THE USE OF LEARNING ALGORITHMS FOR REAL-TIME IMMERSIVE DATA VISUALIZATION IN BUILDINGS

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Abstract

Computational Fluid Dynamic (CFD) simulations are used to predict indoor thermal environments and assess their response to specific internal/external conditions. Although computing power has increased exponentially in the past decade, CFD simulations are time consuming and their prediction results cannot be used for real-time immersive visualization in buildings. A method that can bypass the time consuming simulations and generate "acceptable" results will allow such visualization to be constructed.
This paper discusses a project that utilizes Artificial Neural Network (ANN) as a learning algorithm to predict post-processed CFD data to ensure rapid data visualization. The technique has been integrated with an immersive Augmented Reality (AR) system to visualize CFD results in buildings. ANN was also evaluated against a linear regression model. Both models were tested and validated with datasets to determine their degree of accuracy. Initial tests, conducted to evaluate the user's experience of the system, indicated satisfactory results.

1. Introduction

CFD simulations of flow movements provide accurate views of three-dimensional behavior of complex systems. These systems are currently being used in building design and evaluation. Visualization of CFD results has evolved from two to three dimensional analyses. Recently, several research efforts were conducted to utilize CFD data in Virtual Reality (VR) and Augmented Reality (AR) environments [1-3]. In addition, Human-Computer Interaction (HCI) techniques have been used to interface with CFD data results to allow efficient data manipulation and comprehension [4].

Despite the significant advances in CFD visualization techniques and computer hardware, real-time data visualization remains a challenge. This is primarily due to the time-delay associated with solving simulation equations. Several research projects were conducted to enable rapid explorations of post-processed data. Examples of such research include the following studies: parallelized computation [5], out-of-core particle tracing [6], load balancing [7], and immersive CFD data visualization [8]. In addition, techniques utilized to lower the time spent in data generation were also developed. These include the following: selective visualization [9] and feature extraction [10,11].

Despite the efforts of these researchers, these techniques cannot be employed for real-time data visualization. One approach to solve this problem is using approximation techniques to bypass time-consuming simulations and generate "acceptable" results to allow real-time visualizations, figure 1. Owing to their generalization, learning algorithms can aid in data approximation.

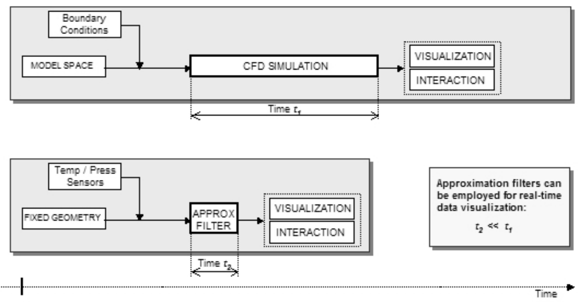


Figure 1. Data generation methods – traditional CFD simulations and data approximation.

Learning algorithms gain knowledge based on the input / output of system behavior. These algorithms include both supervised and unsupervised learning, and have been widely used for variety of applications such as speech recognition, genetic mapping, etc [12]. While supervised learning algorithms (e.g., linear regression, neural network, etc.) require extracting features that can be used as training sets, unsupervised learning algorithms (e.g., reinforcement learning, Q-learning, etc.) neither rely on supervision nor require extracting features [13]. Learning algorithms can be used to develop systems that will predict the building behavior based on their learning experience.

This paper describes the use of a learning algorithm model for real-time data visualization. The model utilizes Artificial Neural Network as a learning algorithm and compares it to a linear regression algorithm. In addition to detailed descriptions of the experimental setup, constraints, and results, this paper presents a comparison of the two algorithms, and proposes future directions.

2. Data approximation model

The Data Approximation model consists of two modules – space representation and learning algorithms, figure 2. Space representation accounts for room geometry, its properties, and internal obstructions. The learning algorithm used is an Artificial Neural Network that is trained using input / output data based on the building thermal behavior.

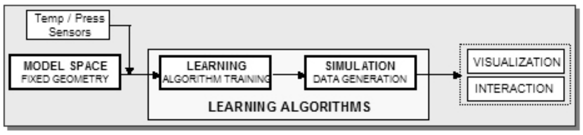


Figure 2. Data Approximation model.

The generated data is integrated with an AR visualization module to test its applicability for real-time data visualization [8].

The space used for training was a 7.16m (length) x 4.80m (width) x 3.66m (height) room that is located in an interior zone, i.e., with no exposure to exterior conditions. The boundary conditions of the room were constant except for the air and temperature changes caused by a mechanical system through an air diffuser. The training utilized1224 nodes that represent the indoor space in terms of X-Y-Z axes. The boundary conditions were the temperature (T_i) and pressure (P_i) of the air supply.

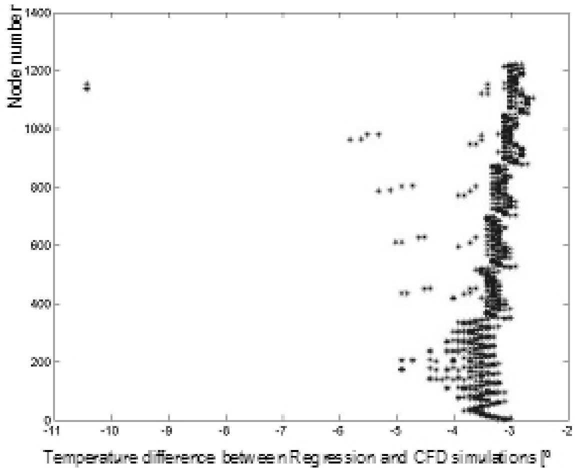
To generate the training set, CFD simulations were performed by changing the boundary conditions, specifically changing the inlet-temperature (T_i) from 25°C to 35°C, and varying the inlet-pressure (P_i) from 0.2 to 0.25 Pascal. The inlet-temperature and pressure were incremented by 0.5°C and 0.05 Pascal respectively. The output of the nodal temperature and velocity in the three-dimensional space was fed to two learning algorithms to investigate their potential in generating acceptable results for rapid visualization. Table 1 presents the input / output parameters for the learning algorithms.

Table 1. Description of input-output variables.

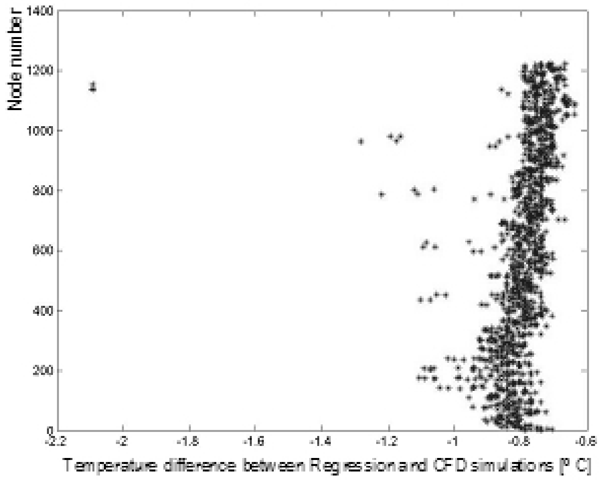
Parameters		Input/Output	Data Type
Inlet temperature	T_i	Input	Numeric
Inlet pressure	P_i	Input	Numeric
Temperature at every node	$T_{o(xyz)}$	Output	Numeric
Velocity magnitude at every node	$V_{o(xyz)}$	Output	Numeric

2.1. Learning using statistical analysis

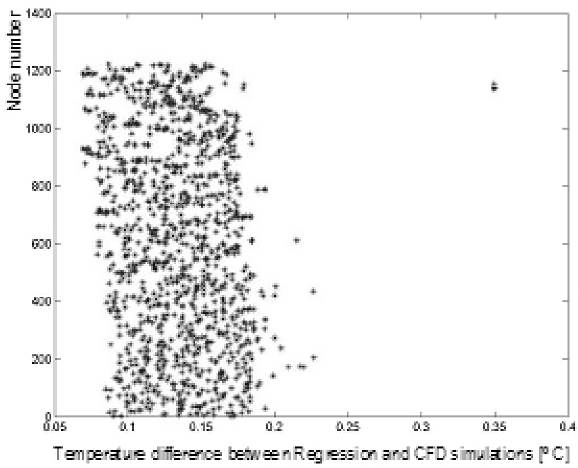
Linear Regression is a simple statistical approach for fitting a curve through a set of input / output points with a generalization error [14]. Linear regression allows a variable to correlate with two or more independent variables by *least squared fit*. For comparison purposes, linear regression algorithm was integrated to the approximation model. Data generated using CFD simulations were used for training. After sufficient training and validation, the linear regression learning algorithm was tested with new inlet temperature and pressure values, and compared with regular CFD simulations, figures 3-6.



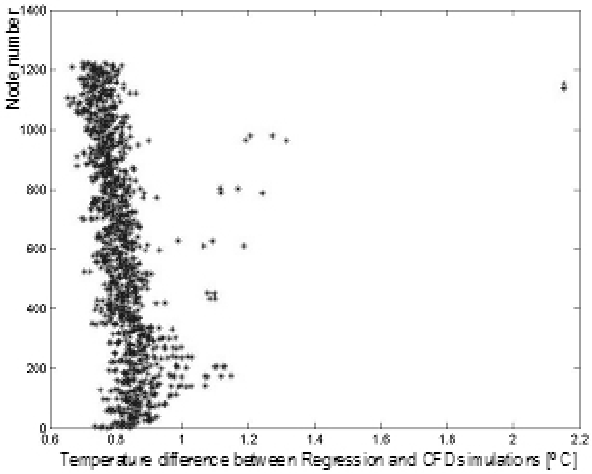
Figures 3. Inlet temperature maintained at 10°C.



Figures 4. Inlet temperature maintained at 20°C.



Figures 5. Inlet temperature maintained at 30°C.



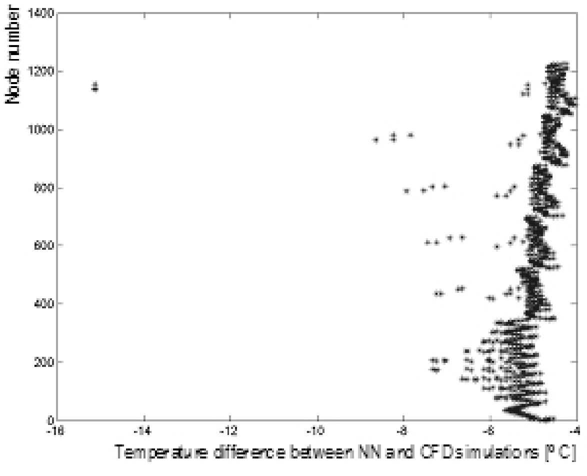
Figures 6. Inlet temperature maintained at 40°C.

Learning using the linear regression algorithm was satisfactory only for training sets that were inside the training range. A different algorithm to allow better generalization is needed. This prompted the use of the ANN learning algorithm described in the next section.

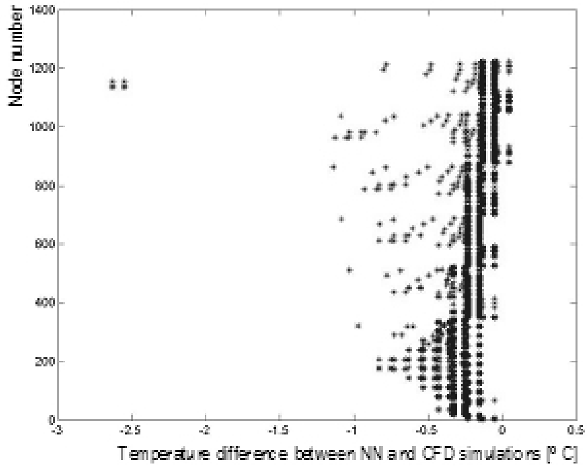
2.2. Learning using artificial neural network

Back Propagation Network (BPN), a type of ANN, was used. BPN utilizes the Widrow-Hoff learning rule that iteratively adjusts the weights of the connection matrix in order to maximize the quality of re-organization of the input parameters [15]. The BPN consists of a four-layered neural network, with two hidden layers and two neurons each that represented the functional relationship between the inputs and outputs.

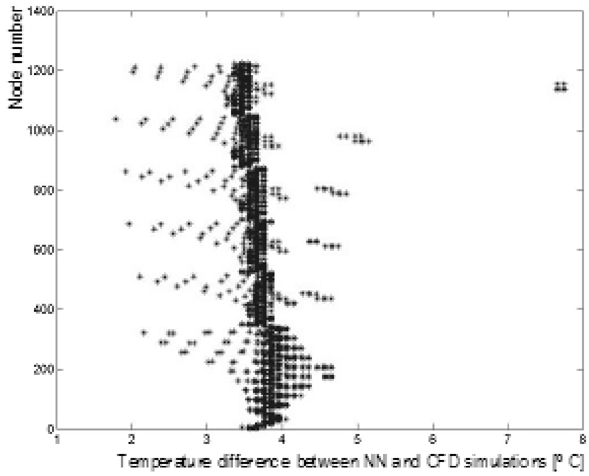
Simulating the ANN learning algorithm with training data resulted in varied weights for input / output variables. The learning algorithm was tested with validation datasets to determine the degree of accuracy the model can achieve. After satisfactory training, the model was provided with new inlet temperature and pressure values to generate corresponding nodal temperature and pressure data. The model predictions were compared with regular CFD simulations, figures 7-10.



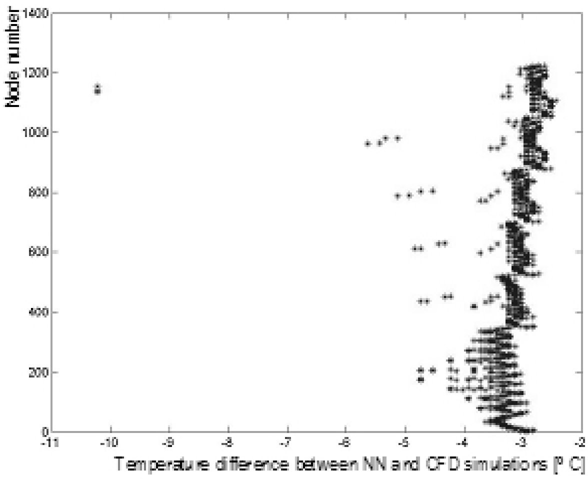
Figures 7. Inlet temperature maintained at 10°C.



Figures 8. Inlet temperature maintained at 20°C.



Figures 9. Inlet temperature maintained at 30°C.



Figures 10. Inlet temperature maintained at 40°C.

Artificial Neural Network learning was satisfactory for input ranges that were both inside and outside the training data ranges. However, generalizing with small datasets is difficult using ANN learning algorithms. This might lead to erroneous results. In addition, for any new spatial geometry, new sets of training data are required for sufficient generalization of the algorithm.

3. Human building interaction framework integration

The Data Approximation model was integrated with an interactive, immersive AR system for real-time data visualization, figure 11. This system is an interactive speech and gesture recognition-based, immersive AR system specifically designed to visualize and interact with buildings and their thermal environments [8]. As the boundary conditions of the room changed, the integrated ANN learning model generated corresponding CFD datasets. They were stored in Virtual Reality Modeling Language (VRML) format as iso-planes and iso-surfaces for quick display on Head Mounted Device (HMD). Data manipulation in real-time was achieved by intelligent speech and gesture recognition mechanisms. While the speech interface established the context, the gesture mechanism transformed the user's actions into a set of functions for data manipulation. Based on the user's action, corresponding VMRL data were passed onto the HMD for real-time immersive visualization. Initial tests conducted to evaluate the user's experience indicated satisfactory results.

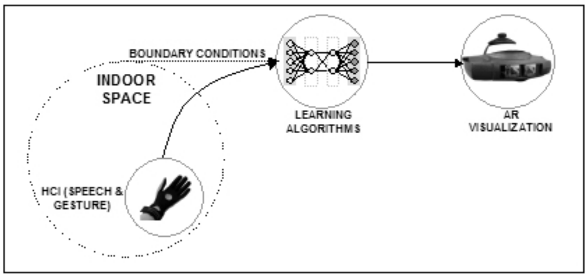


Figure 11. Integration of Human-Building Interaction and Data Approximation model.

4. Conclusions

The Data Approximation model demonstrated the potential of real-time data visualization with the aid of learning algorithms. Although linear regression and Artificial Neural Network learning algorithms enabled such visualization, the space was limited in terms of geometry and shape. In addition, good generalization of the algorithms require massive training datasets which are time consuming and often, infeasible. The study showed ANN learning algorithm as a definite improvement over linear regression learning for a fixed geometry. In both cases, modification of spatial geometry required new training datasets. This demands massive training datasets to predict for a variety of spatial configuration, which is infeasible.

To develop a generic learning model for real-time data visualization, a more rigorous learning algorithm is needed. Such an algorithm can generate CFD datasets for a wide range of spatial configurations. This calls for algorithms that adapt to "on-line" learning without relying on supervision. One such learning model is *Reinforcement Learning* that utilizes a formal framework defining the interaction between a learning agent and its environment.

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