Artificial Neural Networks based Thermal Energy Storage Control for Buildings

Kasun Amarasinghe, Dumidu Wijayasekara, Howard Carey, Milos Manic
Virginia Commonwealth University
Richmond, Virginia, USA
amarasighek@vcu.edu, misko@ieee.org

Dawei He, Wei-Peng Chen
Fujitsu Labs America
Sunnyvale, California, USA
dhe@us.fujitsu.com, Wei-Peng.Chen@us.fujitsu.com

***Abstract*—Heating, Ventilation and Air Conditioning (HVAC) system is largest energy consumer in buildings. Worldwide, buildings consume 20% of the total energy production. Therefore, increasing efficiency of the HVAC system will result in significant financial savings. As one solution, Thermal Energy Storage (TES) tanks are being utilized with buildings to store excess energy to be reused later. An optimal control strategy is crucial for optimal usage. Therefore, this paper presents a novel control framework based on Artificial Neural Networks (ANN) for optimally controlling a TES for achieving increased savings. The presented ANN controller utilizes 3 main inputs: 1) current TES energy availability, 2) predicted building power requirement, and 3) predicted utility load/price. In addition to the design details of the control framework, this paper presents implementation details of the ANN controller. Further, experiments on several test cases were carried out and the paper presents the experimental setup and obtained results for each test case. Performance of the presented ANN control framework was compared against a classical proportional derivative (PD) controller. It was observed that the presented framework resulted in better cost savings than the classical controller consistently for all the experimental test cases.**

Keywords—Artificial Neural Networks; Thermal Energy Storage; Optimal Control; Building Energy Management Systems

I. INTRODUCTION

Building Energy Management Systems (BEMS) are responsible for controlling the Heating Ventilation and Air Conditioning (HVAC) and lighting systems in buildings. It is documented that more than 20% of the total energy production are consumed by buildings [1]. In the United States, buildings account for 40% of the total energy consumption [1]-[3]. Due to the high energy consumption, buildings are also one of the major contributors to greenhouse gas production [4]. These numbers are projected to increase due to economic growth and various other factors [1], [5].

In a building, HVAC system is the largest energy consumer [6]. It has been documented that over 30% of the building energy consumption is accounted for by the HVAC [6]-[9]. Thus, increasing energy efficiency of the HAVC would result in substantial financial gains. Therefore, significant research is being carried out to devise methods to increase energy efficiency in buildings. One such methodology is to use energy storage tanks to store energy when the rates are cheaper and to reuse the stored energy when the power rate is higher. Thermal Energy Storage (TES) tanks are water tanks which are used to store thermal energy [10]. TES tanks can be utilized to store hot or chilled water with a loss of 1-2% per day under usual conditions [11]. Using TES tank for energy efficiency improvement has been studied in recent research work [12]-[16]. Furthermore, the possibility of using TES in power peak shaving has been studied in [17].

Regardless of the application, in order to acquire maximal benefit from TES, it is important to optimize the process of extracting and storing energy in the tank. Therefore, research has been conducted in the recent years to devise an optimal control methodology for using TES tanks to obtain financial savings. In [11], the authors presented a framework for using TES for building cooling with multiple chillers to cool the TES water. In their work, the number of chillers used and their times of operations were made variable. In their presented framework, costs were minimized by shifting chiller demand to an overnight period. The authors have used linear programming to perform the minimization operation subject to constraints. In [18], the authors proposed to define the optimization problem as a Mixed Integer Linear Programming problem and solve it using a branch and bound algorithm. The authors used predicted thermal demand and electricity price of the future in the optimization. In [19], the authors present a supervisory control scheme known as the Market Responsive Control to control the TES to achieve financial savings. The optimization of the control is achieved by the authors by solving a convex optimization problem. Model Predictive Control has been proposed to be used as a control mechanism for TES [20], [21]. Predictive control was also proposed to use for achieving peak reductions using TES [22], [23].

This paper presents a novel control framework for TES based on Artificial Neural Networks (ANN). The proposed control framework is entirely data driven and it leverages from three main inputs; 1) current TES energy availability, 2) predicted building power requirement, and 3) predicted utility load/price. These inputs provide information to the TES control signal to make the optimal control decision. The ANN based control module attempts to minimize the cost of energy by utilizing the energy in the TES optimally. The emphasis of this paper is on the ANN based control module. Therefore, for purposes of this paper, Inputs 1, 2 and 3 are assumed to be already available and prediction methodologies are considered to be out of the scope of this paper. In addition to the presented framework for ANN based TES control, this paper presents the implementation details for the presented controller. Further, in order to validate controller and its implementation, different experiments were carried out and the performance of the presented controller was compared against a traditional PD controller. This paper elaborates the used experimental set up and the results obtained for each test case.

The rest of the paper is organized as follows. Section II elaborates the presented framework. Section III presents the implementation details of the ANN based controller. Section IV and V present the experimental set up and the results obtained by the implemented framework. Finally, Section VI presents conclusions for the paper.

II. Presented ANN Based TES Control Framework

This section elaborates the complete control framework for the TES. In the context of this paper, the phrase "controlling a TES" is referred to controlling the amount of energy extracted from the TES. The energy extraction from the TES is directly governed by controlling the valves that control the flow rate of water going out of the tank. In addition to controlling the amount of energy extracted from TES, the recharging of the TES is considered to be in the scope of the presented controller. In building cooling, cooling the tank back down is considered recharging the tank.

The overall framework is shown in Fig. 1. The presented framework is depicted for using a TES for cooling a building. In the framework, the water pumped from the TES is sent through a chiller. The chiller cools the water down to a predefined temperature before sending through the BEMS. It is assumed that the chiller is entirely powered by the power purchased from the utility. Once the water is run through the BEMS it is returned to the TES. Thus, the temperature of the TES gradually increases. I.e. the tank discharges. Therefore, the tank is recharged using the chiller (TES cooling loop in Fig. 1).

The presented ANN based controller leverages outputs from three modules (green blocks in Fig. 1). As mentioned, for the purposes of this paper, these models are assumed to be implemented and are producing outputs with sufficient accuracy. The main emphasis of the presented work is the ANN based controller. Therefore as the main controller of the TES, the output from the ANN is the amount of power that is used from the TES for the next time step.

As mentioned, the objective of utilizing a TES is to store energy when power costs are lower and reuse the stored energy when the power rate is higher. The controller should be able to take into account the predicted building power requirement, predicted utility load profile, and the TES behavior, and determine the optimal usage of TES, so as to achieve this goal. Information about the future will enable the controller to make a well informed decision about when and how to use TES power. Thus, both building power requirement and utility load is utilized to provide information about the power requirements and power prices of the future. Furthermore, the available chillers has to be able to cool the TES back to a given temperature during cooling hours, which results in power usage. Thus the controller should also consider and control the

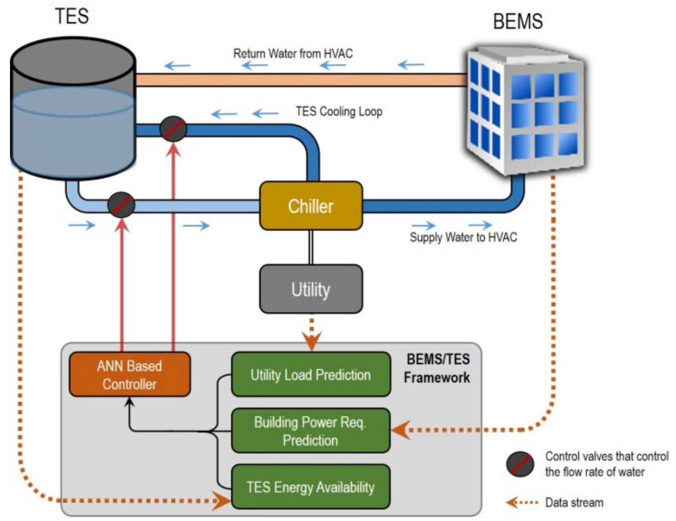

Fig. 1. Presented ANN based TES control framework for using a TES for cooling

re-cooling of the TES. Therefore, the controller has to take into account how much power that is needed to cool the building, how much energy is available in the TES as well as how the utility load is going to be, to optimize the cost, while using the TES to a level such that it can be cooled back down. Thus, outputs from each green block in Fig. 1 will be used to generate the final control signal.

The presented controller is designed as an Artificial Neural Network (ANN). ANNs are computational intelligence architectures based on biological neural networks and have the capability of "learning" interdependencies and trends in data. The basic unit of an ANN is a neuron which is functionally similar to a biological neuron and has a set of inputs and produces an output based on the inputs. An artificial neuron aims at achieving the same by using weights, a threshold value and producing an output vector for a given input vector. [24], [25]. The most used ANN learning methodology is the Error Back Propagation (EBP) method using the Levenberg - Marquardt algorithm [26] – [28]. However, since the control of the TES needs to be optimized, the ANN is trained using an optimization algorithm as opposed to EBP. The optimization methodology is elaborated below.

The ANN controller is optimized subject to three variables. 1) Total cost of cooling the building as well as re cooling the TES, 2) Total amount of wasted money because of overshooting the power required by the building, 3) The difference between the preset TES temperature lower limit and the actual TES temperature at the start of each week.

The cost of building can be calculated trivially when the total power purchased from the utility is known. The wasted amount of money due to overshooting can be calculated once the wasted power is calculated. Wasted amount of power due to overshooting can be calculated using the following Equation.

$$PowerWaste = (PowerOut_{TES} + PowerOut_{CHILLER}) - P_{BUILDING} \tag{1}$$

TABLE I. TRAINING AND TESTING DATA USED IN EXPERIMENTATION

Data	Start	Finish
Training Data	05/06/2013 1:00AM	05/27/2013 1:00AM
Testing Data	05/06/2013 1:00AM	09/30/2013 1:00AM

Where $PowerOut_{TES}$ is the power produced from the TES at current time step, $PowerOut_{CHILLER}$ is the power used by the chiller to cool the water down to the pre-defined temperature at the current time step, and $P_{BUILDING}$ is the total power required by the building for cooling the building down at the current time step. The difference between the actual temperature of the tank and the ideal temperature of the tank is considered because the recharging or re-cooling of the TES is in the controller's scope as mentioned before.

In order to achieve minimum cost, an error value is calculated. The calculated error value is then minimized using an optimization technique. In calculating this error value, four cost values are calculated at each time step. The four cost values are calculated as follows:

$$Cost_{NO\_TES} = \frac{\left(P_{BUILDING}/1000\right) \times CTU}{100} \tag{2}$$

$$Cost_{CHILLER} = \frac{\left(PowerOut_{CHILLER}/1000\right) \times CTU}{100} \tag{3}$$

$$Cost_{REMAINING} = \frac{\left(PowerRemaining/1000\right) \times CTU}{100} \tag{4}$$

$$Cost_{WASTED} = \frac{\left(PowerWaste/1000\right) \times CTU}{100} \tag{5}$$

Where, $Cost_{NO\_TES}$ is the hourly cost of power if the power was bought from the utility rather than TES, $Cost_{CHILLER}$ is the hourly cost of power bought from utility to run the chillers, $Cost_{REMAINING}$ is the hourly cost of power bought from the utility to run the HVAC to make up for the power deficit from TES., $Cost_{WASTED}$ is the hourly cost of wasted power by overshooting the actual power required by the building, and *CTU* is the cost to purchase power from the utility at a given time.

For each of the cost values that was calculated in Eq. (2) – (5), a total cost value is calculated over the period for the time of consideration. I.e. the hourly calculated cost values are summed up to get four total cost values. Then, the total cost values are used to calculate the following percentages that will be used in error value,

TABLE II. PRICING INFORMATION USED FOR EXPERIMENTATION

Peak/Off Peak	Price per kWh	Time
Peak hours	\$0.09001	7:00 AM to 8:00PM
Off-peak hours	\$0.02405	8.00PM to 7.00AM

$$PercentSpent = \frac{\left(TotalCost_{CHILLER} + TotalCost_{REMAINING}\right)}{TotalCost_{NO\_TES}} \tag{6}$$

$$PercentWasted = \frac{TotalCost_{WASTED}}{TotalCost_{NO\_TES}} \tag{7}$$

Where, the *PercentSpent* is the percentage of the cost that goes in to purchasing power from the utility when the TES is operational over the cost when TES is not used. *PercentWasted* is the percentage of cost that is wasted due to power wastage. Trivially, both these values should be minimized for optimal control.

Finally, in order to take into account the cooling back of the TES, the following sum is used,

$$\begin{aligned} Recharging = & \\ & \sum_{t=1}^{SimTime} currentTankTemp(t) - TESLowerTemp \\ & \forall t : day(t) = 1 \cap hour(t) = 6 \end{aligned} \tag{8}$$

Where *Recharging* is the summation of the difference between the actual temperature of the tank and the pre-defined temperature of the tank over the period of testing. This entity should be minimized to keep the water of the tank as close as possible to the predefined temperature.

Thus, using the above variables, the error value that is to be minimized can be calculated as follows,

$$\begin{aligned} ErrorValue = & \left(PercentSpent \times w_s\right) + \\ & \left(PercentWasted \times w_w\right) + \\ & \left(Recharging \times w_c\right) \end{aligned} \tag{9}$$

As mentioned above, the minimization variables can be weighed according to the requirements of the user, and thus the weight variables w_s, w_w, w_c can be user specified constants according to the contextual importance of each variable. Thus, the *ErrorValue* is minimized using an optimization algorithm. The weights of the ANN is found by minimizing the error value through the optimization algorithm.

TABLE III. DETAILS OF THE DIFFERENT TANKS USED FOR EXPERIMENTATION

Tank Variable	Unit	Small Tank	Medium Tank	Large Tank
TES height	m	5	10	15
TES radius	m	1	7	15
Tank wall thickness	m	0.3	0.3	0.3
Thermal conductance	W/mK	0.1	0.1	0.1
Gallons in tank	Gallons	4,000	400,000	2,800,000
TES temp. upper limit	ºC	17	30	30
TES temp. lower limit	ºC	2	2	2
Max flow rate	kg/s	0.5	5	
Efficiency Ratio of TES	None	0.85	0.85	0.85
Efficiency Ratio of chiller	None	0.9	0.9	0.9

The re-cooling control of the TES is based on a set of preset hard thresholds. A re-cooling time is the time interval in which the TES will be re-cooled. During this time the TES will not be used to cool the building. A desired temperature threshold to which the chillers will cool the water is set for the TES. The chillers will operate at maximum capacity until the desired temperature is reached, or the re-cooling time is over.

III. EXPERIMENTAL SETUP AND IMPLEMENTATION

This section presents details of the setup used for experimentation and implementation of the presented method.

A simulated building was used to carry out the experimentation. A building with 10 floors was considered. Each floor was designed to have 5 occupant zones. An assumption was made that all floors are identical and thus the cooling demand of each floor is identical.

Since the TES is being presented in a building cooling context, data were gathered for the presented building for the summer months. Data were simulated for the period of 05/01/2013 – 09/30/2013. For the said time period, data were gathered in hourly time steps. The training and testing periods are given in Table I

TABLE IV. SPECIFICATIONS OF THE CHILLER USED

Chiller	Small Tank	Medium Tank	Large Tank
Chiller Watts	40,000	100,000	150,000

In order to calculate the costs for the peak and off peak hours, real world pricing information was used. The prices was obtained by a power company existing in Richmond, Virginia [29]. Pricing information used for calculations are given in Table II.

In order to experiment with different sizes of TES, 3 tanks were specified. Each tank was specified with different sizes and maximum flow rates. Table III provides details of the different tanks that were used for testing. For testing purposes a specific chiller was used for each tank size. The chiller specifications are given in Table IV.

The presented ANN controller was designed to consider predictions for the immediate next time step (next hour) for building power requirement and utility load. The inputs used for the ANN controller is given in Table V. The optimal architecture for the ANN was chosen by experimenting with architectures with different complexities. Initially, an ANN with one hidden layer and 2 neurons was implemented. Then, gradually the complexity of the ANN was increased by increasing the number of neurons per layer and the number of hidden layers. The optimization process was repeated for each architecture and the least complex ANN architecture which yielded the best results was selected. Therefore, the presented results are obtained by an ANN consisting of an input layer, 2 hidden layers and an output layer. The layers contained 6, 8, 6 and 1 neurons respectively in the final ANN architecture.

TABLE V. INPUTS TO THE CONTROL ANN

Inputs	Units	Range		Description
		Min	Max	
Predicted power requirement of the building for the next time step	Watt	0	11615	Predicted power requirement of the building for cooling at time step *t*. The prediction is for the next time step. Multiple time steps can be used for a more informed decision.
Predicted utility load for the next time step	Percentage	10	95	Predicted utility load percentage at time step *t*. The prediction is for the next time step. Multiple time steps can be used for a more informed decision.
Power availability of the TES	Watt	0	N/A	The current power availability of the TES. Identifying the current availability of power, in order to determine the amount of extraction for the next time step.
Hour of day	Integer	1	24	Identifying the hour of the day since the hour of the day affects cooling patterns. (E.g. – 9AM-5PM in an office building)
Day of week	Integer	1	7	Identifying the day of the week since the cooling patterns for different days will be different. (E.g. – Weekday and Weekend)
Current outside air temperature	Celsius	12.61	34.40	The current outside air temperature. This is taken as an indication of the prevailing weather conditions.
Current averaged room temperature	Celsius	20	28	This is the averaged room temperature of the whole building across all floors

TABLE VI. EXPERIMENTAL RESULTS FOR THE THREE TEST CASES

Test Case	Tank Size	Controller	Cost without TES ($)	Cost with TES ($)	Savings ($)	Savings Percentage (%)	Wasted Cost ($)
Test Case 1	Small	PD	8370.508	7455.746	914.761	10.928	3.703
		ANN		**7428.485**	**942.023**	**11.254**	**3.326**
Test Case 2	Medium	PD		4761.879	3608.628	43.111	546.578
		ANN		**4217.703**	**4152.804**	**49.612**	**57.504**
Test Case 3	Large	PD		5459.915	2910.592	34.772	494.534
		ANN		**5257.788**	**3112.719**	**37.187**	**136.023**

The optimization problem of finding ANN weights was solved in the implementation using the Particle Swarm Optimization method (PSO) [30]. PSO is an optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. The basic idea behind the algorithm is that a set of solutions, called particles, will move in the solution space. The goal is to optimize a value known as the fitness function which is a measure of the goodness of the solution. The movement of the particles are affected by the best solution at the current iteration, the direction and amount of movement of that particle in the previous iteration, and some random number. More details on PSO can be found in [30].

ANN controller was compared against a classical Proportional Derivative (PD) controller. The PD controller was chosen for comparison since it is a widely used control algorithm. Therefore, the performance of the presented control algorithm could be benchmarked using one of the most popular control algorithms. The PD controller determines the amount of power to be used from the TES for the next time step, utilizing the current and previous power requirements of the building. The control equation for the PD controller is as follows,

$$\begin{aligned} &PowerFromTES(t+1) = \\ &\quad (\alpha \times P_{BUILDING}(t)) + \\ &\quad (\beta \times (P_{BUILDING}(t-1) - P_{BUILDING}(t-2))) \end{aligned} \tag{10}$$

where, α and β are constants that are determined by optimizing the controller using the training data specified in Table I. $PowerFromTES(t+1)$ is the power that is extracted from the TES for the next time step (next hour).

In the implementation, the re-cooling/ recharging of the TES was carried out based on a preset hard thresholds. A re-cooling time is the time interval in which the TES was re-cooled. During this time the TES was not be used to cool the building. A desired temperature threshold ($TESLowerTemp$ in Eq. 8) to which the chillers cooled the water down, was defined for the TES. The chillers was assumed to operate at maximum capacity until the desired temperature was reached, or the re-cooling time was over. The re-cooling time was set to be 9.00PM to 6.AM. The $TESLowerTemp$ was set to 2^0 Celsius.

The optimization criteria and other specifications were unchanged for both ANN and PD controllers. In order to test the effectiveness of the presented methodology three TES tanks (see Table III) was tested on the simulated building: **Test Case 1:** Small Tank, **Test Case 2:** Medium Tank, **Test Case 3:** Large Tank.

IV. EXPERIMENTAL RESULTS

This section presents the results obtained for the three test cases defined in Section III.

As mentioned, the goal of the TES is to decrease cost. Therefore wasted cost and the re-cooling were taken into consideration. Thus the experimental results for each test case in described are given in terms of 6 values: 1) Cost to cool the building if TES was not used, 2) Cost to cool the building with TES, 3) Amount saved in US dollars, 4) Percentage of savings and 5) Wasted cost.

Table VI presents the results for the three test cases in terms of the above mentioned values. It was noticed that the ANN controller achieved better cost savings for all the test cases when compared to the PD controller. It was noticed that the medium tank provided the best performance for both PD and ANN controllers. When using the medium tank, the ANN controller was able to produce a 6.501% increase in savings when compared to the PD controller. Using the ANN controller with the medium tank, the experiments yielded a savings of $4152.804 for the testing period. Thus, this method could be used to gain significant financial savings over longer periods. It should be noted that the cost without the TES remains the same for all the test cases since the same building was used for all the experiments.

Furthermore, it can be noticed that the wasted cost is much less in the ANN controller when compared to the PD controller. When using the medium sized tank, the PD controller wastes power which accounts to $546.578 while the ANN controller only wastes power which is worth $57.504. In addition, the ANN controller performed much better in terms of wasted cost in the two other test cases as well.

Therefore, from the experimental results obtained, it can be concluded that the presented ANN based controller outperforms the PD controller in all aspects, for the presented test cases.

V. CONCLUSIONS

This paper presented a ANN based control framework for a TES. The presented controller leveraged three main inputs: 1)

Current TES power availability, 2) Predicted Building power requirement for the next hour, 3) Predicted Utility load for the next hour. For the purposes of the paper, the three inputs were assumed to be already available. In addition to details about the proposed architecture the paper presented implementation details for the ANN based controller. The presented architecture implementation was tested by carrying out several experiments. The paper presented details about the experimental set up and the experimental results for each test case. In order to perform a comparative analysis, a classical proportional derivative (PD) was implemented. For each test case, the presented framework was compared against the PD controller. Results showed that the presented controller outperformed the classical PD controller in all of the cases. The presented ANN controller not only increased the financial savings but also reduced the cost wastage which occurs from overshooting the power requirement. Further experiments should be carried out to further improve the controller using different optimization algorithms.

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