A Review on HVAC Controller for High Energy Efficiency Commercial Building

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Abstract

The ever-increasing population and advancing municipal business demands for new building construction are often regarded as the most significant contributors to energy management. For many practical applications, machine learning is a promising method. In this perspective, we demonstrate machine learning development and application. One best way of decreasing energy usage in new buildings is to look at energy efficiency at an early stage in the design. Efficient power management and intelligent renovation can improve existing stock's energy performance. For optimal decision-making, all of these systems include an exact energy forecast. In recent years, machine learning (ML) and artificial intelligence (AI) technology have been introduced to predict building energy consumption and performance in specific terms. This article addresses hard, soft, and hybrid control systems, as well as machine learning techniques including artificial neural networks, clustering, and support vector machines which are frequently utilized in building energy performance forecasts and improvement. The hybrid approach suggestion significantly expands machine learning applications.

Keywords: HVAC, Demand Response, PID, Artificial Neural Network (ANN),Energy Management, Machine Learning .

1 Introduction

Buildings will play a leading role in ensuring that the future energy system operates securely and efficiently, representing around 40% of world energy use annually. Flexible loads, control on the side of demand, and peak scrub are not new notions; demand response was employed in certain grids in the 1970s [8]. For the robust home energy management and heating, ventilation, and air conditioning control (HVAC) systems scheduled to be developed for smart home appliances to improve building energy versatility, the development of advanced requirement side management controls has an essential role [20]. In addition, precise predictions of energy demand in the face of uncertainty are important to district management of urban energy systems through the application of a hierarchical methodology [6]. There is no universal flexibility quantification approach for sophisticated building energy systems that considers thermal-electric energy sources, Cooling, heating, and electrical energy storage, also adaptive energy management methods are all specimens of solar to electric and electrical to thermal conversions. Second, advanced nonlinearity and complexity of energy predictions, such as modeling generation and computing load, not been able to effectively and efficiently addressed, mainly when multi-level uncertainty factors are considered. Accurate forecasts of building energy with simpler prototypes and machine learning techniques have a lot of possibilities for aiding energy-efficient structures. Third, no academic research has been performed on the progress of sophisticated controllers for small duration building energy forecasting under complex scenario uncertainty. The influence of sophisticated controllers on the energy flexibility of buildings should be fully examined. Meteorological factors, Temperatures of cold water supplied and returned, interior air set point temperature, and other variables are all linked to real-time system functioning. At initial stages building energy consumption is found by using evaluation technique which is an instructive tool for giving decision-makers an energy efficiency comparison index. Commonly, during a certain time formed by floor area, the energy consumption of buildings is utilized to describe an enactment (kWh/m2/period) known as the EPI or energy intensity (EUI) The energy evaluation of buildings is divided into four primary groups: Engineering, Simulation Benchmarking and Machine Learn and Statistical Modeling (ML). Technically the rules of derivation of construction energy consumption on the entire or subsystem level are employed in engineering methodology. Internal and external characteristics are considered for all construction components also the complicated mathematics or building dynamics employ the most exact methodologies for the derivation of correct energy use [18]. Simulation of power efficiency building comprises performance simulation tools and computer models with a predetermined status. Computer simulation may generally be utilized in several areas, for example in lighting and HVAC system design. The use of updated methodologies to evaluate energy performance has been made possible by the availability of building energy data. The methods of statistics employ historical data on buildings and commonly use regression in models of building energy consumption/performance [18].

2 Related Work

Dynamic processes with temporal delays cannot be controlled successfully by on or off controllers. Only if operating circumstances do not differ from tuning settings [1] is a satisfactory performance of the PID controller guaranteed. PID Gain-Scheduling shows increased stability compared with regular PID controllers, however, the linear areas must be identified and logic to switch regions must be developed. The PID controller needs to be manually tuned and might be tough. In the evaluations of [13] [15] and [12] many metrics have been taken to compare the results of various controls. However, they do not take into account fully the possibility for flexibility. In the recent decade, MPC research has accelerated. The fact is the control approach can save energy while preserving or even increasing thermal comfort in buildings is widely recognized and demonstrated. To utilize demand-side flexibility that construction could give, researchers are showing alternative ways to employ MPC in building control systems in conjunction with thermal energy storage systems. The temperature of the zone is also the standard experimental control variable. [9] An MPC was integrated into an HVAC system and the robustness of the MPC was enhanced as well as the tracking performance of the PID controller. This case study investigates and compares the usage of a revolutionary deep reinforcement learning algorithm for controlling building space heating in a computationally efficient method. In a simulated scenario, the suggested method beats rule-based control by 5-10% for a variety of price signals. We find that, while not optimum, the proposed approach has significant practical advantages over other well-established methods, such as quicker calculation times and improved resistance to non stationarity in building dynamics. Reinforcement learning (RL) [13] has emerged as a viable alternative to MPC in several fields in recent years. The attraction of RL is its potential to approach or exceed the optimum degree of control given by predictive model controls while learning from sensor data directly, that is, without the presence of a model beforehand. ANN may be used to determine energy performance evaluation criteria for buildings. [11]proposes a pre-determination technique for the coefficient of total heat loss, total heat capacity, and the recovery factor, which are the important factors for energy efficiency calculation. [5] ANN uses 6500 energy labels in Italy as a method for evaluating the correctness of energy building certifications. A new combination of input variables is investigated in the study to decrease the number of training features. Using the ANN output, a new index for the correctness of energy certificates declaration data with a low 3.6 error is presented. The scholarly scholars did an unclear study of the needs of construction and of renewable. The multi-target optimization was carried out in the viewpoint of renewable generations [17], integrating uncertainties in renewable energy and forecasting demand projection errors. From its results, the suggested technique to optimization has been efficient in optimizing several targets with uncertainties and lowering local emissions of pollutants. A complex multi-sector target program has been designed to give building owners additional flexibility to supply In unpredictably and imprecise situations, an efficient renewable energy strategy of different renewable energies [17]. From the outcomes of the suggested approach, sustainable development has been achieved effectively. About energy demand in buildings [10], the uncertainty on overall energy consumption in buildings was around 14%. [4] The insecurity study was performed with the Monte Carlo technique, on the behavior of the people and on building envelopes.

3 Methodology

Control strategies may be classified into two parts: (1) single component control (local control) and (2) Entire energy system control. The total functioning of the energy system is smooth because the local controller guarantees that the process is in control and that the proper set point is maintained at all times, while the monitoring controller organizes all of the local controllers. [16] Hard control, soft control, and hybrid control are the three types of control mechanisms. Classical controls are included under hard controls by Naidu et al. [16], but classical controls are considered a separate category of HVAC control systems by [1]. [7] Only differentiate b, on the other hand, Figure provides an overview of several HVAC control methods.

Figure 1 HVAC Control System

Classical Control

For the most part, PID pertains to the most frequently used control methods, such as the ”on/off,” ”P,” ”PI,” and ”PID” strategies. An on/off controller manages a process so that it stays within set lower and upper thresholds. P, PI, and PID controllers use error dynamics to modulate a controlled variable and provide precise control. PID controller Auto-tuning or optimal tuning techniques for these systems are the subjects of investigation [1].

Hard Control

MPC -Hard controllers use optimum control, robust control, nonlinear control Model Predictive Control (MPC), and adaptive control to control systems [14], [13]. Hard controllers are typically very simple to interpret. Because of their predictability and consistency, and the computing load of practical methods is usually low to moderate. Fuzzy logic, neural networks, and evolutionary algorithms are used in soft control systems. Hybrid controls are a mix of harsh and soft control techniques that make use of the benefits of each. Even though MPC may be utilized for supervisory control, soft control is generally used for supervisory control while hard control is used for local control [13]. MPC Points of Strength and Weakness Nonlinear dynamics supervisory control, time-varying disturbances, and, time-varying dynamics are some of the primary problems that an HVAC system faces. MPC is a form of control that solves these issues. [13] The summary of MPC's major features are:

1 - MPC is a system evolution predictor, not a remedial control.
2 - An incorporated disturbed model can explicitly manage disturbances.
3 - It is capable of openly dealing with uncertainties and restrictions.
4 - It is capable of coping with time-delayed procedures.
5 - Energy conservation methods can be incorporated into the controller design.
6 - Using appropriate cost function formulations, several objectives can be met.
7 - MPC may be utilized for both supervisory and local control.
8 - Explicitly incorporates passenger behavior, equipment usage, and weather forecasting.

Soft Control

Artificial neural networks

The use of neural networks for estimating the energy consumption of buildings has become increasingly common. Building energy estimate has long been a popular use of neural networks, which are the most widely used ML approaches in this field. They've been used to simulate non-linear issues and complicated systems with great success. ANNs may be resistant to faults and noise while learning important patterns in constructing systems by employing a variety of approaches. The ANN's basic concept comes from the realm of microbiology. Recurrent networks, Radial Basis Function Networks, and Feed-Forward Networks are examples of ANNs that have been proposed for various purposes (RNN). Each ANN is composed of numerous layers of neurons and activation functions that link them together (at the very least two layers). Some of the most often utilized functions are linear, sigmoid, and hard limits. In FFN, there are no cycles between input and output neurons which were the earliest and simplest NN architecture. Pieces of information travel in one way in the network. Figure 2 shows the basic structure of FFN, which includes input, output, and one hidden layer. By enabling loops from output to input nodes, RNN leverages its internal memory from which to learn previous encounters. Several architectures, together with fully linked,

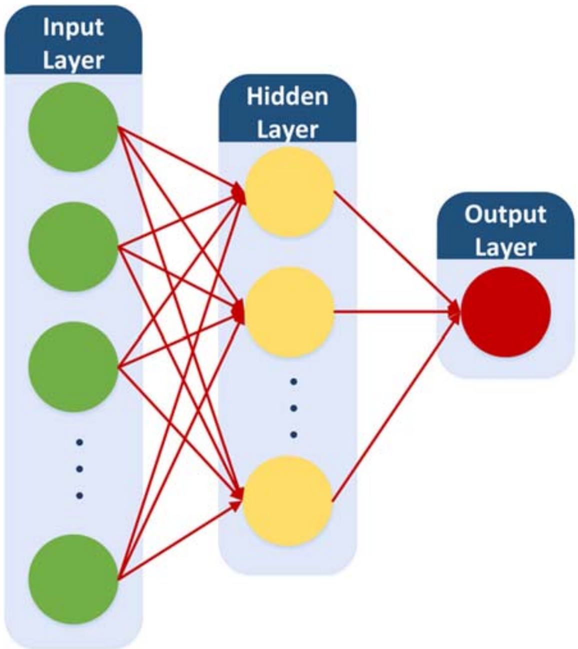

Figure 2 General Structure of Neural Network

recursive, and long-term memory have suggested RNNs and multi-layer architectures. The following are some of the advantages ANNs give over more traditional engineering solutions:

1 .They can quickly construct models with non-linear data connections.
2 .They forecast fast: the training process is long, but predictions are predicted in milliseconds after they are trained.
3 .If they have a class example for an area, they can generalize better than traditional models: they do well to evaluate structures never seen by the model since the model was trained with an example that is comparable to the one that has never been seen.
4 .They are capable of handling enormous amounts of data.

The aim of this initiative is to an ANN-based approach for measuring a building's energy efficiency. To do so, by analyzing the energy efficiency of several of the buildings in northern Spain, we produced a dataset, with an emphasis on residential structures. We trained and evaluated many alternative ANN designs using this dataset. The process is described in the following sections [2].

Other Control Techniques

3.4.1 Reinforced Learning

The building simulator described in [15] is used for testing and benchmarking of Proposed Reinforced Learning (RL) algorithm's learning features and abilities. The simulator is an ETP model written in Python that mimics the heating and cooling of the inside building, depending on a restricted number of lumped factors, including external temperature and heating features. It is a predetermined second-order model that takes the heat in the envelope into account and cools it in cases of external reduction or lack of thermal energy. The simulation is modeled according to the normal high-level heat reaction of Belgium and the Netherlands structures, adopting the entire structure as a single thermal zone. A heat pump for room heating that modulates air source is assumed to be the equipped building; Figure 3 shows a display of the control environment.

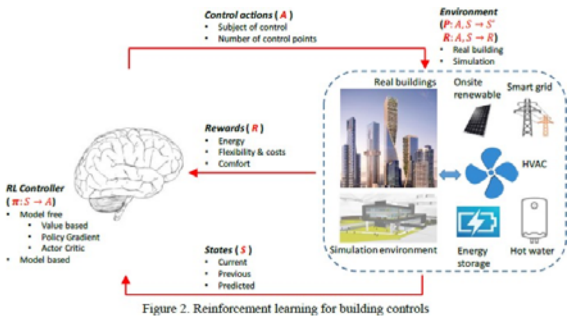

Figure 3 Reinforcement learning for building controls [19]

Hybrid Control

In hot climate locations, occupant behavior patterns uncertainty was a major factor, but in cold climate regions, building envelope characteristics were a major factor. [21] Under high-level uncertainty, suggested an algorithm for optimizing total performance using optimal solutions in design. According to their conclusions, using the new strategy reduced the number of simulations by 97.8 percent of Monte Carlos, with less than 3.5 percent of projected imprecision. Given the significant amount of unpredictability in building energy systems, it's worth mentioning. Only a little research has concentrated on developing demand-side controls to increase flexibility of building energy. Quantifications of energy flexibility in Building energy systems that are integrated (including thermal storage systems, electric systems, and renewable energy, and building services systems) a collection of multi-dimensional indicators of energy flexibility. Simpler models for short-term building energy are being developed projections that are both efficient and accurate. The creation of sophisticated controllers, as well as the application of short-range building energy forecasts, for the increase of building energy suppleness. This study's uniqueness may be described succinctly as follows. 1) Integrated building energy systems' energy flexibility has been measured using several flexibility indicators that take account of different energy types, sophisticated energy conversions, varied energy storage systems, and flexible methods. 2) The sophisticated non-linearity and complexities of building energy predictions were created to simplify the replacement model. The technique of supervised machine learning is the method chosen for the substitute model. The substitute model aims to increase calculations efficiency without losing accuracy since the TRNSYS 18 building energy systems were highly complex in both the modeling and simulation procedures. 3) The anticipated control signal in the real-time energy management system was adopted to increase the flexibility of building energy, by moving the substitute model for interim prediction of building energy performance. Advanced controller's motive and concept are to correspond with renewable generation and demand of construction energy via the intelligent building equipment operations, HVAC systems, and interior air temperatures.

4 Discussion

The cargoes must maintain adequate service quality and fulfill their key objectives whilst offering control measures. AI can thus only be supplied with loads with variable requirements. Different load categories were found as appropriate for AI provision. The current situation for thermally controlled building energy charges, plug-in hybrid electric carloads, and interruptible industrial and household loads, among other things. Electric batteries can also help to increase grid flexibility, but they do have certain inconveniences, such as being costly, not being too environmentally friendly, and restricted functionality. The HVAC systems are particularly suitable to provide services on the demand side since they use substantial quantities of power and have the flexibility to demand. They are also suited to provide high-demand services. Furthermore, a building management system is installed in most commercial buildings, making it simple to implement the complex control techniques required to deliver AI services. The fundamental goal of building control is to keep occupants comfortable while reducing operational expenses. A building's thermal capacity allows it to have a variable electricity requirement. This flexibility may be used to either shift the building's usage from peak to off-peak hours or to directly give flexibility to the grid (e.g., secondary frequency control service).

5 Conclusion

Construction and building energy usage optimization have gained considerable efforts have been devoted to this sector in recent years since it is recognized to be the major source of air pollution and fossil energy use.

By use of intelligent controls or sensors or upgrades, guidelines and increasing fuel prices have obliged owners to decrease their energy consumption. This issue has grown increasingly pressing in the large constructed sector, where huge amounts of energy are lost owing to poor management.

As a result, many smart solutions for energy conservation have been implemented. The fast growth of contemporary technologies such as data collection has resulted in an enormous amount of sensors, wireless network connection, cloud computing, information and smart devices. 1.Conventional modeling is needful for fast and accurate predictions that are important for strategic decision systems is not met by software and statistical technology producing energy. 2. ML models have demonstrated tremendous promise as an alternate option for energy modeling and evaluation in many types of buildings. Several studies compare the suggested ML technique against traditional regression models or another basic ML model without giving enough structural information. Consequently, it is advised to thoroughly examine these approaches with tuning models to simplify decision-making for experts picking MLS to anticipate energy.

In addition to building energy modeling, buildings based on different input parameters make energy benchmarking far easier and better. Intelligent identification of reference constructions leads to more exact labeling of energy compared to the traditional definition of conceptual structures. In addition, an estimation of the reference structures for future instances is possible through a mix of clustering and classification.

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Biography

Ganesh Murade. Received a B.E degree in Electrical engineering from the Pune University, Maharashtra, in 2010 and M.Tech. degree in Power System Engineering from the RGPV University, Bhopal, in 2016. He currently works as an assistant professor at the Dr. Vithalrao Vikhe Patil College of Engineering, Department of electrical, Pune University. His current research interests include the Machine Learning and control of HVAC systems.