Neural Network Based Downscaling of Building Energy Management System Data

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***Abstract*—Building Energy Management Systems (BEMSs) are responsible for maintaining indoor environment by controlling Heating Ventilation and Air Conditioning (HVAC) and lighting systems in buildings. Buildings worldwide account for a significant portion of world energy consumption. Thus, increasing building energy efficiency through BEMSs can result in substantial financial savings. In addition, BEMSs can significantly impact the productivity of occupants by maintaining a comfortable environment. To increase efficiency and maintain comfort, modern BEMSs rely on a large array of sensors inside the building that provide detailed data about the building state. However, due to various reasons, buildings frequently lack sufficient number of sensors, resulting in a suboptimal state awareness. In such cases, a cost effective method for increasing state awareness is needed. Therefore, this paper presents a novel method for increasing state awareness through increasing spatial resolution of data by means of data downscaling. The presented method estimates the state of occupant zones using state data gathered at floor level using Artificial Neural Networks (ANN). The presented method was tested on a real-world CO_2 dataset, and compared to a time based estimation of CO_2 concentration. The downscaling method was shown to be capable of consistently producing accurate estimates while being more accurate than time based estimations.**

***Keywords*—Data Downscaling, Building Automation, Artificial Neural Networks, Building State Awareness**

I. Introduction

Building Energy Management Systems (BEMS) are highly complex multi input multi output systems, which are responsible for maintaining indoor environment by controlling, Heating Ventilation and Air Conditioning (HVAC) and lighting systems in buildings.

Worldwide, buildings consume more than 20% of the total energy production [1]. Similarly, 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 green house gas production [4]. Due to economic growth and various other factors, these numbers are projected to increase [1], [5].

Building HVAC systems are the largest energy consumers in buildings [6]. It has been shown that over 30% of the building energy consumption is utilized by HVAC [6]-[9]. Thus, increasing building energy efficiency using BEMS can result in substantial financial gains. Furthermore, it has been shown that with close monitoring of the state of the buildings coupled with advanced control schemes, building energy efficiency can be increased by up to 40% [10]. Thus, improving HVAC control via BEMS is the most cost effective method to improve building energy efficiency [9].

A comfortable work environment has been shown to increase productivity and overall satisfaction of employees [11]. Thus, in addition to improving building energy efficiency, BEMSs should maintain a comfortable indoor environment [12]. This is achieved by closely monitoring factors such as temperature, humidity and CO_2 levels [13] inside the building and maintaining them within specified limits.

Thus, in order to maintain and improve both energy efficiency and occupant comfort, close monitoring of the building environment is necessary [2], [3], [14]. To achieve this, modern buildings rely on thousands of sensors strategically placed throughout the building [15]. However, with increased number of sensors, the cost is increased and the robustness of the system is decreased [15]. Thus, many buildings lack the instrumentation required for high resolution state awareness. Further, commissioning of the sensors and control system in buildings is done at the building design phase [12] and can be suboptimal if changes to floor-plans are made. Hardwired sensor networks are difficult to maintain and are inflexible [16] [17].

Therefore, this paper presents a novel methodology for increasing state awareness of buildings without the need of increasing the number of sensors. The presented method utilizes data downscaling to increase spatial resolution of data. This is achieved by estimating the state of occupant zones by utilizing data gathered at floor level of the building. The presented method uses Artificial Neural Networks (ANN) that are capable of learning the functional dependencies between the coarse spatial resolution floor level data and fine spatial resolution zone level data.

The data downscaling method presented in this paper was applied to a real-world CO_2 concentration dataset gathered from an office building in the Pacific Northwest. The presented method was capable of estimating zonal CO_2 level with high accuracy. Furthermore, the presented method was compared against a time based estimation of the CO_2 level and was shown to be more accurate than the time based estimation.

The rest of the paper is organized as follows. Section II introduces data downscaling. Section III briefly discusses ANN and discusses the presented ANN based data downscaling method. Section IV gives specific details about implementation and the dataset used in this paper and presents experimental results. Finally, Section V concludes the paper.

II. Data Downscaling

Data downscaling refers to the process of obtaining fine spatial resolution data from coarse spatial resolution data [18], [19]. Data downscaling identifies the functional dependencies between coarse data and fine data to derive the latter from the former. This enables estimation of the state of a smaller local area based on the state of a larger global area. The main advantage of data downscaling is the ability of gaining state awareness using spatially concentrated sensors. Thus, it is possible to reduce overall cost, communications and increase security without sacrificing state awareness. Data downscaling was initially developed to address the need of increased spatial resolution of environmental data [18].

Two main categories exist for data downscaling; process based nested models and empirical methods [18]. Process based methods involve solving the physical dynamics of the system explicitly [18]. Hence, they require detailed domain knowledge and exhaustive modeling of the system. For many applications obtaining such domain knowledge is difficult and modeling such systems can be computationally expensive [18]. Empirical downscaling methods are data driven techniques which use historical data to approximate the functional dependency between fine and coarse data. Thus, with limited domain knowledge and using lower computational resources empirical methods can be applied for data downscaling. Hence, due to the ease of implementation and the need of lower computational requirements empirical methods are more widely used [18]-[21].

A wide array of empirical downscaling methods which use statistics based models are documented in literature [18], [19]. Out of these, Statistical Downscaling Model (SDSM) [22], which uses Multiple Linear Regression method, is the most widely used statistical model [18]. Furthermore, methods such as stochastic modeling [24] and downscaling using interpolation [19] have also been used. Computational Intelligence (CI) methods such as K-Nearest Neighbor (KNN) [25], Artificial Neural Networks (ANN) [18], [25], [27] have been utilized for data downscaling as well. In literature, it can be found that the aforementioned downscaling methods are mostly applied in areas such as climate research [18], [21], [26], [27] and geological research [19]. In [27], the authors used Temporal Neural Networks (TNN) to downscale precipitation values and temperature that relates to climate variability and extremes. Furthermore, in [27] the authors compared TNN to a regression-based statistical downscaling method and showed that TNN outperforms the regression based model. In [19], several empirical downscaling methods were used for geological remote sensing.

III. ANN Based Data Downscaling for Building Sensor Data

This section first discusses Artificial Neural Networks (ANN), and then details the presented ANN based data downscaling method for building sensor data.

A. Artificial Neural Networks

ANN are Computational Intelligence (CI) architectures which are a proven methodology for optimization, forecasting, data mining, multidimensional nonlinear function approximation and many other areas [28], [29]. ANN are based on biological neural networks and have the capability of acquiring, storing and utilizing experiential knowledge [30].

The basic unit of an ANN is a neuron. Artificial neurons are modeled to behave in the same way as a biological neuron; each neuron has a set of inputs and produces an output based on the inputs.

Similar to a biological neuron, an artificial neuron produces an output by comparing the sum of each input to a threshold value. Based on that comparison, it produces an output. In addition, it is able to differently weigh each input according to the priority of the input.

An artificial neuron achieves that by using input vectors, weights, a threshold value and output vectors. For each input x_q there is a weight w_q assigned. The weighted sum of a neuron can be given as,

$$z = \sum_{q=1}^{n} w_q x_q \tag{1}$$

where, n is the number of inputs.

The output of the neuron is controlled by the activation function, value of which, act as a threshold. The output of the neuron a is given by:

$$a = f_s\left(\sum_{q=1}^{n} w_q x_q\right) \tag{2}$$

where, $f_s(x)$ is called the activation function, and in this case was the sigmoid activation function:

$$f_s(x) = \frac{1}{1 + e^{\lambda_s x}} \tag{3}$$

A neural network comprises of multiple interconnected neurons, arranged in several layers. There are one input and one output layer and multiple hidden layers. The neurons in the input layer have the activation function $f_s(x) = x$.

The output of neuron i in layer $l+1$ is calculated as:

$$x_i^{l+1} = \sum_{j=1}^{S_l} w_{ij}^{l+1} a_j^l + b_i^{l+1} \tag{4}$$

where S_l denotes the number of neurons in layer l, w_{ij}^{l+1} is the

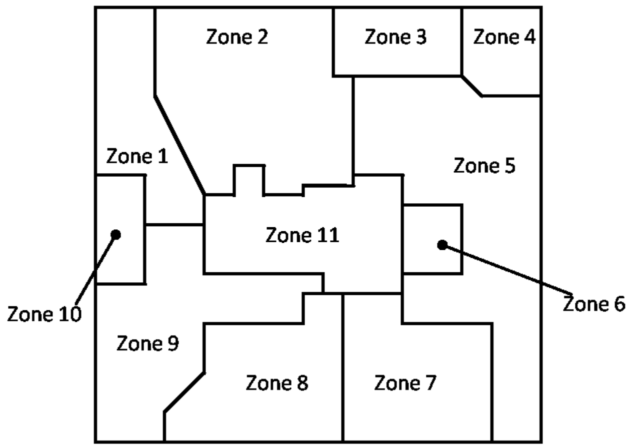

Fig. 1 Selected occupant zones for gathering fine spatial resolution CO_2 concentration data

weight of the connection from neuron j in layer l, b_i^{l+1} is the bias of neuron i and a_j^l is the output of neuron j in layer l.

The output of neuron i in layer $l+1$ is given by:

$$a_i^{l+1} = f_s^{l+1}(x_i^{l+1}) \tag{5}$$

For a given layer L we can calculate the error if the desired output is known using:

$$E = \sum_{p=1}^{P}\sum_{m=1}^{M}(d_{pm} - x_{pm}^{L})^2 \tag{6}$$

where, P is the number of patterns, M is the number of outputs and d_{pm} is the desired output pattern p and output m.

B. ANN Based Data Downscaling for Buildings

As mentioned, data downscaling entails the estimation of information at a certain point in space using known information from a point that is located at a different place in space. For this to be feasible, a functional dependency between the known information and the estimated information should exist:

$$I_e(t) = f(I_k(t), U) \tag{6}$$

where, $I_e(t)$ is the estimated information at time t and $I_k(t)$ is the known information at time t. U is a set of other factors that affect I_e that is independent from I_k, and $f()$ is the functional dependency between I_e and I_k. If the functional dependency $f()$ and the set of factors U are known then I_e can be calculated using I_k. However, in complex systems and environments, the functional dependency and the set of factors that affect I_e independently is difficult to identify and model.

In a constrained environment such as a building, the set of factors that affect I_e independently of I_k (U) is minimal. Furthermore, if the estimated information I_e and known information I_k are gathered simultaneously, and are in close proximity the effect of U on $f()$ is minimal. Therefore, in this work U is assumed to be an empty set:

$$U = \{\} \tag{7}$$

However, as shown in Fig. 2 the functional dependency between I_k and I_e, as well as I_e and t is highly non-linear and complex. Therefore, this paper proposes a methodology that utilizes the well documented function approximation capabilities of ANN to identify the functional dependency between I_e and I_k using historical data.

The presented method utilizes historical data gathered from the location of the estimated information to learn $f()$. Once $f()$ is learnt, the ANN is capable of estimating I_e given I_k. To further enhance the learning of $f()$, k previous time steps along with the first derivative of each time step is also used as inputs for the ANN:

$$P = \{I_k(t), I_k(t-1)\ldots I_k(t-k), \frac{d(I_k(t-1))}{dt}\ldots\frac{d(I_k(t-k))}{dt}\} \tag{8}$$

$$O = I_e(t) \tag{9}$$

where, P is the set of inputs to the ANN and O is the set of outputs. Thus, the number of inputs to the ANN is $2k + 1$.

Fine spatial resolution data is required for initial training of the neural networks. This can be gathered by implementing a temporary set of sensors for data collection or by using a state-based estimation model of the building.

Thus, using the presented methodology, a better state awareness of building environment can be obtained without increasing the number of existing sensors. This information can then be used for advanced control of HVAC systems for improved energy efficiency and occupant comfort.

IV. Implementation and Experimental Results

This section presents the dataset used for this paper, the specific implementation parameters and then details the results acquired from the experiment.

A. Dataset

Indoor Air Quality (IAQ) refers to the quality of the air that building occupants consume indoors and it is the most important criterion of a HVAC system [31]. In addition to comfort and building energy efficiency, IAQ is directly related with occupant health and can be causes of illnesses such as, Sick Building Syndrome (SBS) and Building Related Illness (BRI) [32]. IAQ is adversely affected substantially by gaseous pollutants such as Carbon Monoxide (CO) and Carbon Dioxide (CO_2) [32]. Furthermore, accurate CO_2 concentration information can be used for advanced building automation for improved energy efficiency.

Thus, the presented method was tested on a CO_2 concentration dataset gathered from a multi-floor office building in the Pacific Northwest.

For testing purposes, CO_2 concentration data with fine spatial resolution was gathered by implementing a temporary, wireless sensor network in one floor of the building. Nine different occupant zones were identified and wireless CO_2 sensors were deployed in each zone. Fig. 1 shows the selected

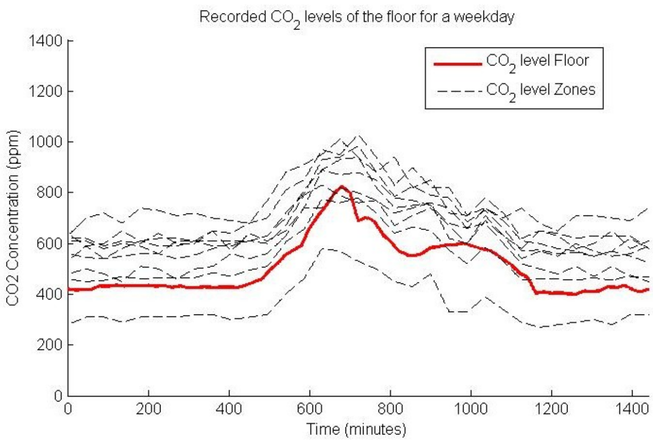

Fig. 2 Fine and coarse spatial resolution CO_2 concentration data gathered for a weekday

occupant zones. Zones 1 through 9 were identified as occupant zones and zones 10 and 11 are unoccupied zones. Temporary wireless CO_2 sensors were placed in the occupant zones.

The coarse spatial resolution data was CO_2 concentration data that was extracted from the existing BEMS. This CO_2 concentration sensor is located in the return air duct of the air handling unit of the selected floor. Using the presented ANN based data downscaling method, the functional dependency between the coarse floor level CO_2 concentration and fine zone level CO_2 concentration will be indentified.

The experimental data was gathered for a time period of one month at one minute time intervals. Both fine and coarse spatial CO_2 concentration data was measured in terms of Parts Per Million (PPM) and the observed minimum was 280ppm and maximum was 1229ppm. Fig. 2 shows the variations of zonal CO_2 concentrations and CO_2 concentrations of the floor on a typical weekday. In order to facilitate faster learning and easier manipulation all the data was normalize between -1 and 1 using the observed minimum and maximum values.

TABLE I

TRAINING AND TESTING ERRORS OF THE TWO METHODS TESTED

Error	Time Based CO_2 Estimation	Downscaling Based CO_2 Estimation
Training MSE	5.1×10^{-4}	1.3×10^{-4}
Testing MSE	3.4×10^{-3}	1.6×10^{-3}

B. Implementation of Data Downscaling

The presented data downscaling method was implemented for the data described above. Since CO_2 concentration of each zone has a different functional dependency to the higher level spatially coarse value, a separate ANN for each zone was trained. Thus, 9 ANNs were trained. Each ANN trained contained 2 hidden layers with 9 and 7 neurons in each. The input layer contained 11 neurons while the output layer contained 1 neuron.

The aforementioned architecture was selected after evaluating the results for different NN architectures. First, an architecture with two layers with 2 neurons in each layer was tested. Then, the results were evaluated by increasing the number of neurons in each layer and number of layers. The selected architecture was identified as the architecture which produced the best results. Furthermore, the results did not show a significant improvement when the number of neurons were increased beyond that point.

As mentioned in Section III, for higher accuracy k historical steps and derivative of each step of the coarse data is provided as inputs. In this case, k was set to 3, i.e. sensor values for 3 minutes prior to the current value and their derivatives were used as the inputs. All inputs were normalized and once the outputs were generated, they are normalized to retrieve the actual CO_2 concentration in PPM.

The first 18 days (60% of the data) of the collected data

TABLE II

COMPARISON OF RESULTS OBTAINED BY TIME BASED ESTIMATION AND ANN BASED DATA DOWNSCALING METHOD

Zones	Time Based				Data Downscaling. Based			
	MSE $\times10^{-3}$	Max Absolute Error (ppm)	Max Percent Error %	Standard Deviation (ppm)	MSE $\times10^{-3}$	Max Absolute Error (ppm)	Max Percent Error %	Standard Deviation (ppm)
Zone 1	2.17	58.24	10.14	41.06	1.33	41.21	8.45	26.5
Zone 2	3.62	56.11	9.54	35.32	2.58	34.02	4.21	18.11
Zone 3	2.57	110.69	15.32	40.05	1.89	24.91	5.78	6.63
Zone 4	4.63	134.02	14.54	43.87	2.63	54.61	9.35	27.4
Zone 5	2.12	40.34	7.21	23.89	0.88	12.53	2.14	7.29
Zone 6	1.14	38.58	5.21	21.07	0.93	17.32	3.53	8.03
Zone 7	1.83	67.23	10.43	39.36	1.43	38.16	5.12	14.82
Zone 8	11.23	154.56	17.24	62.09	1.48	40.83	6.31	15.37
Zone 9	1.39	65.36	11.65	34.31	1.53	53.6	5.12	25.93

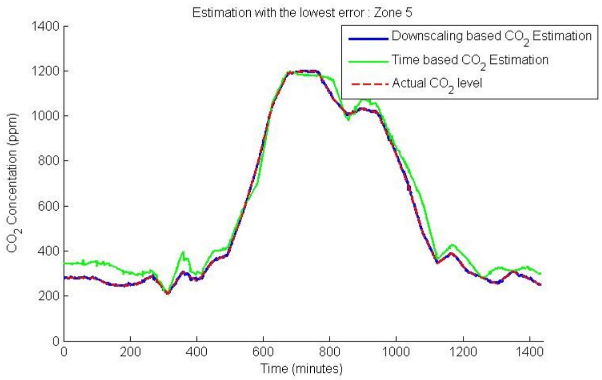

Fig. 3 Estimated and actual CO_2 concentration for zone 5 on day 6. (Zone with the lowest estimation error)

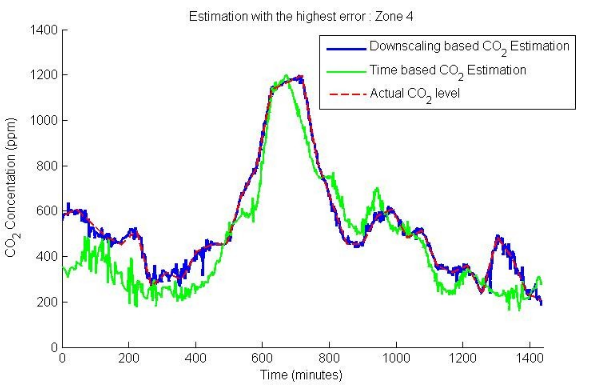

Fig. 4 Estimated and actual CO_2 concentration for zone 4 on day 11 (Zone with the highest estimation error)

were used for training and the remaining 12 days were used for testing.

C. Experimental Results

The presented data downscaling method for buildings was applied to the dataset described above. The performance of the presented method was evaluated using Mean Square Error (MSE), the absolute error, standard deviation of the absolute error, and the percent error.

The presented method was compared to a purely time based estimation of fine spatial data. For this, the relationship between the time of day and the CO_2 concentration was utilized and the same ANN architecture was used with the exception of the input layer. The time of day and the day of the week were used as inputs for the time based estimation. Furthermore, the same set of training and testing portions was used to train the time based ANN.

Table I shows the overall training and testing errors for the time based estimation and the presented data downscaling based method. Table II elaborates the results of the two for each zone for the 12 testing days. It can be observed that for all zones the presented downscaling method estimated the CO_2 level more accurately than the time based method. The observed maximum percentage error was lees that 10% in all cases for the downscaling method. Furthermore, the low standard deviation of the presented method indicates the capability of consistently estimating the CO_2 value.

The lowest testing MSE for a zone was 8.8×10^{-4} and was for zone 5, whereas the highest testing MSE was for zone 4 and was 2.6×10^{-3}. Fig. 3 and Fig.4 respectively depict the zones with the lowest and highest errors achieved by the presented method for a time period of a day.

V. Conclusion

This paper presented an Artificial Neural Networks (ANN) based method for data downscaling for improved building state awareness. The presented method utilizes existing, sensors with coarse spatial resolution to estimate data with a finer spatial resolution.

The presented method was tested on a real-world CO_2 sensor dataset gathered for a time period of a month, from an office building in the Pacific Northwest. The presented method was tested against estimation which was based on time alone, and was shown to be more accurate. Further, the standard deviations of errors in the presented downscaling method was lower compared to the time based estimation, confirming that the presented method is consistent it estimating high resolution CO_2 data.

As future work, the presented method will be implemented for other sensors such as, temperature, occupancy, humidity, etc. In order to increase the estimation accuracy, other factors that affect building environment will be added to the presented method. Furthermore, the feasibility of utilizing the presented method for advanced control of BEMS will be explored.

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