

# Application of General Regression Neural Network (GRNN) in HVAC Process Identification and Control

Osman Ahmed, P.E.  
Member ASHRAE

John W. Mitchell, Ph.D., P.E.  
Fellow ASHRAE

Sanford A. Klein, Ph.D.  
Member ASHRAE

## ABSTRACT

*A simple yet effective general regression neural network (GRNN) paradigm is suggested for heating, ventilating, and air-conditioning (HVAC) control applications. Unlike the popular backpropagation paradigm, the proposed GRNN is simple to implement, requires only one parameter, and works well with sparse and random data. A simple local HVAC control example for a heating coil is chosen to test the GRNN effectiveness. The GRNN is used to capture the static characteristics for both valves/dampers and coils. Both simulated and experimental characteristics are used as identification as well test data for the GRNN. The GRNN captures the characteristics remarkably well and, due to its simplicity, it exhibits promise for implementation in real controllers. A combined feedforward and feedback control algorithm is explored that can utilize the GRNN method to identify static characteristics and can then subsequently be used in a feedforward controller to generate control signals based on the identified characteristics.*

## INTRODUCTION

In recent years, neural networks have been used for a wide range of HVAC applications, including predictions of building energy use (Anstett and Kreider 1993), adaptive control of heating coils (Curtiss et al. 1993), predicting return time from night setback (Miller and Seem 1991), and capturing complex predictions of mean vote (PMV) psychrometric relationships (Mistry and Nair 1993). All of these applications used a feedforward neural network trained using a backpropagation method (Rumelhart and McClelland 1986). In spite of the reported success, there are certain limitations that restrict the practical implementation of the backpropagation method. These limitations include computationally long learning times and appropriate selection of the number of layers, the number of neurons, the learning coefficients, and the initial values of weighting coefficients.

A memory-based network is described here that captures the input-output regression (linear or nonlinear) characteristics of the system. The neural network requires only a single parameter and, unlike backpropagation, does not involve any iterative training process. This general regression neural network (GRNN) has a theoretical basis using the Parzen window estimator (Parzen 1962) and was first applied as a neural network by Specht (1991). Compared to the conventional regression, the GRNN does not require a priori specification of the regression equation. In addition, compared to the nonlinear regression, the bounds of the independent variables, initial values, and convergence criteria do not have to be selected. This makes on-line implementation of the GRNN straightforward. The major limitations of the GRNN or any other memory-based neural network are long computation times when dealing with a large data set, which also requires more memory. In such cases, clustering techniques are suggested to reduce the number of data sets to increase the computation time and reduce the memory requirement.

A simple control topology combining feedforward and feedback algorithms (Kraft and Campagna 1989; Psaltis et al. 1987) is chosen here to demonstrate the principle of GRNN and to discuss the role of GRNN in identifying and controlling HVAC control processes. The control topology is shown in Figure 1.

The feedforward controller has identification and control blocks. The identification block captures and updates the process characteristics based on the process input control signals and the measured variables. The identification block passes the updated characteristics periodically to the control block for control action. The feedforward control block acts upon receiving a setpoint signal and provides a control signal based on the identified characteristics of the process. The feedback controller uses the error between the setpoint and the measured variable as input. The outputs from the feedforward and feedback blocks are used to control the HVAC system. The combination of feedback and feedforward controls has been successfully applied in industrial applications (Lorenz

---

Osman Ahmed is a senior principal engineer at Landis & Gyr Powers, Buffalo Grove, Ill., and a Ph.D. candidate and John W. Mitchell and Sanford A. Klein are professors in the Solar Energy Laboratory at the University of Wisconsin, Madison.

THIS PREPRINT IS FOR DISCUSSION PURPOSES ONLY. FOR INCLUSION IN ASHRAE TRANSACTIONS 1996, V. 102, Pt. 1. Not to be reprinted in whole or in part without written permission of the American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., 1791 Tullie Circle, NE, Atlanta, GA 30329. Opinions, findings, conclusions, or recommendations expressed in this paper are those of the author(s) and do not necessarily reflect the views of ASHRAE. Written questions and comments regarding this paper should be received at ASHRAE no later than March 6, 1996.

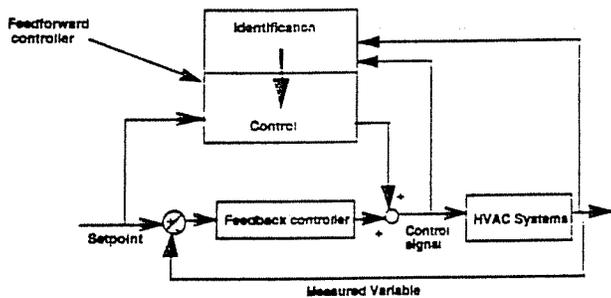


Figure 1 Combined feedforward and feedback control topology.

and Lawson 1987; Lorenz and Novotny 1988). The aim of the feedforward-feedback combination topology is to generate the majority of the control signal from the feedforward block such that the feedback block only deals with a small steady-state error and thus requires considerably less tuning than a feedback-only controller. Unlike feedback, the feedforward loop acts only upon the setpoint value and does not require the measured value of the variable. As a result, the feedforward signal can enhance control speed in tracking the setpoint change. The most common method of employing feedback is the traditional approach of the proportional-integral-derivative (PID) algorithm. The complete control topology is further discussed in the example of a heating coil control process.

The specific control topology shown in Figure 1 is particularly suitable for identifying and controlling room- or zone-level processes that are often referred to as a *local HVAC controller*. This local controller uses valves and dampers to modulate the flow of water and air, respectively, with heating coils used to provide local heating. Both valve and damper are flow-restricting devices and, by capturing the characteristics of the valve or damper and of the heating coil, a feedforward block can be suitably developed for local HVAC control process. The local controllers are found in large numbers in mid-size to large buildings and must have limited memory and processing capability to remain inexpensive. Hence, a scheme is needed that will be simple, easy to implement, cost effective, and that provides substantial enhancement in performance by coupling feedforward and feedback algorithms. Instead of reacting to a control affected by the dynamic response of the coil and valve signal, signal-static characteristics of these devices are stored and updated in the feedforward block. The GRNN method provides an effective means of capturing static characteristics of the coil and valve.

It is hoped that the paper will contribute by identifying a specific neural network paradigm and then illustrating the implementation in an HVAC control application. This will demonstrate the benefits and limitations of the method.

## IDENTIFICATION AND CONTROL OF A HEATING PROCESS

This section presents an overview of the identification process for the characteristics of a heating system and its control similar to the control topology shown in Figure 1. Following discussions on GRNN and modeling of a coil and valve/damper in the next sections, simulated and experimental results are presented to illustrate the identification process of a heating coil.

A simple system of heating air by water flow is chosen to demonstrate the application of the GRNN. The physical process is shown in Figure 2 and involves two components: a valve/actuator assembly and the heating coil. The valve/actuator characteristics are similar to those of a damper/actuator used to modulate the airflow rate in an HVAC air distribution system.

Therefore, the GRNN method described here for capturing the valve characteristics is equally applicable to damper/actuator characteristics. The water flow rate through the valve will depend on the valve open area and the authority,  $a$ . The authority is defined as the ratio of the pressure loss across the valve to the circuit pressure loss when the valve is fully open or, for each valve,

$$a = \frac{\Delta P_{valve}}{\Delta P_{circuit}} \Big|_{valve \text{ is fully open}} \quad (1)$$

Expressing the valve characteristics in terms of authority, percent valve open, and percent maximum flow rate is typical (ASHRAE 1992).

For a single-circuit system, in practice, the circuit pressure drop will be small compared to the valve, which will make  $a$  close to 1.0. However, for a system with multiple circuits, as shown in Figure 3, the pressure loss becomes significant in the main segment compared to the branch segment as the distance between the pump and the coil increases. As a result, the authority varies depending on the ratio of pressure loss, as indicated in Equation 1. The authority of any circuit is time dependent, as the flow in each circuit varies with the time. The valve authority can be calculated using basic relations between design pressure drop and flow rate or by measuring static pressures at the pump outlet and valve inlet at the design flow conditions.

As shown in Figure 1, a control signal,  $C_s$ , is generated based on the heating demand and is sent to the valve/actuator. In the case of a damper, the signal will be generated in

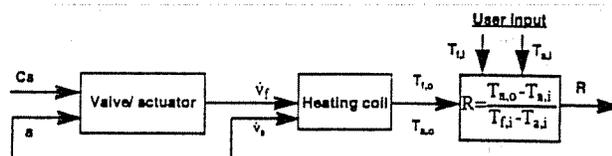


Figure 2 Physical process of water-to-air heating coil.

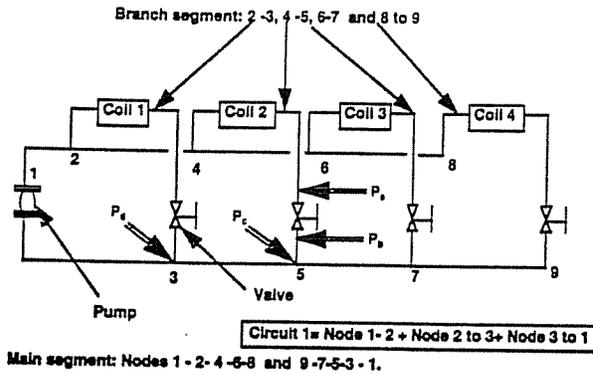


Figure 3 Water distribution system for HVAC applications.

response to the demand for airflow rate. The heating coil has inputs of water and airflow rates and inlet air and water temperatures. The coil outputs are water and air outlet temperatures. Since water outlet temperature is not directly linked to the supply air thermal capacitance, it is not considered in the identification.  $R$  is used as a nondimensional variable combining water inlet temperature ( $T_{f,i}$ ) and air inlet and outlet temperatures ( $T_{a,i}$  and  $T_{a,o}$ , respectively).  $R$  is defined as

$$R = \frac{T_{a,o} - T_{a,i}}{T_{f,i} - T_{a,i}} \quad (2)$$

Both  $T_{f,i}$  and  $T_{a,i}$  are usually known constants for a given system as user input parameters. The dimensionless variable,  $R$ , also can be viewed as coil effectiveness. Normally, the denominator of  $R$  is about 145°F (62.78°C) for a  $T_{f,i}$  of 200°F (93.34°C) and  $T_{a,i}$  of 55°F (12.78°C). Hence, choosing a range of  $R$  from .02 to .45 will yield values of  $T_{a,o}$  from 58°F (14.45°C) to 120°F (48.89°C). Such a range of  $R$  will cover coil applications for a wide range of HVAC systems.

The identification process described above provides the outputs as a function of inputs. The identification needs to be inverted when used in a controller to produce the desired control signals to the valve. The control scheme can be explained using Figure 4. The entire control scheme is divided into feedforward and feedback blocks. The feedforward block is activated upon receiving a signal of the coil outlet air temperature setpoint,  $T_{a,o|sp}$ . The feedback loop is driven by an error between  $T_{a,o|sp}$  and the actual measured coil outlet temperature,  $T_{a,o}$ .

The order of the physical heating process as shown in Figure 2 is reversed in the feedforward block. The coil characteristic is utilized first in the control process to yield the desired water flow rate,  $\dot{v}_f$ , for the desired coil outlet air temperature setpoint,  $T_{a,o|sp}$ , and for the supply airflow rate setpoint,  $\dot{v}_{a|sp}$ . Knowing the water flow requirements and the measured or estimated authority,  $a$ , the identified valve characteristic then generates a control signal combined with the feedback control signal before it is sent to the coil valve.

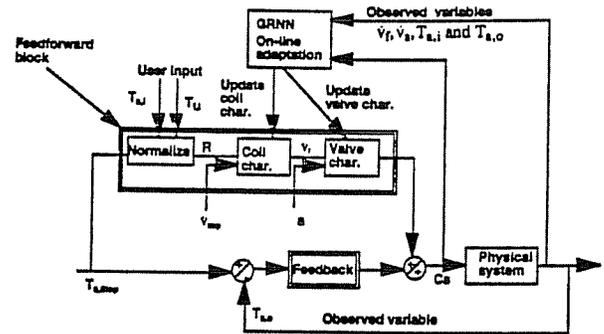


Figure 4 GRNN implementation of identification and control of heating coil.

The observed variables from the system along with the control signal,  $C_s$ , may be periodically collected and used to update the steady-state coil and valve characteristics by a separate GRNN identification scheme indicated as an on-line adaptive GRNN in Figure 4. The observed variables include  $T_{a,o}$ ,  $T_{a,i}$ ,  $\dot{v}_a$ , and  $\dot{v}_f$ . Instead of expensive means of measuring water flow rate, the coil outlet water temperature,  $T_{f,o}$ , can be measured and can be calculated using the following energy balance:

$$\dot{v}_f = k \frac{\dot{v}_a (T_{a,o} - T_{a,i})}{(T_{f,i} - T_{f,o})} \quad (3)$$

where  $k$  is a constant and equals

$$k = \frac{\rho_a c_a}{\rho_f c_f}$$

Equation 3 is proposed to calculate the water flow rate through the local heating coil considering the aspects of cost and practicality. The HVAC control system usually trends the airflow rate through the coil as well as the discharge air temperature for control purposes. The values are updated every second or more. The values for coil air and water inlet temperatures are also available from the central air-handling unit and chiller plant. Thus, by adding a water temperature sensor, the coil water flow rate can be calculated using Equation 3. This is a cost-effective proposition since the flow sensor costs more compared to the temperature sensor and such a cost difference becomes significant considering the large number of local heating coils present in a building. Also, in a retrofit job a strap on the temperature sensor can be installed outside the pipe, avoiding costly job interruptions. On the other hand, a flow sensor needs to be inserted inside the existing pipe, which interrupts the system operation.

A few additional factors favor the use of the temperature sensor. First, Equation 3 will only be used for identification purposes. Hence, dynamic data are not needed to solve for the water flow rate from Equation 3. Instead, only periodic steady-

state data are needed. The steady-state data should not be difficult to obtain given the sample rates of one or more per second.

Second, the governing relationships between the water flow rate and the airflow rate and air- and water-side differential temperatures across the coil are important to estimate the coil water flow rate. Hence, the absolute accuracy of each measurement is not that critical.

Finally, the purpose of the feedback controller in a combined feedforward and feedback block is to compensate for inaccuracies with the identification process, which includes measurement error. Hence, accurate measurement for identification is not required.

### GENERAL REGRESSION NEURAL NETWORK (GRNN)

The GRNN is chosen to identify the coil and valve characteristics due to its simplicity, robustness, and excellent capabilities in system identification. Unlike a conventional neural network, it requires minimal computational time to effectively capture the system characteristics. Specht (1991) discusses the theory of GRNN in detail. The following is only a brief account of GRNN to illustrate its implementation in identification of the components discussed in this paper.

The input to a GRNN is a series of data that can have multiple dimensions. For sample values of  $X_i$  and  $Y_i$  of input vector  $X$  and the scalar output  $Y$ , an estimate for the desired mean value of  $Y$  at any given value of  $X$  is found using all of the sample values in the following relations:

$$\hat{Y}(X) = \frac{\sum_{i=1}^n Y_i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^n \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \quad (4)$$

where the scalar function,  $D_i^2$ , representing the Euclidean distance from the given value, is given by

$$D_i^2 = (X - X_i)^T (X - X_i) \quad (5)$$

and  $\sigma$  is the single smoothing parameter of the GRNN.

Equations 3 and 4 are the essence of the GRNN method. The estimate  $\hat{Y}(X)$  is essentially a weighted average of all the observed samples,  $Y_i$ , where each sample is weighted exponentially according to its Euclidean distance from each  $X_i$  denoted by  $D_i$ . In that sense,  $D_i$  resembles the weighting coefficients of a backpropagation scheme. For a small value of the smoothing parameter,  $\sigma$ , the estimated density assumes non-Gaussian shapes but with the chance that the estimate may vary widely between the known irregular points. When  $\sigma$  is large, a smooth regression surface is achieved. In case an input is outside the range of observed samples, the GRNN will be able to predict an output based on the nearest samples in the observed data. However, the performance of GRNN can be enhanced by including that specific sample in the database.

When using measured data, it is necessary to find the optimum value of  $\sigma$ , as the parent distribution between  $X$  and  $Y$  is usually not known. As a preprocessing step, all input variables are normalized to obtain the same scale using the ranges of observed samples. The value of  $\sigma$  can then be calculated by a simple yet effective scheme known as the "holdout" method; holdout is one of several methods that are available to find an optimum value of the smoothing parameter,  $\sigma$ . In the holdout method, one sample at a time is removed from the set and the network is constructed using the remaining samples. The network is then used to estimate  $Y$  for the removed sample; each estimate  $Y$  is compared with the actual  $Y$  and the mean-squared error between the estimate and the actual value is computed and stored. The process is repeated for each sample. The value of  $\sigma$  is chosen so as to minimize the mean-squared error. The holdout method to compute a single parameter,  $\sigma$ , can be formulated as a single-parameter minimization problem while the training process in backpropagation adjusts multidimensional weighting coefficients, which is computationally intense and inherently slow.

A GRNN is shown in Figure 5, in which Equation 3 is represented in a neural network architecture. For a given  $X$ , the connections between the input and the first layers computes the scalar  $D_i$  based on observed samples ( $X_i$ ) and the smoothing parameter ( $\sigma$ ) and then takes the exponent of  $D_i^2$ . A node in the second layer sums up the exponential values for all samples, while the other nodes calculate the product of the exponent value and the corresponding observed output  $Y_i$  for each sample observation. The node in the third layer adds up all the product values; this is then supplied to the output node, where the ratio of the sum of the exponent and the product values is calculated. Compared to the backpropagation method, the weighting coefficients between the layers depend upon the observed samples of  $X_i$ ,  $Y_i$ , and the smoothing parameter,  $\sigma$ . As a result, instead of training the weighting coefficients, only a suitable single value of  $\sigma$  is needed to predict the output. The GRNN is thus able to represent the characteristics in a much shorter time than with a backpropagation method.

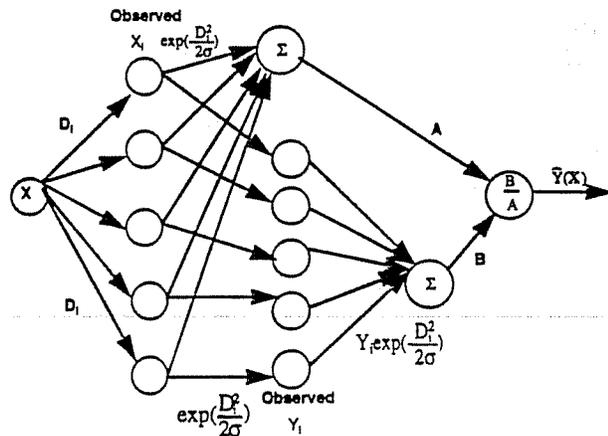


Figure 5 General regression neural network architecture.

The implementation of GRNN to the characteristics of a heating coil or valve/damper also offers advantages over the conventional methods of identification. In a traditional regression method for identification, the operator has to input a priori knowledge of the equation type or has to search for the best-fit equation exhaustively. The code requirement for a nonlinear regression is intensive and may be prohibitive for effective on-line use. In contrast, the GRNN does not require any user input for the functional form of the characteristics and uses a strikingly simple code. Moreover, the GRNN algorithm can be imbedded into a neural hardware processor, thereby eliminating the software development process to a large extent since software coding during field installation is not necessary. The choice of sample size and specific sample values are important in designing a GRNN in general. However, such issues are not so critical for HVAC applications. Only a small data set is needed to cover the normal operating range of HVAC equipment. The data provided then allow a satisfactory identification of characteristics.

### MODELING OF COIL

A simple model for the coil is used to generate simulated data to test the application of the GRNN. A simple effectiveness heating coil model is selected to achieve the desired objective. The steady-state coil heat transfer in terms of airflow rate and temperature is

$$q = C_a(T_{a,o} - T_{a,i}). \quad (6)$$

The coil effectiveness,  $\varepsilon$ , is defined as the ratio between the actual and maximum heat transfer rates or

$$\varepsilon = \frac{q}{q_{max}}. \quad (7)$$

The maximum rate of heat transfer occurs when the fluid with the minimum product of flow rate and specific heat changes temperature from its inlet to the entering temperature of the other fluid. Hence, the actual coil heat transfer rate,  $q$ , can be rewritten as

$$q = \varepsilon C_{min}(T_{w,i} - T_{a,i}). \quad (8)$$

Combining Equations 6,7, and 8 yields

$$T_{a,o} = T_{a,i} + \varepsilon \left( \frac{C_{min}}{C_a} \right) (T_{w,i} - T_{a,i}). \quad (9)$$

To calculate heating coil effectiveness, the following equation for a crossflow heat exchanger such as a heating coil is used (Holman 1989):

$$\varepsilon = \frac{1}{C_r} \left[ 1 - e^{(-C_r(1-\varepsilon^{-NTU}))} \right] \quad (10)$$

where

$$\begin{aligned} C_r &= C_f/C_a \\ NTU &= UA_{coil}/C_{min} \\ C_{min} &= \min(C_f, C_a), \\ \text{and} \\ C_{max} &= \max(C_f, C_a). \end{aligned}$$

For identification and test purposes, values are generated using Equations 5 through 9 with a value of  $\varepsilon = 0.70$  and  $UA_{coil} = 60 \text{ Btu/min}\cdot^\circ\text{F}$ .

### MODELING OF VALVE/DAMPER

A damper or a valve is essentially a variable fluid resistance device. Both exhibit similar fluid characteristics and their performance is expressed in terms of identical variables and hence can be represented by the same models. The models represented here are used in the HVACSIM+ simulation program (Clark and May 1985) and are capable of representing both linear or nonlinear behavior in terms of inherent characteristics. For clarity, only the term "valve" will be used, although the model is also valid for dampers. The model consists of a valve, a branch pipe (or duct) section upstream, and a pipe (or duct) downstream of the valve. For fixed upstream and downstream pressures, the models compute the flow rate by knowing the valve position. The valve position is linked to the actuator position, which is commanded by the controller. The model assumes that both inlet and outlet pressures are known and fixed, that the heat transfer is negligible, that the frictional coefficient in the flow range under consideration remains constant, and that the flow is fully developed.

The relationship between pressure and flow can be described by the following empirical equations:

$$P_a - P_b = K_{ab}(v_f)^2, \quad (11)$$

$$P_b - P_c = K_{bc}(v_f)^2, \quad (12)$$

and

$$P_c - P_d = K_{cd}(v_f)^2 \quad (13)$$

where  $P_a$  is the valve inlet pressure,  $P_b$  is the valve outlet pressure,  $P_c$  is the pressure at the junction between the branch and the return circuit, and  $P_d$  is the circuit pressure before another branch joins the circuit. The locations for different pressures are shown in Figure 3.

Equations 12 through 14 also will be valid for dampers except that the volumetric water flow rate through the valve,  $v_f$ , must be replaced by the airflow rate,  $v_a$ , through the damper.  $K_{bc}$  and  $K_{cd}$  are assumed based on design conditions and standard HVAC design procedures (ASHRAE 1994).  $K_{ab}$  is expressed as (Clark and May 1985):

$$K_{ab} = \frac{W_f K_o}{[(1-\lambda)r + \lambda]^{2.0}} + (1 - W_f) K_o \lambda^{(2r-2)}. \quad (14)$$

In Equation 13 the parameter  $W_f$  determines the nonlinearity of the valve/damper. A value of  $W_f = 0$  indicates a truly exponential valve whereas 1.0 means a linear valve. The term  $\lambda$  is a leakage constant that prevents infinite flow resistance when the valve is fully closed. The valve flow resistance coefficient at the fully open position is denoted by  $K_o$ , whereas  $r$  represents the normalized (0 - 1) commanded position by the

controller. By using system authority as a simulation variable, it is possible to duplicate the installed performance of a valve. Fixing the value of  $a$  allows the coefficient  $K_{ab}$  to be a variable. Solving Equations 11 through 14 simultaneously will determine the value of  $K_{ab}$  based on the fixed authority and flow rate. The values of  $K_{ab}$  for various  $a$  are listed in Table 1 along with other parameters considered when simulating valve characteristics. In Table 1, negative values of  $K_{ab}$  for authorities of 1.0 and 0.70 have no physical significance because they are obtained by assuming arbitrarily selected values for  $K_{bc}$ ,  $K_{cd}$ ,  $P_a$ , and  $P_d$ .

### SIMULATION AND IDENTIFICATION OF COIL AND VALVE CHARACTERISTICS

Coil and valve characteristics were generated using the models described above and subsequently used in the GRNN to identify the characteristics. The physical variables are first normalized. Besides  $R$  and authority,  $a$ , whose range is 0 to 1, other normalized variables used are

$$\begin{aligned} nC_s &= \frac{C_s}{C_{smax}} \\ nv_s &= \frac{v_s}{v_{smax}} \\ nv_f &= \frac{v_f}{v_{fmax}} \end{aligned} \quad (15)$$

The values of  $c_{smax}$ ,  $v_{fmax}$ , and  $v_{smax}$  are 1.0, 2,500 cfm (1,180 L/s), and 1.0 gpm (.0631 L/s), respectively. Using the value of  $R$  required to meet the load and a given value of  $nv_s$ , a value of  $nv_f$  can be determined which can be subsequently used in a valve model along with the given authority to generate a control signal,  $nC_s$ , as indicated in Figure 6. The coil and valve characteristics data are generated using normalized variables and the models described above.

TABLE 1 Valve Simulation Parameters

$\lambda = .00001$ ;  $W_f = 1$ ;  $K_{cd} = .08641(64.89)$ ;  $K_Q = .042(31.54)$ ;

Authority	$K_{ab}$	$\frac{ft. \text{ of } H_2O}{(gpm)^2} \left( \frac{kPa}{(L/s)^2} \right)$	Maximum $v_f$ , gpm (L/s)
1.00	-.086	(-64.58)	3.00 (0.1893)
.70	-.034	(-25.53)	2.50 (0.1577)
.50	.037	(27.78)	2.12 (0.1337)
.20	.407	(305.63)	1.34 (0.0845)
.10	1.02	(765.97)	0.95 (0.0599)
.05	2.25	(1689.64)	0.67 (.0423)
.01	12.13	(9109.02)	0.30 (.0189)

The GRNN method can be best explained by using an example of regressing valve data for a constant authority. For example, choosing  $a$  to be 0.1, a nonlinear relation, shown in Figure 6, is established between the normalized control signal and normalized flow. For a constant authority, there is only one input and the vector  $X$  in Equation 2 becomes a scalar series of normalized flow rate,  $nv_f$ . In Equation 2, the scalar function  $D_i^2$  can be computed where  $X_i$  is the  $i$ th sample in the  $nv_f$  series. Equation 1 can then be solved using  $D_i^2$  and corresponding  $Y_i$  as the  $i$ th sample of  $nC_s$  in the identification data. The simulation of coil and valve characteristics as well as GRNN is performed using the Engineering Equation Solver (Klein and Alvarado 1994). The simulated data in Figure 6 are shown by the solid line, while the points are generated by using GRNN Equation 1 for various smoothing parameter values. The simulated data contain 14 samples obtained by varying  $nC_s$  from 0.0 to 1.0 in increments of 0.1 and  $nC_s$  of 0.05, 0.15, and 0.25.

The holdout method is used to calculate the optimum value for  $\sigma$  and is found to be .01. The effect of choosing a higher value of  $\sigma$  is apparent in Figure 6. With the larger value of  $\sigma$ , a smooth, nearly linear trend is found while with smaller values, the GRNN attempts to approximate all samples. For  $\sigma = 0.01$ , the average error between the predicted and simulated signals is found to be 2.62%, while the maximum error of 14% is observed for the lowest value of control signal that is not included in the identification data ( $nC_s$  of .35). A slight error is also observed at the higher value of  $nv_f$  because the control signals become highly sensitive to the normalized flow rate. However, the relative error at the higher end of the valve curve is much smaller compared to the lower end due to the higher absolute value of the control signal at this end. The sample size and the choice of samples, therefore, are important variables along with the smoothing parameter,  $\sigma$ . In fact, by including the sample of  $nC_s = 0.35$  in the identification data, the error between the simulated and the predicted control signal for that specific sample can be decreased from 14% to

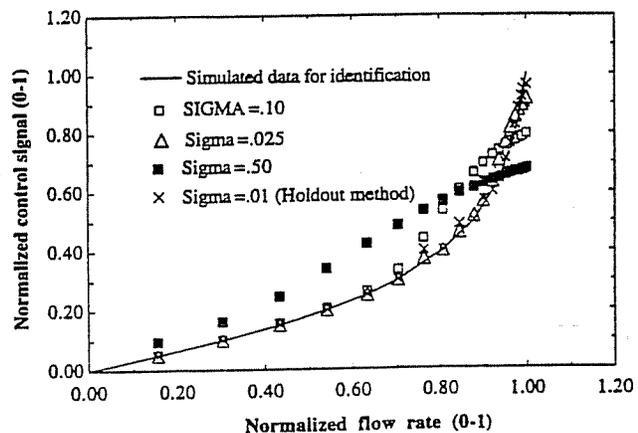


Figure 6 Simulated valve data ( $a = 0.1$ ) for identification and to predict use of GRNN.

less than 1% while the average error can be dropped from 2.62% to 1.31%. To identify damper/valve characteristics, only 200 samples at most will be required to cover the entire range of operation. This is based on the assumption that the authorities can be varied between 0.001, 0.01, 0.05, and 0.1 to 1 in increments of 0.10 while the control signal can be varied between 0.05, 0.075, 0.01, 0.15, 0.20, 0.25, 0.30, 0.35, and 0.40 to 1.0 in increments of 0.1. Any state-of-the-art local controller will be able to process the 200 sample values with ease and speed. In reality, however, the total number of points to cover the actual operating range will be much less, i.e., within 100.

Next, a range of valve authority between 0.5 and 0.1 is chosen to test the method of GRNN. Again, the holdout method is used to determine the optimum smoothing parameter,  $\sigma$ , which is now 0.05, and which produces a sum-of-squares error of 0.189 over an identification data size of 30 samples. The identification data set includes values of authority of 0.10, 0.30, and 0.50 and  $nC_s$  between 0.10 to 1.0 equally spaced. The test data set varies  $nC_s$  from 0.05 to 0.95 in increments of 0.10 and also includes intermediate authorities of 0.20 and 0.40. The average error of about 3.0% is low compared to the range of the data set. Some errors higher than the average are found for higher values of the control signal where the curve becomes very steep with the normalized flow rate,  $n\tau_f$ .

The operating range for the valve or damper is typical of these control applications. Hence, the method of GRNN in identifying characteristics using a small data set is promising and implementable in a real controller on an on-line basis. In a real application, operating characteristics over the entire operating range can be developed during commissioning by varying the damper open area. Once captured, the operating characteristic will be stored in the feedforward controller and the control signal will be generated based on the stored data using GRNN. The time and effort required to tune the feed-

back loop will decrease, as the error for the feedback loop will always have a low value. Reduction of commissioning cost and time and enhancement of system performance are the two major factors in favoring a combined feedforward and feedback controller for building HVAC distribution system.

The measured data obtained during the commissioning process will be used only to initialize the identification process. As the system operates and more operating data are collected, the identification will be updated accordingly. The essence of combined feedforward and feedback control is to generate a rough estimate of the control signal with the feedforward block while the refinement is made with the feedback block. In fact, the feedforward block also has a feedback mechanism that updates the identification. The identification process, however, is kept separate from the control process for ease of implementation and cost effectiveness.

Another method for implementing GRNN in a real controller will be to generate the characteristics using the simulated data. The characteristics can be stored and updated as the real data become available and replace the simulated data. Figure 7 shows both the identification and the test data covering the entire operating range of a valve. The control signals varied between 0.1 and 1.0 for each authority in the identification set while the authorities vary from 0.01 to 1.0. Also, additional samples are duplicated from the test set to the identification set at low values of authority and control signal. In total, 160 samples are used in the identification set while 150 samples are included in the test set. The holdout method using a smaller data set with authorities of 0.01, 0.10, 0.25, 0.50, and 1.0 is used to optimize the value of  $\sigma$ . A smaller data set having sparse values still yields a good choice of  $\sigma$  of 0.01 for the data set shown in Figure 7. The plot comparing simulated and predicted control signals is shown in Figure 8.

Again, higher than average errors occur for large control signals as well as for low authorities. The large error for a

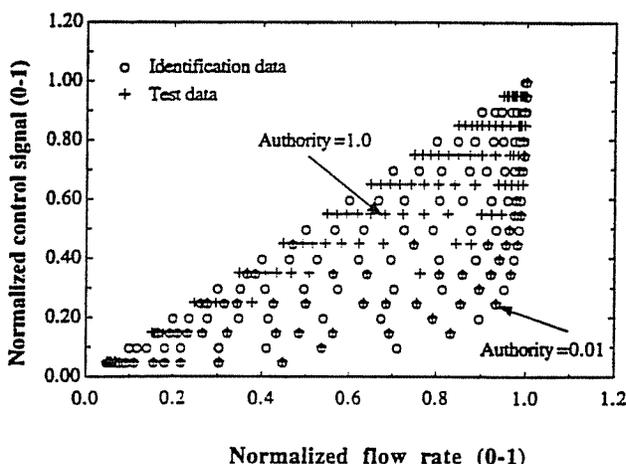


Figure 7 Simulated valve data ( $1 > a > 0.01$ ) for identification and to predict using GRNN.

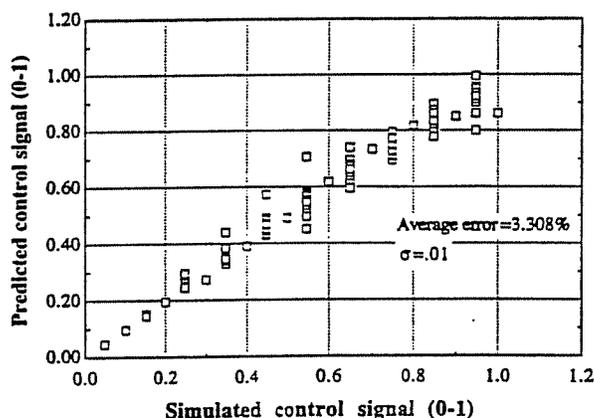


Figure 8 Comparison between simulated and predicted control signals using GRNN for valve ( $1 > a > 0.01$ ).

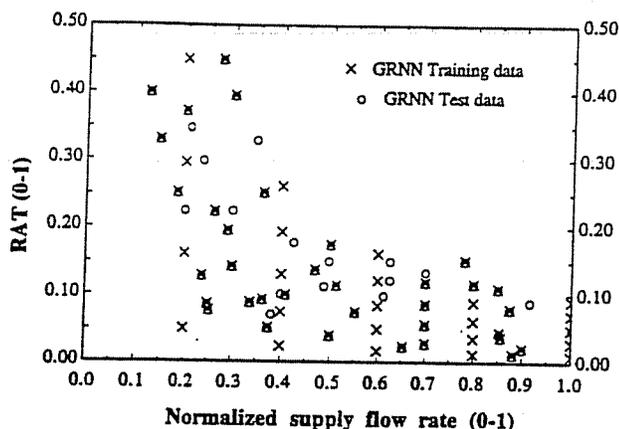


Figure 9 Simulated coil data for identification and to predict using GRNN.

specific sample can be vastly decreased by including that sample in the identification set. This can be easily achieved in a real controller by comparing the control signal sent to the valve and the damper and the control signal generated by the feedforward control signal (Figure 5). If the difference between the feedforward and the total control signals increases more than a prefixed threshold value, the control signal and corresponding normalized flow rate,  $nv_f$ , and authority can be put back into the identification set.

Finally, the GRNN is used to identify the characteristics of a heating coil. Referring to Figure 4, the GRNN predicts the required water flow rate through the coil for a given  $R$  and airflow rate. For randomly selected values of normalized supply airflow rate,  $nv_s$ , and  $R$ , the normalized flow rates,  $nv_f$ , are calculated using Equations 7 through 11. A portion of the simulated data is used for identification purposes while the rest is set aside to test the GRNN algorithm. The test samples are purposely chosen to cover the entire operating range. Figure 9 shows both the identification and the test data.

An average error of 2.6% between the predicted and simulated normalized flow rates is found. Unlike the valve, in which a definite pattern is evident, the coil plot in Figure 9 appears random. Even with such sparse and random distribution, the GRNN is able to predict the coil flow rates with good accuracy.

### IDENTIFICATION OF DAMPER CHARACTERISTICS USING MEASURED DATA

In addition to the simulated data, measured damper characteristics are also used to test GRNN. Two sources were used to obtain the measured values: (1) test data taken to calibrate damper performance and (2) active damper performance at a job site using a building automation system (BAS). In the first case, damper curves are experimentally generated for three damper authorities, as noted in Figure 10.

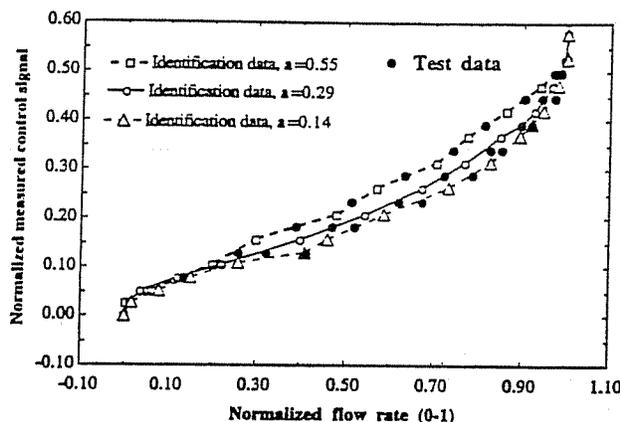


Figure 10 Damper test data for identification and prediction by GRNN.

The test sensors are similar to those used in commercial building control systems. For a given control signal, the flow rate through the damper is noted and normalized using Equation 14. The GRNN is identified using the measured values of the control signals, flow rate, and authorities while intermediate points on the authority curves are used to test the GRNN as shown in Figure 10.

Compared to the simulated data, the measured curves in Figure 10 exhibit more randomness, as expected. At low flow rates, the three authority curves converge into a single one, indicating the measurement difficulty of flow rate when the damper is barely open. At high flow rates and low values of authority, increasing the control signal will not increase the flow. The accuracy of the GRNN in predicting the measured test data is shown in Figure 11. The GRNN predicts the measured values with an average accuracy of 4.30%, which is encouraging considering the error associated with the measurement and data collection system. The holdout method is used to determine the optimum smoothing parameter,  $\sigma$ , of 0.066. The error increases with the higher flow rate as the authority curves become highly sensitive, as can be seen in Figure 10. The range of the test data for GRNN was chosen in the normal operating range of the damper—between 10% and 100%.

In the second case, the authority of the damper remain unchanged at 7% during the collection of data. Figure 11 shows the characteristics of an active damper at a job site. The plot indicates more randomness than for the test damper, as expected. For the same flow rate, the damper control signal varied over a wide range at both high and low flow rates. The GRNN output is tested for each sample observation that has been used in the identification data. Preprocessing of the raw measured values is not used before the data are fed to the GRNN for identification. A preprocessing filter could be used on measured values to reduce the uncertainty with the

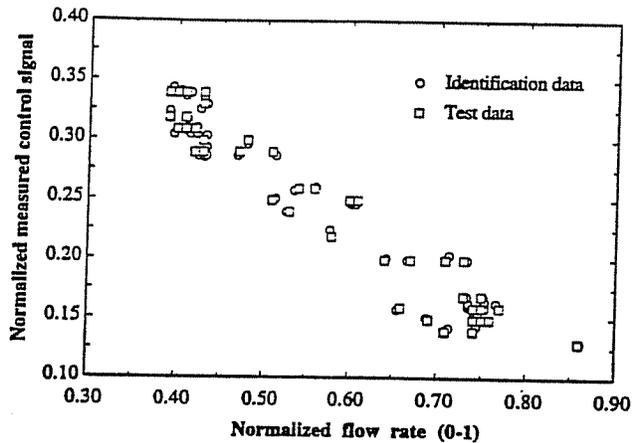


Figure 11 Data from BAS for identification and to predict using GRNN.

measured values. The purpose here is to test the GRNN most conservatively, considering all sample values. Figure 12 shows the accuracy of GRNN in predicting control signals within 6%. A linear regression of valve characteristics was also used for the data shown in Figure 11, and yielded an average error of 7%. However, the essence of GRNN is the capability to predict both non-linear as well as linear characteristics with no user input for fixed smoothing parameters. In case of a regression tool, significant user input is required, which often limits the actual on-line implementation of regression analysis for identification. Therefore, the results demonstrating that the performance of GRNN exceeds that of linear regression are encouraging.

## CONCLUSIONS

The method of a general regression neural network (GRNN) holds promise to effectively identify characteristics of HVAC components for subsequent use in controls. The strength of the GRNN is apparent, as it has demonstrated its ability to adapt to both linear and nonlinear relations using both simulated and measured sample observations. Unlike a traditional regression equation, however, a priori knowledge of the equation type is not necessary to implement GRNN. The nature of the GRNN algorithm allows the method to be imbedded in a neural network architecture, which makes hardware implementation possible. The smoothing parameter is the only variable that needs to be selected and it can be determined using the holdout method or another method. Since a small data set is needed for local HVAC control components, i.e., valves, dampers, and heating coil characteristics, the GRNN provides a promising means of characterizing static performance of HVAC components for use in a feedforward block coupled with the feedback controller.

Based on the results using measured data, a conservative estimate of 6% error with the GRNN method of identi-

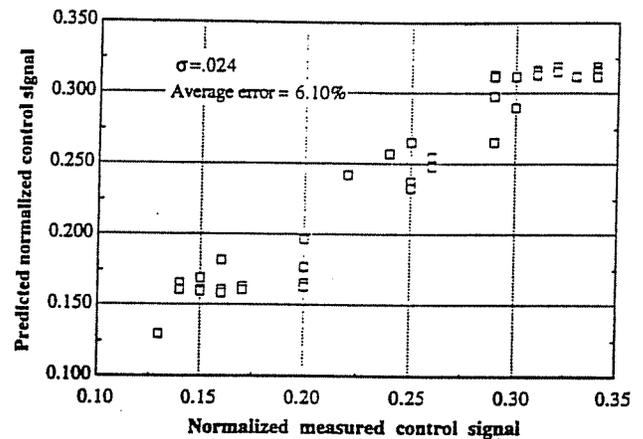


Figure 12 Comparison between data measured from BAS and predicted by GRNN.

fying coil and valve characteristics is reasonable. Hence, a control signal can be generated with an average accuracy of 8.8% ( $\sqrt{(6.0^2 + 6.0^2)} = 8.8$ ) using the GRNN in a feedforward controller. The average error of 8.80%, based on a simple quadrature formula and individual valve and coil errors, is quite encouraging. The feedback controller will be adequate to generate a control signal in order to eliminate a residual error of less than 10%. However, the feedback controller will require minimum tuning since the error range is anticipated to be in a fixed low range. The use of a combined feedforward and feedback controller therefore enhances performance while reducing commissioning cost. For a large data set, performance of GRNN will be degraded because for each sample the estimating algorithm will use a large number of stored identification data. Moreover, for such applications, a clustering technique (Specht 1991) is suggested to reduce the size of the identification data set. Although the output,  $Y$ , is treated in this paper as a scalar, multiple outputs also can be handled by GRNN (Specht 1991). As a part of the ongoing research, the combined control topology as shown in Figure 1 will be compared with the feedback controller for laboratory HVAC applications.

## NOMENCLATURE

- $A_{coil}$  = area of the coil ( $\text{ft}^2$  [ $\text{m}^2$ ])
- $c_a$  = specific heat of air ( $\text{Btu/lb}\cdot^\circ\text{F}$  [ $\text{kJ/kg}\cdot\text{K}$ ])
- $c_f$  = specific heat of water ( $\text{Btu/lb}\cdot^\circ\text{F}$  [ $\text{kJ/kg}\cdot\text{K}$ ])
- $C_a$  = capacitance rate of air through coil ( $\text{Btu}/\text{min}\cdot^\circ\text{F}$  [ $\text{kJ}/\text{min}\cdot^\circ\text{C}$ ])
- $C_f$  = capacitance rate of water through coil ( $\text{Btu}/\text{min}\cdot^\circ\text{F}$  [ $\text{kJ}/\text{min}\cdot^\circ\text{C}$ ])
- $K$  = frictional coefficient (in. w.c./ $[\text{lb}/\text{s}]^2$  or  $\text{kPa}\cdot[\text{kg}/\text{s}]^2$ )
- $P$  = pressure (in. w.c. [ $\text{kPa}$ ])
- $q$  = rate of thermal energy across coil ( $\text{Btu}/\text{min}$  [ $\text{kJ}/\text{min}$ ])

- $\rho_a$  = density of air (lb/ft<sup>3</sup> [kg/m<sup>3</sup>])  
 $\rho_f$  = density of water (lb/ft<sup>3</sup> [kg/m<sup>3</sup>])  
 $T_{a,i}$  = entering coil air temperature (°F [°C])  
 $T_{a,o}$  = leaving coil air temperature (°F [°C])  
 $T_{f,i}$  = entering coil water temperature (°F [°C])  
 $T_{f,o}$  = leaving coil water temperature (°F [°C])  
 $U$  = overall coil heat transfer coefficient (Btu/min·°F·ft<sup>2</sup> [W/min·K])  
 $v_a$  = airflow rate through coil (cfm [L/s])  
 $v_f$  = water flow rate through coil (gpm [L/s])

## REFERENCES

- Anstett, M., and J.F. Kreider. 1993. Application of neural networking models to predict energy use. *ASHRAE Transactions* 99(1).
- ASHRAE. 1992. *1992 ASHRAE handbook—HVAC systems and equipment*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
- ASHRAE. 1994. *1994 ASHRAE handbook—Fundamentals*. Atlanta: American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.
- Clark, D.R., and W.B. May. 1985. *HVACSIM+ building systems and equipment simulation program—User guide*. Gaithersburg, Md.: National Bureau of Standards (now NIST).
- Curtiss, P.S., J.F. Kreider, and M.J. Brandemuehl. 1993. Adaptive control of HVAC processes using predictive neural networks. *ASHRAE Transactions* 99(1).
- Holman, J.P. 1989. *Heat transfer*. New York: McGraw-Hill.
- Kraft, G.L., and D.P. Campagna. 1989. A comparison between CMAC neural network control and two traditional adaptive control systems. American Control Conference, Pittsburgh, Pa., June 21-23.
- Klein, S.A., and F.L. Alvarado. 1994. *Engineering equation solver*. Middleton, Wis.: F-Chart Software.
- Lorenz, R.D., and D.B. Lawson. 1987. Performance of feed forward current regulators for field oriented induction machine controllers. *IEEE Transactions on Industrial Applications*, vol. 1A-23, no. 4.
- Lorenz, R.D., and D.W. Novotny. 1988. A control systems perspectives of field oriented control for AC servo drives. *Proceedings of the Controls Engineering Conference*, Chicago.
- Miller, R.C., and J.E. Seem. 1991. Comparison of artificial neural networks with traditional methods of predicting return time from night or weekend setback. *ASHRAE Transactions* 97(2).
- Mistry, S.I., and S.S. Nair. 1993. Nonlinear HVAC computations using neural networks. *ASHRAE Transactions* 99(1).
- Parzen, E. 1962. On estimation of a probability density function and mode. *Annal of Mathematical Statistics* 33: 1065-1076.
- Psaltis, D., A. Sideris, and A.A. Yamamura. 1987. A multilayered neural network controller. IEEE International Conference on Neural Networks, San Diego, Calif.
- Rumelhart, D.E., and J.L. McClelland. 1986. *Parallel distributed processing: Explorations in the microstructure of cognition*. Cambridge, Mass.: MIT Press.
- Specht, D.F. 1991. A general regression neural network. *IEEE Transactions on Neural Networks* 2(6).