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Pseudo dynamic transitional modeling of building heating energy demand using artificial neural network

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ABSTRACT

This paper presents the building heating demand prediction model with occupancy profile and operational heating power level characteristics in short time horizon (a couple of days) using artificial neural network. In addition, novel pseudo dynamic transitional model is introduced, which consider time dependent attributes of operational power level characteristics and its effect in the overall model performance is outlined. Pseudo dynamic model is applied to a case study of French Institution building and compared its results with static and other pseudo dynamic neural network models. The results show the coefficients of correlation in static and pseudo dynamic neural network model of 0.82 and 0.89 (with energy consumption error of 0.02%) during the learning phase, and 0.61 and 0.85 during the prediction phase, respectively. Further, orthogonal array design is applied to the pseudo dynamic model to check the schedule of occupancy profile and operational heating power level characteristics. The results show the new schedule and provide the robust design for pseudo dynamic model. Due to prediction in short time horizon, it finds application for Energy Services Company (ESCOs) to manage the heating load for dynamic control of heat production system.

1. Introduction

The global concerns of climate change and regulation in energy emissions have drawn more attention toward researchers and industries for the design and implementation of energy systems for low energy buildings. According to IEA statistics [1], total energy use globally accounts for around 7200 Mtoe (Mega Tonnes Oil Equivalents). Residential and commercial buildings consume 40% of final energy use in the world and European countries consume 76% of energy toward thermal comfort in buildings. The small deviations in design parameters of buildings could bring large adverse effect in the energy efficiency and which, additionally, results in huge emissions from the buildings. It is estimated that improvement in energy efficiency of the buildings in European Union by 20% will result in saving at least 60 billion Euro annually [2]. So, research is very active in driving toward the sustainable/low energy buildings. In order to accomplish this and to ensure thermal comfort, it is essential to know energy flows and energy demand of the buildings for the control of heating and cooling energy production from plant systems. The energy demand of the building system, thus, depends on physical and geometrical parameters of buildings, operational characteristics of heating and cooling energy plant systems, weather conditions, appliances characteristics and internal gains.

There are various approaches to predict building energy demand based on physical methods and data-driven methods (statistical and regression methods and artificial intelligence methods) as mentioned by Zhao and Magoules [3]. Physical methods are based on physical engineering methods and uses thermodynamics and heat transfer characteristics to determine the energy demand of the building. There are numerous physical simulation tools developed as EnergyPlus [4], ESP-r [5], IBPT [6], SIMBAD [7], TRNSYS [8], CARNOT [9] etc. . . to compute the building energy demand. A simplified physical model based on physical, geometrical, climatic and occupant model was presented by Duanmu et al. [10] to bridge the complexities of collecting more physical data required in simulation tools. Other possible approaches for building energy prediction are semi-physical models like response factor method, transfer function method, frequency analysis method and lumped method [11]. Though methodologies adapted to estimate energy demand of buildings are different in physical and semi-physical models, both are highly parameterized. In addition, physical parameters of buildings are not always known or even sometimes data are missing. And

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also, these models are computationally expensive for Energy Services Company (ESCOs) to manage heating and cooling loads for control applications.

Other approaches to predict building energy demand with limited physical parameters are data-driven methods, which strongly dependent on the measurements of historical data. Statistical and regression methods seem more feasible to predict building energy demand with limited physical parameters. The statistical approaches have been widely used by Girardin et al. [12] to determine the best model parameters by fitting actual data. Different approaches (physical and behavior characteristics based on statistical data) were presented by Yao and Steemers [13] to bridge the gap between semi-physical and statistical methods. In their work, statistical daily load profile was grounded on energy consumption per capita and human behavior factor, and semi-physical method was based on thermal resistance capacitance network. Nevertheless, these statistical models used linear characteristics of input and output variables to evaluate the building parameters and are not adapted to non-linear energy demand behavior. Regression models [14,15] have also been used to predict the energy demand, but, they are not accurate enough to represent short term horizon (couple of days) with hourly (or couple of minutes) sampling time energy demand prediction. In order to find the best fitting from the actual data, this kind of models requires significant effort and time.

In recent years, there is a growth in research work in the field of artificial intelligence (AI) like artificial neural network [3,16] and support vector machines [3,17,18]. These methods are known for solving the complex non-linear function of energy demand models with limited physical parameters. Neural network method has shown better performances than physical, statistical and regression methods. Authors [19,20] used static neural network to predict energy demand of the building and compared results with physical models. For instance, Kalogirou et al. [19] used climate variables (mean and maximum of solar radiation, wind speed, and other parameters as wall and roof type) coupled with artificial neural network (ANN) to predict daily heating and cooling load of the buildings. In their work, results obtained using ANN are similar to those given by the physical modeling tool TRNSYS. Neto and Fiorelli [20] presented a comparison of neural network approach with physical simulation tool EnergyPlus. In this work, authors used climate variables as external dry temperature, relative humidity and solar radiation as input variables to predict daily consumption of the building. Results showed that neural network is slightly more accurate than EnergyPlus when comparing with real data. Static neural network model proposed by Shilin and Zhifeng [21] consider climate variables as dry bulb temperature and information regarding schedule of holiday's to predict cooling power of residential buildings. Dong et al. [17] used support vector machine (SVM) to predict the monthly building energy consumption using dry bulb temperature, relative humidity and global solar radiation. Performance of SVM and neural network model wee compared and results show that SVM was better than neural network in prediction.

Various authors [22–26] performed hourly building energy prediction using ANN. Mihalakakou et al. [22] performed hourly prediction of residential buildings with solar radiation and multiple delays of air temperature predictions as input variables. Ekici and Aksoy [23] used building parameters (window's transmittivity, building's orientation, and insulation thickness) and Dombayci [24] used time series information of hour, day and month, and energy consumption of the previous hour to predict the hourly heating energy consumptions. Gonzalez and Zamarreno [25] used time series information hour and day, current energy consumption and predicted values of temperature as input variables to predict hourly energy consumption of building system. Popescu et al. [26] used climate variables as solar radiation, wind speed, outside temperature of previous 24 h, and other variables as mass flow rate of hot water of previous 24 h and hot water temperature exit from plant system to predict the space hourly heat consumptions of buildings. Li and Meng [18] used SVM to predict hourly cooling load of office building using climate variables as solar radiation, humidity and outdoor temperature. In their work, SVM was compared with static neural network and result showed SVM better than static neural network in terms of model performance. Dynamic neural network method which includes time dependence was presented by Kato et al. [27] to predict heating load of district heating and cooling system based on maximum and minimum air temperature. Kalogirou and Bojic [28] used Jordan Elman recurrent dynamic network to predict energy consumption of a passive solar building system based on seasonal information, masonry thickness and thermal insulation.

For many authors [29–31] occupancy profile has a significant impact on building energy consumption. Sun et al. [29] mentioned that occupancy profile period has a significant impact on initial temperature requirement in the building during morning. In their work, reference day (the targeted day prediction which depends on previous day and beginning of following day based on occupancy and non-occupancy profile period) was calculated based on occupancy profile period. In addition to this value, correlated weather data and prediction errors of previous 2 h were used as input variables to predict hourly cooling load. Yun et al. [30] used ARX (autoregressive with exogeneous i.e. external, inputs) time and temperature indexed model with occupancy profile to predict hourly heating and cooling load of building system and compared this with results given by neural network. Results showed that occupancy profile has a significant contribution in determination of auto regressive terms during different intervals of time and further showed a variation of it in the building heating and cooling energy consumption. The proposed ARX model showed similar performance with neural network. Sensitivity analysis for heating, cooling, hot water, equipment and lighting energy consumption based on occupancy profile was performed by Azar and Menassa [31] for different sizes of office buildings. In their work, they found that heating energy consumption has the highest sensitivity compared to cooling, hot water, equipment and lighting energy consumption for small size buildings. Also, results showed that heating energy consumption is highly influenced by occupancy profile for medium and small buildings during the occupancy period. Moreover, few literatures focused on operational power level characteristics (schedule of heating and cooling energy to manage energy production from plant system). For example, Leung et al. [32] used climate variables and operational characteristics of electrical power demand (power information of lighting, air-conditioning and office equipment which implicitly depends on occupancy schedule of electrical power demand) to predict hourly and daily building cooling load using neural network.

In conclusion, it can be reiterated that physical and semi-physical models [4–11], though give precise prediction of building energy, they are highly parameterized and are computationally expensive to manage the energy for control applications for ESCOs. Data-driven methods which depend on measurement historical data are not effective during the early stage of building operation and construction since measurement data are not available at these stages. When building energy data are available, data-driven methods can be considered if measurement data are accurate and reliable as this kind of models can be sensitive on the quality of measured data. Sensitivity of the accuracy of data driven models, thus, depends on the measurement data. Data-driven models based on statistical and regression methods [12–15,26] cannot precisely represent short time horizon (couple of days) with hourly (or couple of minutes) sampling time prediction, though they perform prediction of energy consumptions of buildings with limited