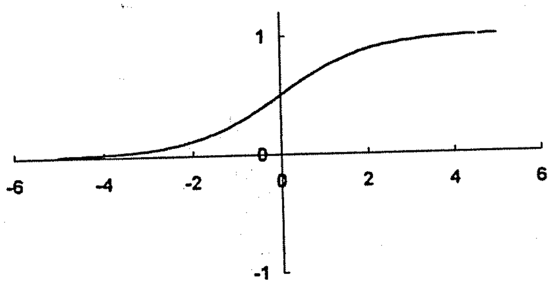

Figure 3 *Diagram of sigmoid function.*

The structure of an ANN model consists of some neurons and their connections. There are hidden layers between input and output layers. Each neuron processes the incoming activation and transfers the outgoing activation to the next neuron if measured data are presented in the inputs. At first, random numbers are installed for all the synaptic weights and the ANN output is far from measured output data. However, the synaptic weights gradually are changed in an appropriate manner by the self-training procedure. The training procedure used in this study is a back propagation method with three-phase annealing described in Kawashima (1994).

A diagram of an ANN is shown in Figure 4. Any data related to the thermal load could be used as inputs. In this study 12 inputs are selected. The outdoor temperature and solar insolation up for few hours in the past are employed because the output has a time delay factor due to its thermal capacity.

After the ANN model is trained, it can be used for load prediction. However, a preprocess is required before the prediction can be made because input data at the target time are needed. In other words, to get a prediction 24 hours ahead, the outdoor temperature and the solar insolation at 24 hours ahead are required. The processes to obtain those weather data for the next 24 hours are described in the next section.

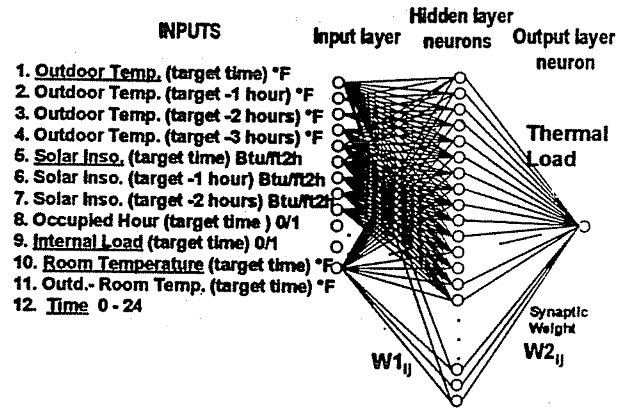

Figure 4 *Diagram of ANN for load prediction.*

FORECASTING TOMORROW'S WEATHER

Hourly outdoor temperature and solar insolation 24 hours in advance are required in the prediction phase. Some of the forecast weather data are available from meteorological centers. It usually is difficult or expensive to get the desired forecast weather data for the next 24 hours in a timely fashion. In this study these data were computed from tomorrow's forecast high and low outdoor temperatures and weather outlook, which could easily be obtained from TV, radio, newspapers, etc.

FORECASTING OUTDOOR TEMPERATURE

The hourly outdoor temperatures (dry-bulb) are calculated by the following formula:

$$T_t = T_H - \alpha_t \times (T_H - T_L) \tag{1}$$

where

T_t = forecast outdoor temperature at time t,

α_t = coefficient at time t,

T_H = forecast high, and

T_L = forecast low.

The α_t shown in Table 1 are coefficients at each time of day presented in the 1993 *ASHRAE Fundamentals Handbook* (ASHRAE 1993, Chapter 26, Table 2). This is a sinusoidal fit to the hourly temperatures based on the daily temperature range. The forecast values of tomorrow's highs and lows (T_H, T_L) in this study were obtained from recorded data and are taken as 100% accurate. The differences in hourly load predictions with accurate and with forecast weather data are discussed in Kawashima (1995).

FORECASTING SOLAR INSOLATION

The solar insolation is forecast in two steps. First, the total amount of solar insolation for the next day ($\dot{Q}_{s,d}$) is calculated by using a polynomial Equation 2. The forecast outlooks for the next day are typically sunny, fine, cloudy, and rainy, which are expressed as levels 1, 2, 3, and 4, respec-

TABLE 1 Coefficients for Hourly Temperature Prediction

t ; hour of the day

t	α_t	t	α_t	t	α_t	t	α_t
0	0.82	6	0.98	12	0.23	18	0.21
1	0.87	7	0.93	13	0.11	19	0.34
2	0.92	8	0.84	14	0.03	20	0.47
3	0.96	9	0.71	15	0.00	21	0.58
4	0.99	10	0.56	16	0.03	22	0.68
5	1.00	11	0.39	17	0.10	23	0.76

tively. The coefficients (a_0, a_1, a_2, and a_3) are calculated by a linear regression using the recorded temperature and outlook data for the entire cooling season:

$$\dot{Q}_{s,d} = a_0 + a_1 \times T_H + a_2 \times (T_H - T_L) + a_3 \times I_{OTLK} \qquad (2)$$

where

$\dot{Q}_{s,d}$ = daily total solar insolation (Btu/ft²·h),
T_H = next day's high outdoor temperature (°F),
T_L = next day's low outdoor temperature (°F), and
I_{OTLK} = next day's outlook (1, 2, 3, or 4).

The hourly solar insolation ($\dot{Q}_{s,t}$) is calculated by Equation 3 using a set of coefficients (β_t) that total 1.0 for a day. The β_t values are chosen so that the hourly solar insolation forecast represents a typical smooth profile of the measured insolation for the cooling season. It is hard to guess the coefficients (β_t) because the actual solar insolation is affected so much by clouds, which causes a relatively large discrepancy between the forecast and measured solar insolation.

$$\dot{Q}_{s,t} = \beta_t \times \dot{Q}_{s,d} \, . \qquad (3)$$

RESULTS OF WEATHER PREDICTION

Scatter plots of the forecast vs. measured weather for outdoor temperature and solar insolation are shown in Figures 5 and 6, respectively. The measured data are for Tokyo in 1991 and are supplied by the Japanese Weather Association. There is fair agreement between predicted and measured temperatures and poorer agreement for solar insolation. These forecast weather data will be used for the thermal load prediction in the following simulations, and the measured weather data are used in the ANN training procedure.

ACCURACY OF LOAD PREDICTION

The pseudo-real-time load prediction will be conducted while the simulation is performed. An ANN model trained by 1991 data was utilized in all cases. Before simulating, the prediction procedure was performed solely for the evaluation of accuracy. The accuracy of the predictions and the results are shown in Table 3 for several weather data sets.

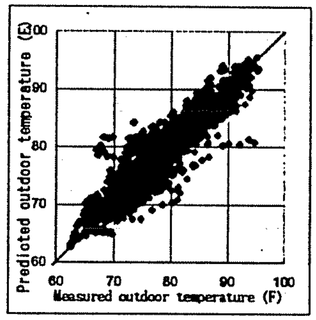

Figure 5 Measured vs. predicted outdoor temperatures.

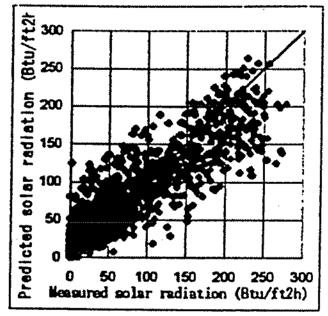

Figure 6 Measured vs. predicted solar insolation.

TABLE 2 Coefficients for Equation 3

t ; hour of the day

t	β_t	t	β_t	t	β_t	t	β_t
0	0.0	6	0.0105	12	0.1239	18	0.01966
1	0.0	7	0.0334	13	0.1207	19	0.001829
2	0.0	8	0.05807	14	0.11294	20	0.0
3	0.0	9	0.08230	15	0.09511	21	0.0
4	0.0	10	0.10517	16	0.07042	22	0.0
5	0.0	11	0.12025	17	0.04572	23	0.0

Case 1 is an impractical situation for applications because it has 100% accurate weather data in the future. Case 2 is a practical case that employs the forecast weather from the accurate high and low for the next day. Case 3 is similar to case 2; however, it predicts loads in 1992 with the ANN model trained by 1991 data. Case 4 shows the accuracy in the prediction with recursive modification discussed in the last part of the "Methodology of Control" section.

Figures 7 and 8 show the scatter plots of measured vs. predicted loads. The expected error percentage (EEP; see Appendix A) of case 2, 4.34%, may be acceptable in practice. The results of cases 3 and 4 suggest that retraining should be done with current data if possible.

SIMULATION STUDY

Four simulations were carried out. The first simulation was for an HVAC system with the chiller priority control for the entire cooling season in 1991. This model simulates a commonly existing ice storage system. After confirming that the building load had been met during the all occupied hours, the outputs (thermal loads and weather data) were transformed into an ANN training data set. Then, the ANN was trained sufficiently. Next, the trained ANN model data (weighting matrices) were built into the second simulation. The second

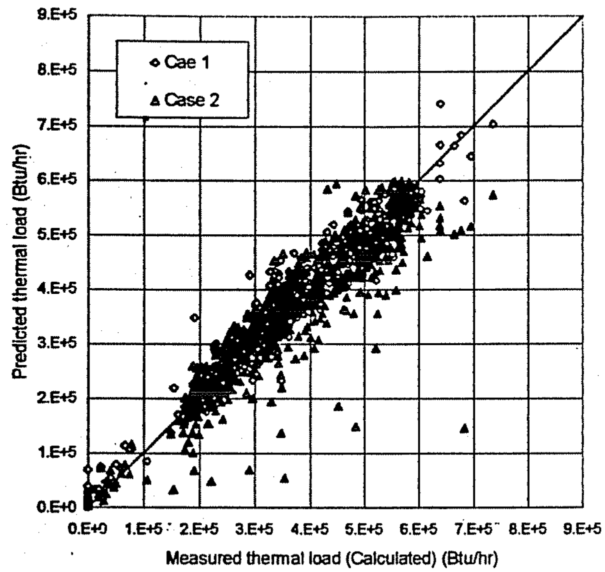

Figure 7 *Measured vs. predicted loads (cases 1 and 2).*

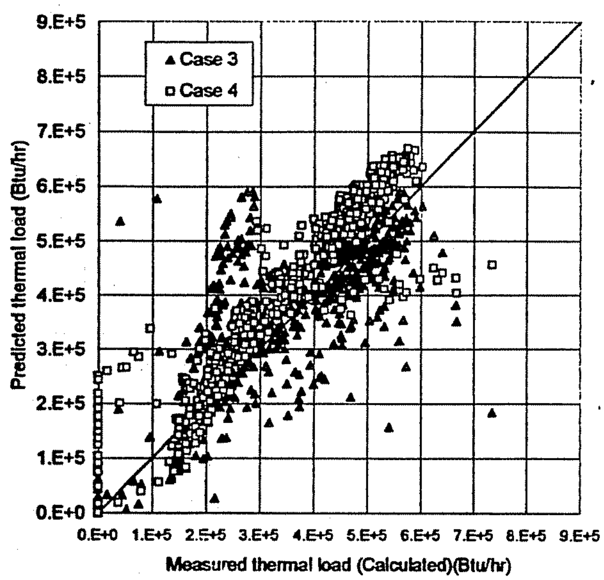

Figure 8 *Measured vs. predicted loads (cases 3 and 4).*

simulation used the predictive control under the same conditions as the first simulation. Next, a third simulation with chiller-priority control was carried out with the 1992 weather data. Finally, the fourth simulation used predictive control for 1992 with the ANN model trained with the 1991 data set.

SYSTEM MODELING

The HVAC system with ice storage is shown in Figure 9. The building is a commercial building located in Tokyo with an air-conditioned area of 27,225 ft^2 (2,530 m^2). The ice tank capacity (247 ton-hours [3.13 GJ]) and the chiller capacity (25 tons [316 MJ/h] × 2 units) were carefully chosen for the building load by presimulations. A physical-based dynamic HVAC

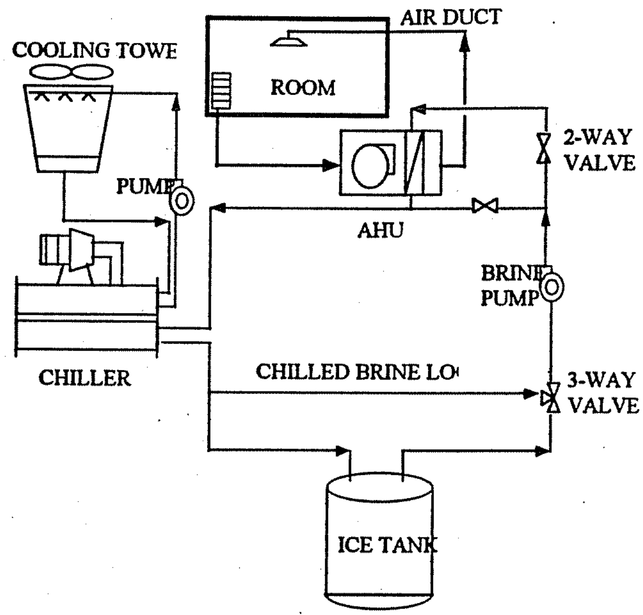

Figure 9 *Target ice storage HVAC system.*

TABLE 3 Accuracy of Load Prediction

	Year of predicted	predicted with	σ	EEP	CV	MBE
			Btu/hr	%	%	%
case 1	1991	accurate weather data	17840	2.42	16.33	0.13
case 2	1991	forecasted weather data	31974	4.34	29.26	-3.08
case 3	1992	forecasted weather data	53187	7.23	51.9	2.21
case 4	1992	forecasted weather data recur. modi.	45852	6.23	44.7	16.6

system simulation program, TRNSYS (Klein et al. 1994), was used for simulations. Nine new components (subroutines) were constructed and five existing components were modified. The weather data set both in 1991 and 1992 in Tokyo were supplied by the Japanese Weather Association.

The time step of the simulation was half an hour and the period of the simulation was the entire cooling season. The occupied hours were from 8:00 to 18:00 for weekdays. With both chiller-priority and predictive control, one chiller was operated during the on-peak hours to keep the supply water temperature under control. If the temperature became higher than the setpoint, the second chiller was operated. The off-peak hours were from 22:00 to 8:00. The electric rates are shown in Table 4 based on the exchange rate of 100.0 yen a dollar.

RESULTS AND COMPARISON

Figures 10 and 11 show examples of the simulation results in the 10th and 11th weeks (Monday through Friday). The bars indicate cooling loads. The dark part represents the ice tank energy and the gray part represents the energy from the chiller.

The black line shows ice inventory with the scale on the right axis. The dotted line in Figure 11 represents the predicted load that was recursively modified during the occupied hours. The load each day for Figures 10 and 11 is the same; however, the utilization of the energy from the ice tank is different. With predictive control the chiller turns off in the afternoon if the load for the day is small. The remaining energy at the end of occupancy is always small with predictive control if the load prediction is accurate. The remaining energy is large with chiller priority, especially if the load of the day is small.

Figure 12 shows the daily cooling load for the entire cooling season for 1991 for chiller-priority control. The black part represents energy from the ice tank and the gray part represents energy from the chiller. The triangular mark indicates the ice inventory at the end of the charging period. Figure 13 shows the results of Figure 12 sorted and plotted in decreasing order (daily load duration curve). The gray area under the dotted triangles, which is energy from chillers, indicates the possibility of further optimization because energy remains in the tank. Figures 14 and 15 show the daily load duration curve for predictive control in 1991 and 1992, respectively. In Figures 14 and 15, the area with no loads on the right side shows the data on Saturdays and Sundays. They clearly show how the energy is utilized.

The percentage of the ice tank energy with chiller priority is smaller than that with predictive control. This indicates that predictive control attempts to maximize the ice tank energy while it meets the loads. The percentage of the ice tank energy in each simulation is shown in Table 5.

The triangles in Figures 13 through 15 indicate that the ice inventory during weekends is large in the chiller-priority control because the ice remains if the load is small on Friday. This causes an energy loss from the ice tank. Also, the ice inventory for the nonhot days with predictive control is smaller than the tank capacity, while the chiller priority always has a full inventory in the morning. It is meaningful to charge ice as much as necessary in early and late summer.

Tables 6 and 7 show the summary of electric consumption in the cooling season for 1991 and 1992. The percentage of off-peak electric consumption was 59.8% for predictive control and 37.8% for chiller priority in 1991. The total electric consumption was 75,764 kWh for predictive control and 70,905 kWh for chiller priority. The total consumption of predictive control was 6.9% larger than that of chiller priority in 1991 because the chiller coefficient of performance (COP) in the ice-making mode was smaller than the COP in the chilling mode; however, shifting electric consumption to the off-peak time is a big advantage for customers and utility companies. The situation for 1992 is similar to the results for 1991.

Figure 16 shows the total operating costs for four simulations. The demand charge was calculated as $936 per month for all simulations based on the demand of 60 kW for the HVAC system. There is a possibility for the predictive control to reduce the demand charge if the system can manage the whole electric consumption for HVAC, lighting, transportation, etc. However, it is difficult to determine the amount of demand charge reduction by our simulation study. Therefore, the same value of the demand charge was used for all controls. The demand charge accounts for 23.6% of the total for chiller-priority control and 27.3% for optimal control in 1991. The on-peak energy charge (the black part) for predictive control was smaller than that for chiller priority. The total operating cost for the entire cooling season was $11,895 for chiller priority and $10,294 for predictive control. The total operating cost of predictive control was 13.5% smaller than that of chiller priority in 1991. This difference is significant because it is the result only of the control strategy. Shifting the chiller operation as much as possible reduces the operating cost without any energy shortage during occupied hours. It shows that optimizing the HVAC control of thermal storage systems significantly can reduce operating cost.

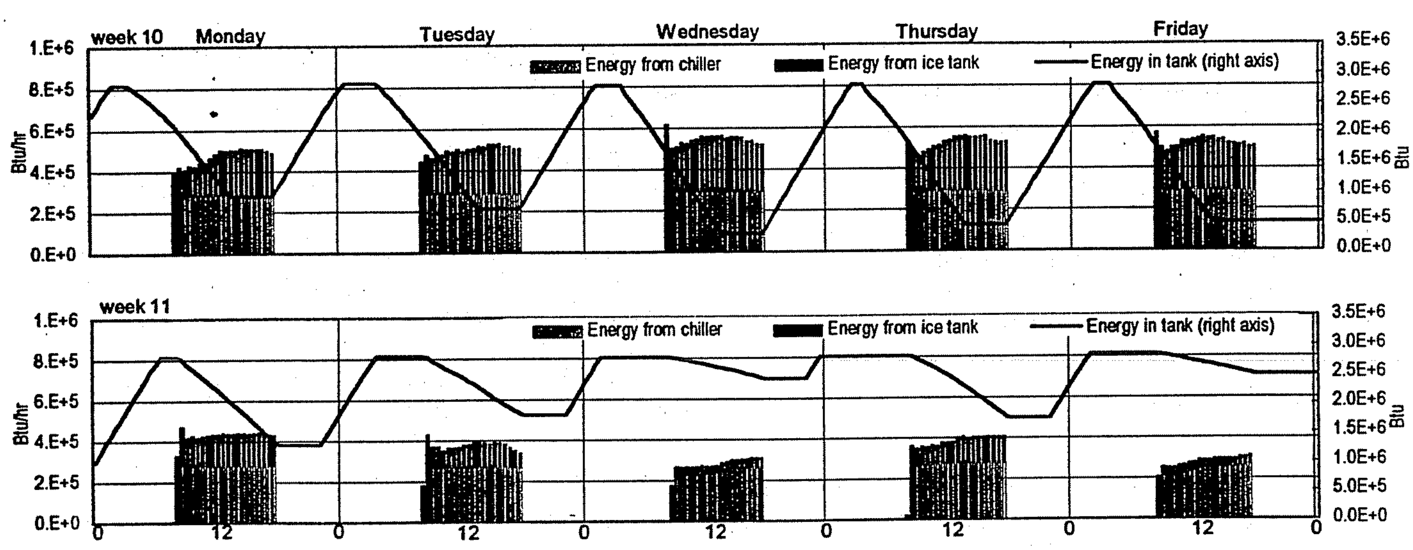

Figure 10 Energy flows for chiller-priority control for 1991.

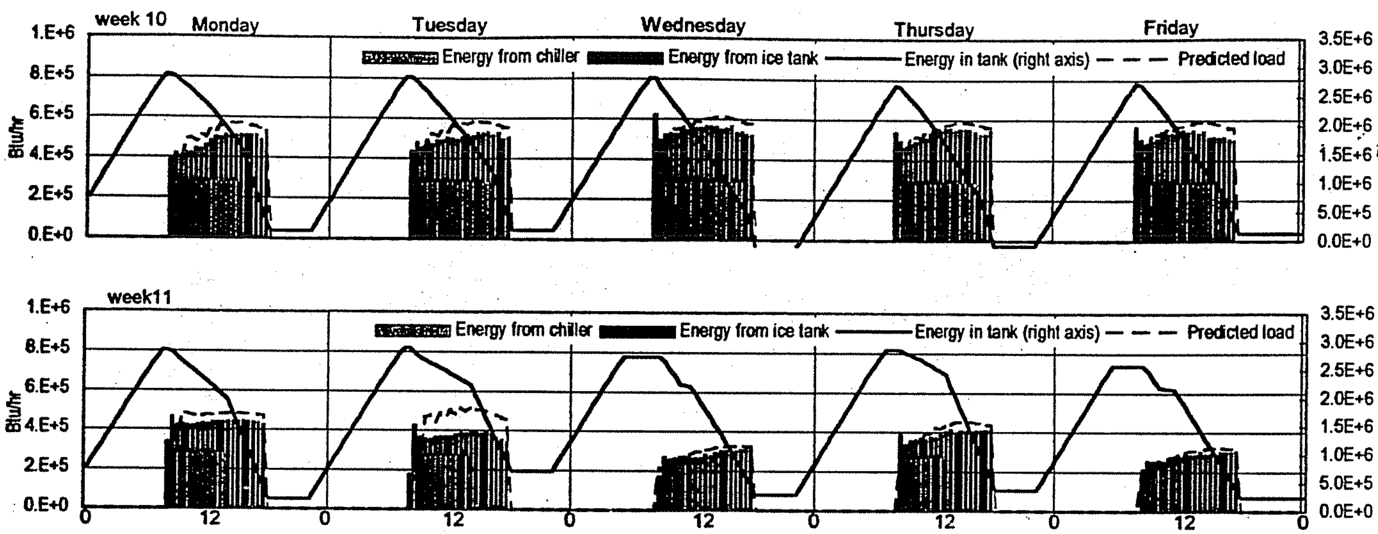

Figure 11 *Energy flow for predictive control for 1991.*

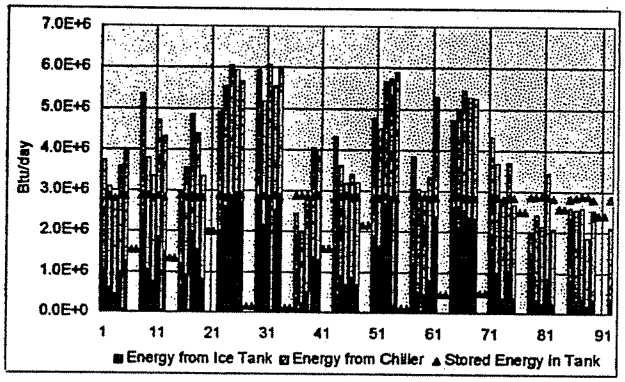

Figure 12 *Daily cooling load with chiller-priority control in 1991.*

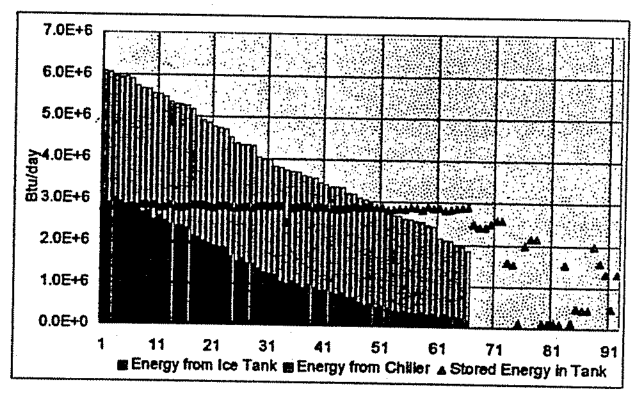

Figure 13 *Sorted daily cooling load with chiller-priority control in 1991.*

POSSIBILITY OF FAULT DETECTION BY NEURAL NETWORK

Maintenance of HVAC systems is a big issue and malfunction of the system potentially could cause damage. Research on automated self-diagnostic systems is of current interest. Petze and Reed (1988) discussed an artificial intelligence (AI) approach for building control systems. Haberl et al. (1989) developed a rule-based diagnosis intelligent system. Anderson et al. (1989) discussed a rule-based expert system with a predictor. Culp et al. (1990) discussed the impact of AI technology in HVAC systems. The ultimate goal of the system is AI, which can detect the inappropriate operational condition at an early stage and advise the maintenance person what should be done before a fatal shutdown. An AI system contains three functions: fault detection, specification, and diagnosis. Fault detection can be performed by the ANN load prediction. Because the ANN can predict the load accurately, a significant discrepancy between the predicted and

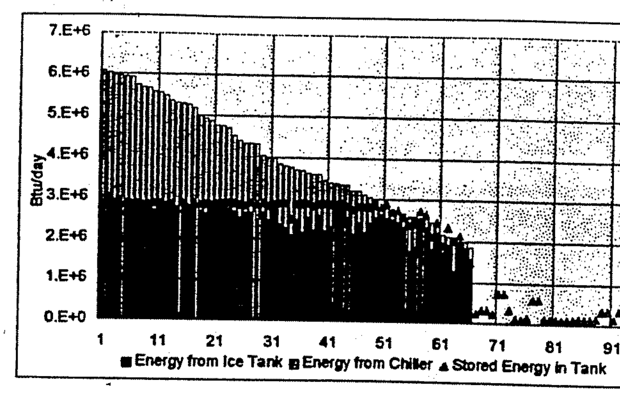

Figure 14 *Sorted daily cooling load with predictive control in 1991.*

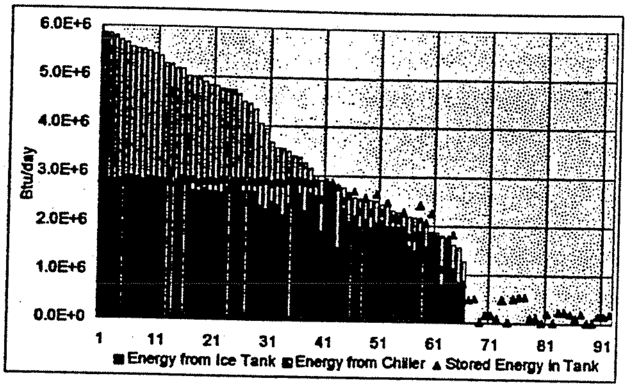

Figure 15 *Sorted daily cooling load with predictive control in 1992.*

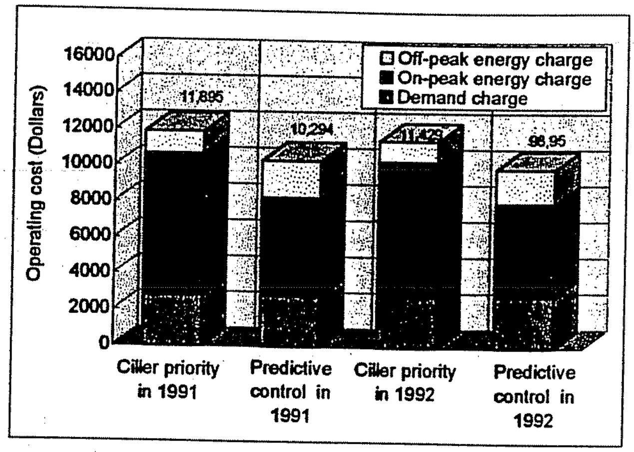

Figure 16 *Operating costs in four simulations.*

TABLE 4 Electric Rates in Tokyo

for summer season

	Rate
Demand charge	$15.60 /kWMonth
On-peak energy charge	$0.1784/kWh
Off-peak energy charge	$0.0454/kWh

TABLE 5 Percentage of Ice Tank Energy for Entire Cooling Load

	Percentage of energy from ice tank (%)
Chiller priority in 1991	34.1
Chiller priority in 1992	34.9
Predictive control in 1991	62.4
Predictive control in 1992	62.7

TABLE 6 Electric Consumption in 1991

1991	Chiller priority	Predictive control
	kWh (%)	kWh (%)
on-peak	44119 (62.2)	30424 (40.2)
off-peak	26786 (37.8)	45340 (59.8)
Total	70905 (100)	75764 (100)

TABLE 7 Electric Consumption in 1992

1992	Chiller priority	Predictive control
	kWh (%)	kWh (%)
on-peak	41821 (62.1)	29056 (40.9)
off-peak	25547 (37.9)	41922 (59.1)
Total	67368 (100)	70978 (100)

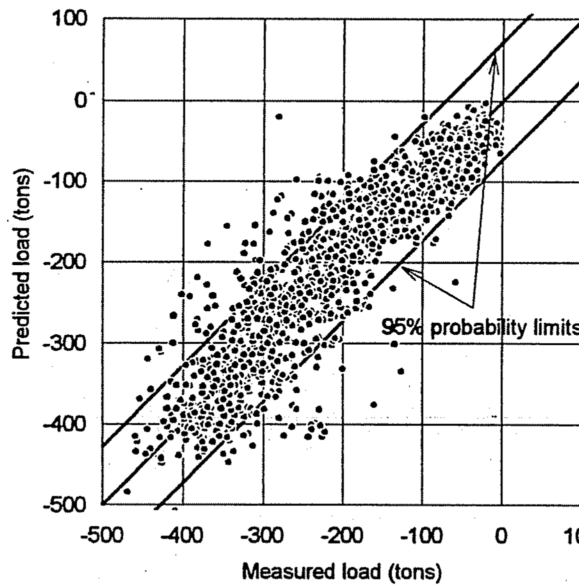

Figure 17 *Scattered plots of measured vs. predicted loads.*

observed loads for a long period indicates the possibility of an existing malfunction of the system even if the occupants are not aware of it. This approach could be a detector of the system fault and a trigger of real-time HVAC diagnostic systems.

Figure 17 shows the scatter plots of the measured vs. predicted hourly loads. If the HVAC system works properly, most of the points will be located within certain probability limits (for example, 95%). If the points start falling outside the limits continuously, it may be an indicator of faults in the HVAC system. Haberl et al. (1989) use similar criteria, but with absolute residuals between regressed and measured loads. Further study is required on the use of ANNs for fault detection.

CONCLUSIONS

Dynamic HVAC simulations, including a thermal model of the target building, were conducted for the entire cooling season to simulate the energy performance for different control strategies. The conventional chiller-priority strategy was compared to predictive control. Energy and cost analysis with the same year's weather data showed that the total electric consumption with predictive control was 6.9% greater than with chiller-priority control. This was a result of operating the chiller at times with poorer COP. However, the operating cost with predictive control was 13.5% less than with chiller-priority control. This was a result of operating the chiller much less during the on-peak hours.

This study shows that predictive control significantly can reduce operating costs and maintain comfort with no energy shortage during occupied hours. System operation with real-time load prediction and an intelligent fault detection scheme is a possibility.

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APPENDIX A

Criteria of Accuracy

To compare the different load predictions, the following criteria for accuracy were defined. The CV and MBE are from Kreider and Haberl (1994). The EEP is defined by Kawashima (1995). The reason for the additional definition is that the EEP is appropriate for load distributions that have many zero values at night.

Standard deviation (σ):

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(y_{pred,t} - y_{data,t})^2}{n}} \quad \text{(A1)}$$

Expected error percentage (EEP):

$$EEP = \frac{\sqrt{\frac{\sum_{t=1}^{n}(y_{pred,t} - y_{data,t})^2}{n}}}{|y_{data,max}|} \times 100. \quad \text{(A2)}$$

Coefficient of variance (CV):

$$CV = \frac{\sqrt{\frac{\sum_{t=1}^{n}(y_{pred,t} - y_{data,t})^2}{n}}}{|\bar{y}_{data}|} \times 100. \quad \text{(A3)}$$

Mean bias error (MBE):

$$MBE = \frac{\frac{\sum_{t=1}^{n}(y_{pred,t} - y_{data,t})}{n}}{|\bar{y}_{data}|} \times 100. \quad \text{(A4)}$$

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.