Neural Networks for Control and Fault Detection in State-of-the-Art Buildings

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Summary

Implementation of neural networks (NN) for building load and energy prediction can optimize equipment design, utilization and operation, resulting in significant monetary savings for building owners and operators. It has been demonstrated that building load and energy usage predictions are best accomplished using NNs. With improved load prediction, NNs can and have been successfully implemented to perform supervisory control over systems such as thermal energy storage and building setpoint control. They have also been used to adjust the setpoints of complex non-linear HVAC processes and have been found to provide superior results for automated HVAC diagnosis of abnormal behavior within vapor compression cycle equipment. Each of the implementations presented here has been tested in real systems that are located in buildings or in a full-scale laboratory.

1. Introduction

As heating ventilating and air conditioning (HVAC) equipment with computer controls and improved data acquisition systems becomes more prevalent and sophisticated, there is increased opportunity for improved control and fault detection capability. Not only do state-of-the-art methods provide improved performance over traditional systems, they also reduce the requirement for trained technicians to install and maintain those systems.

Of the many advances in building automation systems, neural networks (NNs) show tremendous potential for taking building automation to the next level. NN-based algorithms are attractive because they:

1. Are generic algorithms that do not need to be custom designed for specific applications;
2. Learn patterns and can self-calibrate as building envelope or equipment operating characteristics change, thus reducing the need for human interaction;
3. Can model non-linear characteristics found in HVAC applications;
4. Have been found to provide superior results to conventional methods in many areas of building energy management and control, thus reducing operating cost.

Neural Networks applications that are discussed in this paper fall into four general categories. Those categories are:

1. The use of NNs to establish setpoints within the building envelope while minimizing energy consumption;
2. The use of supervisory (global) NN controllers to optimize HVAC systems that are comprised of multiple processes;
3. The use of NNs to control processes. One example will show how NN controls can be used in conjunction with traditional PID control systems and another example will show how NN compares to feedback control systems;
4. The use of NNs to provide reliable and automated diagnostics for HVAC equipment.

Each topic presented here has been tested in real systems that are located in buildings or in a full-scale laboratory. They are well beyond the concept stage and many are ready for implementation today or are currently installed in buildings.

2. The Laboratory

This section briefly describes the laboratory, in which several of the research experiments were conducted. A complete description of the laboratory can be found in Kreider et al. (1999).

The laboratory, is a full scale heating ventilating and air conditioning (HVAC) laboratory, capable of satisfying 236 kW (67 tons) of cooling load and representative of a typical floor of up to 930 m^2 (10,000 ft^2) of a commercial building. The laboratory incorporates a central hydronic heating and cooling plant, ice storage tank, air-handling unit with variable frequency drives on the fans, outside air conditioning station and four load simulator zones, two of which are full scale. The chiller is a packaged dual-circuit unit with semi-hermetic helical-rotary (screw) compressor. The ice storage tank is a 6560 L (1600 gal), 2.4 GJ (190 ton-hour) nominal capacity ice-on-coil with internal melt storage system. Figure 1 is a simplified schematic diagram of the cooling plant.

A significant feature of the laboratory is the data acquisition and control system that allows investigation of optimal supervisory control, system dynamic studies and system/subsystem diagnostics. The laboratory has a data acquisition system that is able to accommodate 198 analog or digital input signals, 28 digital output signals, 58 channels for voltage or current analog output and an unlimited number of virtual points that can be used as mathematical manipulations of any of the other 284 physical points. Because of the special capabilities of the laboratory, much of the research focuses on optimal supervisory control, system dynamic studies and system/subsystem diagnostics.

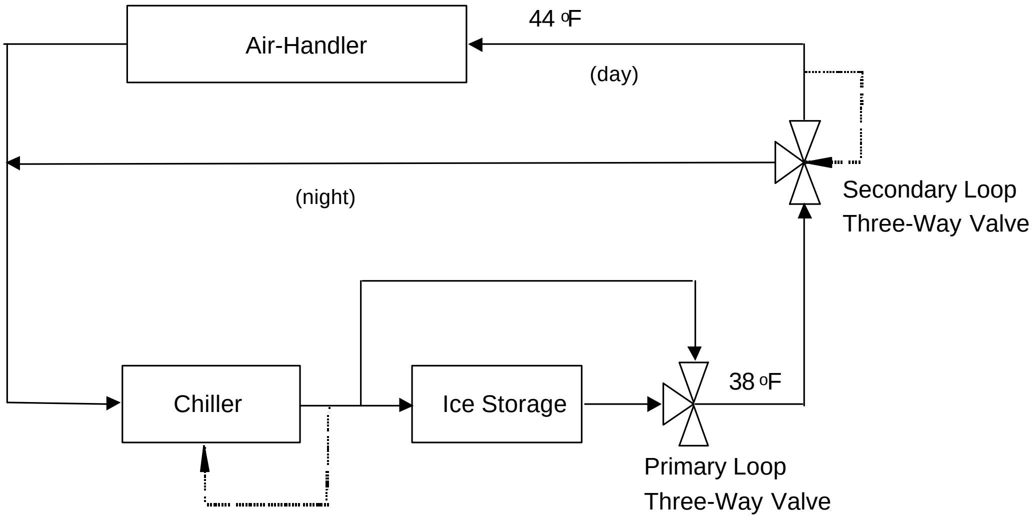


Figure 1. Cooling plant configuration of laboratory.

There are various satellite workstations in the laboratory, where sensor input values and output control can be monitored and controlled. These workstations are connected to an application server that distributes the updated information to Windows NT-based user workstations. The laboratory is BACNet™-compatible.

<u>3. NN Research Projects Survey</u>

This section summarizes research projects undertaken in the past several years that have used NN algorithms to obtain improved results in lieu of conventional techniques. Each project has not only been developed using computer simulations, but has also been tested on full-scale operational systems.

<u>3.1 The Neural Network House</u>

One hurdle to home automation is the aversion by most occupants to program devices such as VCRs, answering machines, automated thermostats and other electrical devices. Not only do occupants dislike programming these electronic devices, Gregorek (1991) found that for some people, operating even a simple set-back thermostat that changes the temperature setpoint is inordinately difficult. It is this dislike and difficulty that is the motivation for the neural network house, Mozer et al. (1995).

In contrast to conventional automated home control systems that must be programmed by users, the neural network house control system self-learns to maintain human comfort while minimizing energy cost. This is accomplished though sensors, such as thermostat, light, sound and motion detectors that feed into neural network and reinforcement learning algorithms. If the NN house were only concerned with human comfort, then the air temperature, for example, could be maintained at a comfortable 22^{o}C.

Likewise, if cost were the only concern, then all devices could be turned off. It is the balance between these two effects that the NN house tries to achieve.

Energy cost is easily computed in dollars. In order to measure human comfort in a common currency, a misery-to-dollar conversion factor is developed. The heating system can be regulated using a neurothermostat as described by Mozer et al. (1997) where relative discomfort (misery) is measured when an occupant manually adjusts a device (e.g. turning up the heat). The house learns the occupant's patterns over time and then adjusts equipment for least cost and adequate comfort. The hardware cost for implementing this type of a system is not prohibitive if the devices are mass-produced and communication uses existing wires or wireless systems.

The neural network house is a currently occupied structure with data collection still ongoing (research is planned for several more years). This research has yet to answer whether there are sufficient statistical regularities in occupant patterns if the occupant's daily schedule should begin to vary significantly. However, early indications are that even though an automated control system may have difficulty with the person who comes home at 5 p.m. one night and 8 p.m. the next, it may still infer that if the person is at home at 3 a.m. then the person will probably be home at 4 a.m. It may also still be able to predict that they will take a morning shower, which could require that the water heater is turned on in time to insure sufficient hot water.

3.2 Supervisory Control in Commercial Buildings

Control of complex HVAC systems often requires the coordinated effort of several components. This section discusses how NNs have been used to provide supervisory control. The use of NNs in process control will be discussed later in this paper.

3.2.1 Global PID Control

Supervisory controllers can be used to govern the operation of the entire HVAC plant and/or building climate control. This type of controller attempts to minimize a cost function associated with the operation of the building under the current conditions. The controller will vary setpoints, perform load shedding, switch cooling modes from mechanical to storage, etc. A basic diagram of a supervisory controller is given in Figure 2.

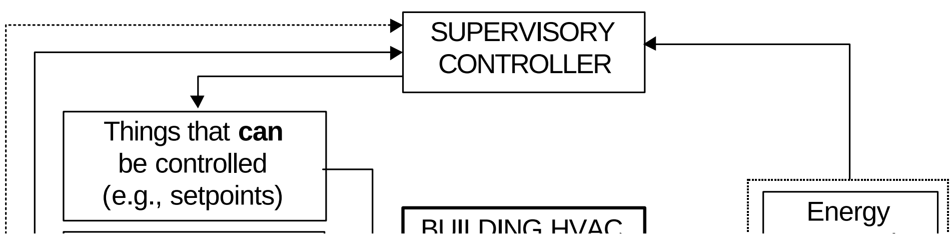


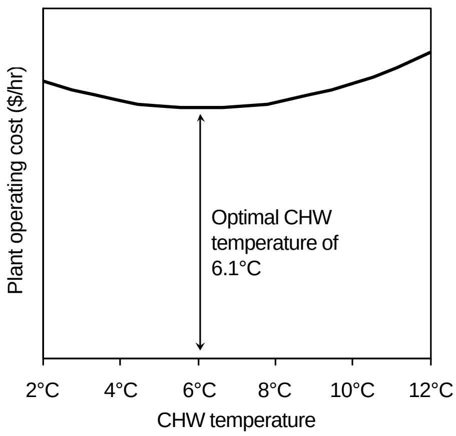
Figure 2. Information flow in HVAC plant supervisory controller

The principle behind the plant-wide optimization is to have a supervisory controller that can learn the behavior of the plant over a wide range of operating conditions. It has been demonstrated (Curtiss et al. 1994) that this can be successfully and easily accomplished using neural networks. The neural network inherently models the energy consumption or cost function with all of the controlled and uncontrolled variables as independent variables. It is relatively trivial to identify the lowest point in the resulting multidimensional surface through an iterative search. The search method can incorporate physical limitations of the equipment or operating fluids (for example, never searching for water temperature setpoints below the freezing point). Even with a reasonable number of controllable variables and heuristics, the searches are sufficiently fast to obtain real-time economically optimum operating conditions.

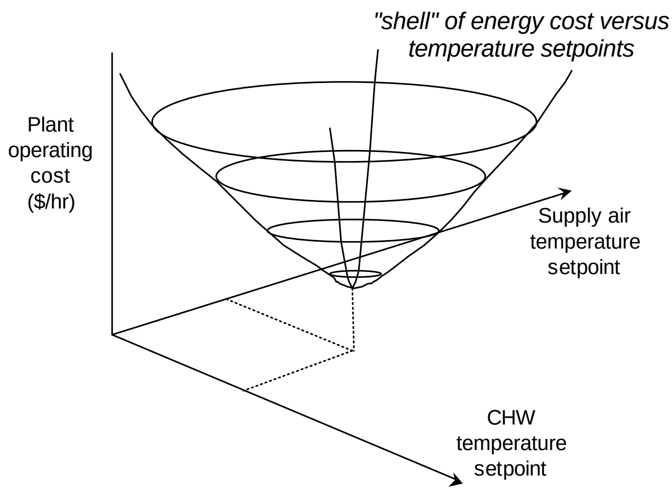
Figure 3 shows two conceptual examples of the results of a building model that has been used to look at the effects of chilled water temperature control (a), and chilled water and supply air temperature control (b) on the hourly cost of operating the HVAC plant.

3.2.2 Optimal Control of Thermal Energy Storage

Thermal energy storage (TES) is a load management and equipment utilization strategy that can reduce utility energy charges and equipment first-cost. It is generally designed to avoid high utility demand charges, which reflect a utility's high cost of producing peak power. The basic operating strategy of a cold storage system is to run chillers during times of low demand and energy costs (usually at night) to charge (i.e., freeze or chill) the storage medium, namely water. During times of high demand or energy charges (daytime) the cold water is used to produce cooling, i.e., the storage is discharged.



a. One controlled variable



b. Two controlled variables

Figure 3. Examples of energy use surfaces

Although it is relatively simple to describe the basics of thermal storage it is not simple to control storage-equipped HVAC systems in such a way that the utility bill is minimized. Control strategies implemented in the field today do not consider the changes in buildings and equipment from year to year, season to season or even day to day. Even for experts with extensive experience in operating cool storage equipment, most users find models to be complex, requiring significant effort to calibrate. As a result, much of the potential cost savings of using thermal storage systems is lost, Sohn (1991).

For TES systems to be of used, ice or chilled water must be formed in advance during periods of low energy cost so that it is available for cooling when energy cost is high. This implies that accurate cooling plant equipment models and load prediction techniques must be available to predict performance and energy consumption over a wide variety of conditions. Kreider and Haberl (1994) showed that connectionist methods provide the best results when predicting building loads. To avoid the problems of modeling equipment by using manufacturer's data or from laboratory testing, as described by Sohn (1991), Massie et al. (1998) developed NN equipment models using equipment in the laboratory that "learned" and self calibrated to equipment operating characteristics.

Massie (1998) developed and operated the first optimal controller for a TES system. The controller is neural network-based and is designed to minimize cost. The controller determines the optimal trajectory of setpoints so that cost is minimized over a planning horizon. Using computer simulation and the equipment models described above, the controller was thoroughly tested over many different real-time-pricing (RTP) and time-of-use (TOU) rates and in each case produced a trajectory of setpoints and charge/discharge rates that minimized the utility bill. Results were in complete agreement with Henze et al. (1997) for those cases that Henze investigated.

The controller was then tested by operating it in the test laboratory. Although space precludes details of this research, Figure 4 exhibits typical results. The upper part of the figure shows the neural network (NN) based controller setpoint schedule produced to minimize cost. The actual chiller output, which varies slightly about the desired schedule, is also shown.

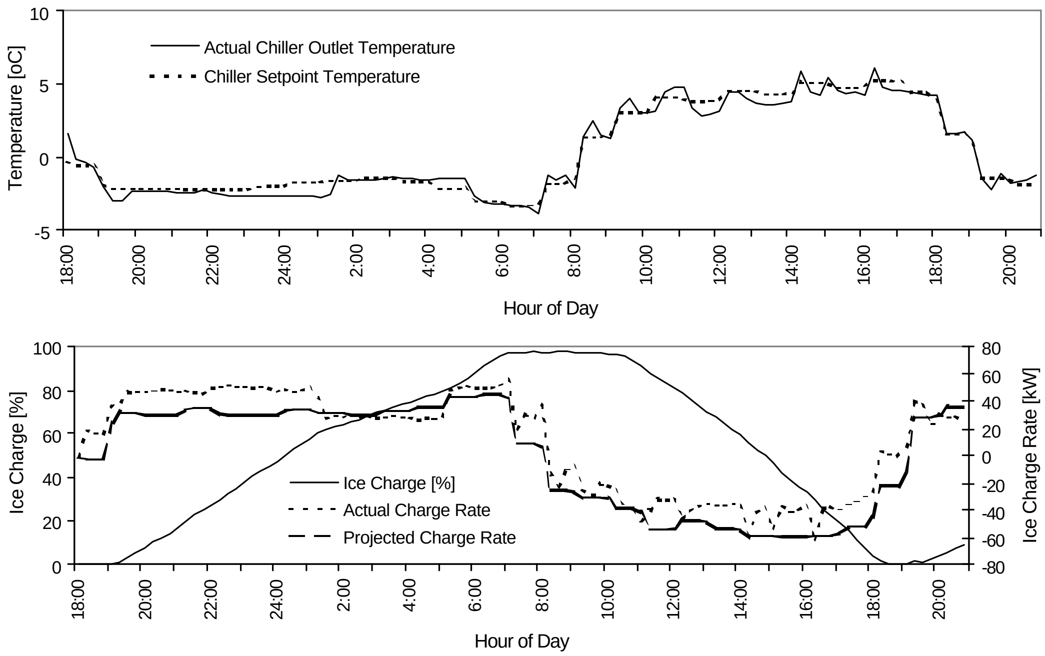


Figure 4. TES Optimal Controller Results. The upper curves show desired and actual temperatures and the lower, total tank charge fraction along with actual and projected charge rates along the right hand axis.

The lower figure shows the measured ice inventory (curve which rises and falls in one diurnal cycle) and the desired and actual charging and discharging rates. Note that the ice tank is fully charged before the onset of the daytime peak rate period and is discharged during the on peak period with its highest electrical rates.

The optimal NN-based controller is a significant improvement over fielded controllers today. They are easy to calibrate and since NN algorithms are generic in nature, using them is straightforward. When installed they will allow building owners to realize the full cost savings potential of their TES systems.

3.3 Diagnostics

Reliable, automated detection and diagnosis of abnormal behavior within VCRC equipment is extremely desirable for equipment owners and operators due to potential performance improvements. Chiller faults have major financial consequences and impose threats to the environment and human health through the emission of ozone depleting refrigerants as well as reduced operational efficiency and increased energy consumption. Given the vast number of chiller installations within buildings around the world, Bailey (1998) developed a fault detection and diagnosis (FDD) system for modern chillers. If broadly implemented, the reliable and automated detection of abnormal behavior and diagnosis of faults within vapor compression cycle equipment would be an extremely valuable tool for building owners and operators.

The objective of Bailey's work included designing and testing the viability of a FDD system for vapor compression cycle equipment. The FDD tool performs the task of analyzing chiller operating data and detecting faults by recognizing trends or patterns existing within the data. The FDD method incorporates a neural network classifier to infer the current state given a vector of observables. Therefore, the method relies primarily upon the availability of normal and fault data for training purposes, so a fault library was assembled for this purpose. The results of the research indicate that the NN classifier is capable of accurately detecting complex relationships and trends that exist within the input space.

The FDD system design criteria included low false alarm rate, the ability to correctly classify faults in both steady-state and transient chiller operation, and the limitation of computing memory. After data were collected, the neural network FDD program trained on chiller data collected during normal and abnormal operating conditions. Faults imposed on the JCEM chiller plant included refrigerant loss and overcharge, oil loss and overcharge, air cooled condenser fouling and the loss of an air cooled condenser fan. Data collection occurred during fault experimentation with a realistic load profile. For example, the refrigerant loss data ranged in fault degree from a minor refrigerant loss of 5% to an extreme loss of 60%. This progression occurred in 5% increments over several days of testing. When presented with the testing dataset, the trained FDD tool was capable of correctly predicting the current state of chiller operation with a misclassification rate of only 2%.

The improvements to on-board chiller diagnostics addressed within this research included the detection and evaluation of performance degradation faults and the assignment of risks to corrective actions associated with each fault. The developed fault detection and diagnostic tool will detect the problem, deduce the most probable cause, and inform service personnel of the calculated risks associated with performing corrective actions to eliminate the problem. The risks are based on replacement, labor and energy costs as well as health and environmental hazard costs if applicable. Compared with traditional diagnostic approaches for chillers, the new work is a major improvement with no additional need for sensors or for a large catalog of chiller data collected under fault conditions, as was formerly the case. This last point is key because extensive fault data sets are costly to construct.

3.4 Process Control

This section discusses the use of neural networks for providing improved control over processes. As will be seen, process control can benefit from NNs when there are major perturbations to the process or when the process is discontinuous as found when equipment is staged.

3.4.1 The network-assisted PID (NAPID) controller

Traditional PI or PID controllers work well for controlling most processes if the processes are operated in the range for which they were tuned. If, however, controllers are not well tuned or there is a major disturbance in the process, then their performance often suffers. To overcome these shortcomings, Curtiss (1996) developed the network-assisted PID (NAPID) controller. Curtiss defined success as the minimum differential between desired and actual process value at the end of a specified time window.

The NAPID controller project demonstrates the use of neural network algorithms in a real-time environment. Using computer simulation, the NAPID controller controls a hot water valve on an air-handling unit (subjected to varying loads) by adjusting the PID gains with a neural network. The NAPID operates as follows. The neural network controller is trained to predict the dynamic behavior of a process – in this case the boiler, control valve and heating coil. The NN “learns” the operation of this system while it is operated by a PID controller. While the PID controller is operating, the NN makes predictions on the current time step process values using the information from past time steps. If the predictions are sufficiently accurate, the NN takes control from the PID algorithm and controls the processes. However, if the NN is not able to predict the process values within satisfactory limits, the PID controller retains control and the NN learns again from the PID controller.

Jeannette et al. (1997) implemented the NAPID controller for the first time by controlling a hot water coil in the laboratory. The three-stage boiler that periodically caused large disturbances in the coil complicated the problem. The NN structure used in this project consisted of 4 inputs and 2 outputs. The inputs to the network are:

2. Hot water supply setpoint temperature – [°C]
3. Boiler outlet temperature – [°C]
4. Boiler stage controller output – [0,1,2,3]
5. 3-way valve controller output – [Voltage ~ 0-100%]

The outputs from the NN prediction are:

1. Hot water supply temperature – [°C]
2. Boiler outlet temperature – [°C]

The NN was able to accurately predict the processes two hours after startup. Using the NN controller to control both the boiler staging and the 3-way mixing valve, control was always at least as good as was possible with the PID controller. After three days, the actual neural network controller "learned" the hot water system process over time and was able to correctly control the air-handling unit leaving air temperature under varying loads with minimal use from PID control. The key improvement offered by the NN controller was that it was able to minimize boiler staging thereby controlling hot water supply temperature more closely under high load and reducing boiler heater switchgear wear.

3.4.2 Lighting Control

Minimizing light levels in buildings has significant energy savings potential. Avoiding the purchase of electricity to run the lights can reduce the building cooling load as well as the lighting load. The lighting control problem, however, is more difficult than it appears at first glance. In a room where there are several light banks, each of which can be set to different intensity levels, there can be multiple settings that can achieve a specified illumination level. Additionally, to accurately determine illumination levels, multiple sensors must be in place to measure those levels. Placement of sensors in the room and errors associated with using inexpensive sensors also contribute to measurement errors that already have a non-linear response to the power required for a given illumination level.

Dodier et al. (1994) investigated the use of neural networks and conventional feedback loop systems for controlling illumination level. He conducted his study in the neural network house described above. Results of this study shows that both PID and NN systems can accurately control illumination levels. However, a major finding of the study is that the neural network approach adjusts light levels 2.5 to 4 times faster than does the feedback loop system. The primary advantage of the NN method is that it is capable of simultaneously mapping multiple outputs versus a single output from a feedback loop system. A feedback system must calculate settings and communicate with each sensor separately, which is time consuming. The time increase is significant because the communications time delay from the conventional system causes a fluctuation of the light level that is annoying to inhabitants. Because of the multiple mapping capability of the NN, information between all sensors and the controller can be transmitted simultaneously.

4. Conclusions

As HVAC and energy engineers develop the next generation of heating and cooling plants for buildings, it appears that NN algorithms will help take the industry to the next level of performance. It has been demonstrated on operating plants that NNs can optimize equipment utilization and operation, resulting in significant monetary savings for building owners and operators. Because NNs are generic algorithms that learn patterns, they do not require programming by experts for individual applications. This coupled with broad implementation makes these advanced algorithms economically feasible from both a hardware and software basis.

5. Acknowledgements

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