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Artificial Intelligence Based Cooling System For Managing The Energy Efficiency

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Abstract:
Dramatic increase in heating, ventilation, and air conditioning (HVAC) units leads to 40% of total energy consumption in a building. The HVAC system shares largest among other devices the energy consumption and it tends to increase further with steady increasing HVAC systems. Optimal management of HVAC operations is hence required to reduce the consumption of energy among the buildings. Certain advancements are hence required to avoid degradation associated with existing equipment and poor control. Optimal control strategy and fault diagnostics needs to be improved further in order to provide higher efficient thermal comfort. In this paper, we design an Artificial Intelligence (AI) powered system to control the cooling load demand and temperature maintenance with maximum thermal efficiency. AI powered system uses Recurrent Neural Network (RNN) to offer cost-effective estimation with temperature conditions as input to the system. The thermal efficiency on the building is maintained using RNN with high level energy consumption. The experimental results reveal that the AI powered module estimates the cooling capacity of entire building with reduced error, which is lesser than 4.34%.

Keywords:
Recurrent Neural Network, Thermal efficiency, Smart buildings, HVAC system.

1. INTRODUCTION

The electricity used by buildings around the world is over 40% world energy usage, including 70% of heating, ventilation and air-conditioning (HVAC) systems [1]. This is why much research has been conducted to enhance the HVAC system operational performance. The sensor is an important part of this initiative. Researchers have discovered, for example, that savings in energy can be made by locking the sensor with the control system in the building [2][3]. In addition, defects of the HVAC isdiagnosed by optimal evaluation on sensors in order to avoid energy waste and unit malfunction [4] [5]. Studies have been aggressively seeking in recent years to combine artificial intelligence technologies with applications of this type to enhance sensor intelligence and usage. Research is under way, in particular, to reduce energy demand and supply by predicting energy [6], improving the advanced technologies of the detection of faults through the process of deep learning [7] and artificial intelligence (AI) [8]. Becoming important for improving the intelligence of buildings, since the data used for AI training comes from the sensors. In potential intelligent buildings, a growing range of sensors can therefore be used [9].

However, it will have to be considered that the advantages of having a growing number of sensors are at a price when attempting to gain sensor dependent knowledge. Firstly, it will incur non-negligible expenses to purchase the sensors themselves [14]. Secondly, the sensors must be connected physically and installed in the HVAC system. This makes the device more complicated and expensive to run. Thirdly, for extra expenses, the sensors need maintenance. The sensors may be malfunctioning or improperly adjusted and must be fixed or replaced [11]. In some situations the sensors are placed in locations that are not readily accessed by maintenance workers. There are several components above the roof or in ducts that are not unusual for an HVAC system [13].

Air Handling Unit (AHU) manages and circulates the air, including crop, heating or refrigeration components, filter racks or chambers, acoustic dampers and attenuators [9]. It attaches to an air-conditioning system in the building that returns the air to AHU. To blast the air conditioning at a suitable pressure, the AHU requires fan power [15]. For this reason, a pressure in the airflow path must be calculated by the AHU method.The calculated pressure within the duct into the AHU is recorded by the sensor to ensure AHU regulates air flow through the desired fan control [17]. However, the integration and repair of the sensor in addition to the expense of the sensor itself may be costly and inefficient due to its place in the device. Therefore, in this article, we analyse the capacity to extract from the target air handle device (AHU) the pressure sensor when attaining the level of expected pressure values identical to the measured values [18].

In this paper we suggest a framework for forecasting the HVAC system's operational dynamics via a deep learning technique [19]-[22] [24]without a pressure sensor. By this approach, we can use other sensorsto control the HVAC and hence reduce the costs of the HVAC system operation. Moreover, we have seen a new methodology for the physical sensor value to be replaced with the recently proposed method Recurrent Neural Network (RNN).In several ways, this method will minimise costs: costs of hardware for each AHU, costs of installation, operations and repair. This paper looks at the effect on the efficiency of RNN based multivariate time series prediction by different input parameters and processing steps. It gives insight into the optimisation of related structures.

2. RELATED WORKS

In a RNN approach, Kato et al. [10] suggested a prediction technique for thermal load more effective than the conventional Multi-Layer Perceptronprocess.Jonathan et al. [6] used ANN as an optimization tool for forecasting energy consumption and for maximising energy supply.Sokratis et al. [13] suggested genetic algorithm to monitor temperature settings with and without occupation.

Park et al. [12] increasedthe productivity using a general room recognition reinforcement learning process. The approach facilitates lighting control over the smartphone of the user and adapts the lighting to the light sensor meaning.Hadi et al. [5] have, however, implemented a fault-based RNN model-based technique with a time-step of 1 for the identification of errors.

William et al. [23] developed a strategy of lowering energy usage and reducing CO_2 levels by using deep augmented learning to monitor HVAC. Artificial intelligence was used to carry out error diagnosis and error forecast of equipment in the sense of HVAC system fault management. Conventional modelling and detection approaches work based on past fault knowledge. Context information.

The ANN was used by Rahat et al. [7] to provide various industry fault detection results, and its output was twice the level of the standardised rule based process, using the ANN.Lee et al. [16] have been observed with five hidden layers of 200 neurons, using more than 95% of defects in an Air Control Network.The approximate flow metre values of Kumar et al. [9] are based on a four-layer neural network and fuzzy preparation. The flow metre value of a valve control device shows the system to work without a sensor by estimating its flow rate.

In this article, we propose to forecast the dynamic of HVAC system without sensors a deep learning approach. This approach shows that a pressure sensing is not sufficient for effective HVAC operation and thus decreases installation and operational costs of HVAC systems.

3. PROPOSED METHOD

A prediction model with pressure sensor for HVAC using RNN is provided in this Section. RNN is used as an input that was not used for training or validation, but to avoid the existing static pressure. The architecture of proposed method is given in Figure 3.

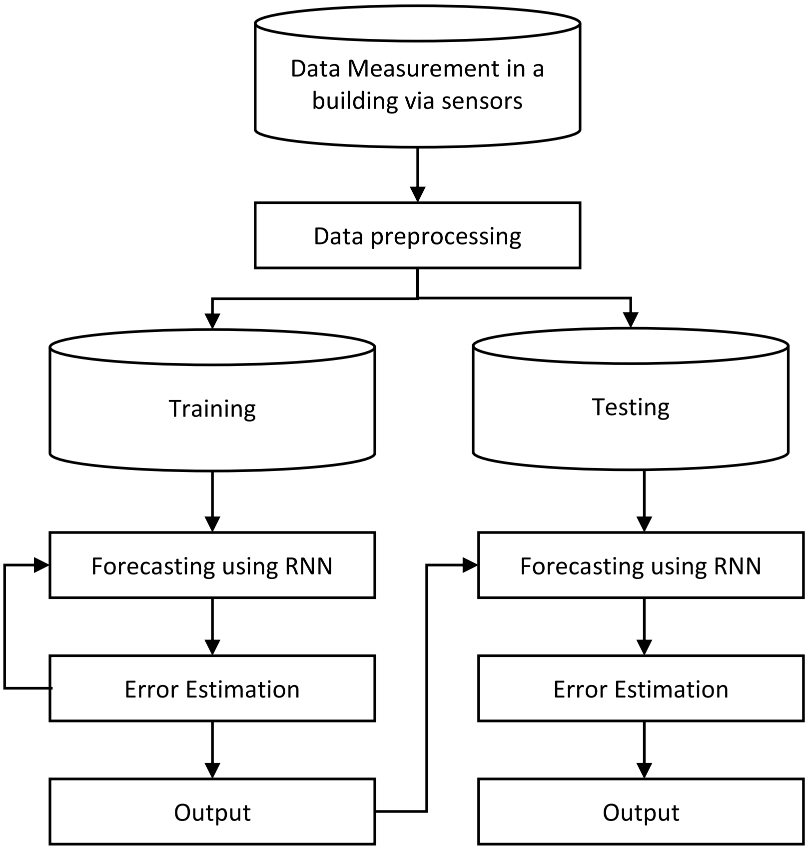

Figure 3. Architecture of proposed model

Following are the RNN model information used by our prediction model:

Input Data Characteristics:

The AHU has a return fan and a supply in the HVAC system structure, which blows air into and drains air from the room. Each ventilator is an inverter and can change its velocity. The pressure and the set-point of pressure control in the supply channel, and the fan returns at a speed close to that of the supply channel. In order to retain a fixed temperature of the room, the quantity and the wind temperature given is calculated and modified.

We defined and tested their features before designing the RNN model, the factors that impact the pressure. In particular, whether there were temporary shifts or unique trends in these variables. The air movements in and out of the conduit are also linked to fan rpm. Fluctuations in the supply of air and return temperature is correlated with the fixed temperature. The fan velocity entirely depends on fixed temperature and the return air temperature when cooled or warmed. If the temperature differential is greater, the speed is higher.

Therefore, the direct variables impacting the pressure in the conduit include the pressure determination point, the working speed of the ventilator, its volume and returned air volume. The RNN input is necessary for these values. We have chosen seven input parameters to influence the dynamics of the deep learning model directly or indirectly. They are pressure set-point, temperature set-point, air supply volume, return air volume, air supply temperature, return air temperature, inverter fan speed.The data used are time-series data, except for temperature and pressure. In order to train the RNN model, our HVAC system used three historical data sets.

When the machine is in a stopped condition the pressure is zero millimetre-aqua. The machine is operational otherwise. Since the input values vary greatly, they needed to be standardised before our profound learning model was used in order to enhance the learning output. The normalisation took place by translating the maximum and minimum values.With this operating test, the required capability could be restated and the setting points re-calibrated after completion of the house.Data from irregular operational environment have been used in the preparation and test results in order to decide whether the model can anticipate statistical pressure during the test procedure and whether the model proposed can override the actual pressure sensor under all planned operating circumstances.

Proposed Deep Learning Model

The RNN is an effective way to learn sequential knowledge among deep learning techniques. It remembers previous input in the secret layer from the internal memory to be used for the input data in data samples in the series. The RNN memory can be treated as a gated cell, and the measurable value of each input is learned. RNN can thus overcome the problem of long-term dependence by introducing the cell condition to RNN hidden layers. Time dependence is an essential element in studying the characteristics of time series results.

Each RNN cell has the following six functions:

$$f(t) = \sigma(x(t)w(xf)+x(t-1)w(hf)+b_f) \quad (1)$$

$$i(t) = \sigma(x(t)w(xi)+x(t-1)w(hi)+b_i) \quad (2)$$

$$C(t-1) = tanh(x(t)w(xg)+h(t-1)w(hg)+b_g) \quad (3)$$

$$C(t) = f(t)+ c(t-1)+i(t)+ c(t-1) \quad (4)$$

$$o(t) = \sigma(w(t)w(x_o)+h(t-1)w(h_o)+b_o) \quad (5)$$

$$h(t) = o(t)+tanh(C_t) \quad (6)$$

Where, W is the weight factor, b is the gate bias in RNN, f_t is the forget gate, σ is the gate sigmoid layer [0,1] which provides the details of total amount of data to be sent via gates.

The sigmoid layer dictates how much of the past knowledge contained in the cell state can be forgotten for the forgotten gate. The cell state helps the gradient to propagate even though the situation is long in the RNN. The forgotten logic scans the product of the previous step and the input at the time and outputs a number from 0 to 1 for each cell state number. A sigmoid value of 1 is meant to preserve the entirety of the information provided, while 0 means to ignore the whole of the data. The RNN model then determines which new data can be stored in the state of the cell. Next, the input gate specifies the values it changes. Second, a hypertangent layer generates a vector that can theoretically add new candidate values to the country. Then the RNN changes the cell state with the old commodity Hadamard, ignoring the details according to the previous judgement. This is the current claimant value, which is the degree to which each state value has been modified. The RNN model determines what is to be delivered. The outcome is a filtered version based on the cell state. First, a sigmoid layer specifies the cell state that is going to be produced. It then brings the cell state via the tanh, squeezing the values between −1 and 1 and multiplying them by the sigmoid gate output. According to its previous judgement, it generates only the pieces. Any input value is determined with the previously expected outcome and passes through the entrance gate. It also governs how the past importance of learning influences new learning, through the use of the forgotten door and the status of the former learned cell.

4. RESULTS AND DISCUSSIONS

The datasets used for the proposed pressure forecast from HVAC system were based on a multi-storey office building. The model may also be used where there was a difference in the number of persons or reasons between the concept and relocation. This will contribute to the unsafe functioning of the air conditioning system. The process is conducted with data such as temperature and humidity within the structure in order to define certain adjustments and determine optimum operating parameters. This research has shown that we can estimate the pressure during this time by using the proposed model.

The results of experiments demonstrate explicitly that the RNN generates values similar to the sensor. The accuracy is contained independently of the service mode and the true pressure can be predicted without a pressure sensor in the pipe given the training data for the RNN network are available. During the running checks, even the most fluctuating values are well forecast. The training and testing is carried out using controlled loads and uncontrolled loads. The controlled loads include Hybrid Split System, Heating and Cooling Split Systems, Mini-Split Duct Free and Wall Air Conditioner. The uncontrollable loads include Unit Heaters, Packaged Terminal Heat Pumps, Packaged Rooftop Heat Pump, Packaged Rooftop Unit and Humidifiers

Load Balancing Accuracy:

In case of multiple buildings, the average of all loads balancing accuracy is estimated. The performance shows the results of controllable loads in Table 1, and it measures the current balancing among the supply phases. It is seen that with increasing number of controllable loads, the balancing increases and makes the system stable. In Table 1(a), the study evaluates the load balancing stability for a three storied commercial building that uses HVAC systems.

Table 1(a): Load Balancing Accuracy (%) in a single smart building

Controllable loads (Nos.)	ANN	ANFIS	4 layered ANN	RNN
Heating and Cooling Split Systems	79.62	81.13	82.66	84.21
Hybrid Split System	91.47	93.24	95.03	96.84
Duct Free (Mini-Split)	91.52	93.28	95.07	96.89
Window Through-the-Wall Air Conditioner	93.61	95.42	97.26	99.12

The Table 1(b) shows improved load balancing accuracy on uncontrollable loads (Packaged Terminal Heat Pumps, Unit Heaters, Packaged Rooftop Unit and Packaged Rooftop Heat Pump and Humidifiers) for a smart commercial three-storied buildings with multiple HVAC devices over ANN, ANFIS and 4 Layered NN algorithms. The result shows that with an increased number of counts for single device lags stability due to reduced load balancing accuracy than the ones with lesser number of device counts.

Table 1(b): Load Balancing Accuracy (%) with more smart buildings

Uncontrollable loads (Nos.)	ANN	ANFIS	4 layered ANN	RNN
Packaged Terminal Heat Pumps	88.66	90.37	92.09	93.85
Unit Heaters	88.57	90.27	92.00	93.75
Packaged Rooftop Unit	88.47	90.18	91.90	93.65
Packaged Rooftop Heat Pump	88.38	90.08	91.80	93.55
Packaged Heating and Air	88.29	89.99	91.71	93.45
Humidifiers	88.19	89.89	91.61	93.35

Energy Efficiency:

Table 1(b) shows improved load balancing accuracy by RNN method for a smart building with multiple devices over ANN, ANFIS and 4 Layered NN algorithms. Further, it shows an increasing number of homes tend to reduce its load balancing accuracy, and it further reduces with reduced bandwidth in the communication protocol used.

Table 2 (a): Energy Efficiency (%) over various deep learning algorithms

Controllable loads (Nos.)	**ANN**	**ANFIS**	**4 layered ANN**	**RNN**
Heating and Cooling Split Systems	69.979	71.284	72.601	73.934
Hybrid Split System	70.091	71.399	72.718	74.054
Duct Free (Mini-Split)	75.589	77.015	78.455	79.914
Window Through-the-Wall Air Conditioner and Humidifiers	78.178	79.660	81.157	82.674

Table 2(a) shows improved energy efficiency by RNN method for a smart building with multiple devices over ANN, ANFIS and 4 Layered NN algorithms. With an increasing number of devices of the same type, it shows reduced energy efficiency than the reduced number of devices with the same type.

Table 2(b) shows improved energy efficiency by RNN method for a smart building with multiple devices over ANN, ANFIS and 4 Layered NN algorithms. Further, it shows an increasing number of homes tend to reduce its energy efficiency, and it further reduces with reduced bandwidth in the communication protocol used.

Table 2 (b): Energy Efficiency (%) with more smart buildings

Uncontrollable loads (Nos.)	**ANN**	**ANFIS**	**4 layered ANN**	**RNN**
Packaged Terminal Heat Pumps	79.13	80.63	82.15	83.69
Unit Heaters	79.05	80.55	82.06	83.60
Packaged Rooftop Unit	78.96	80.46	81.98	83.51
Packaged Rooftop Heat Pump	78.88	80.38	81.89	83.43
Packaged Heating and Air	78.80	80.29	81.81	83.34
Humidifiers	78.72	80.21	81.72	83.25

Latency:

Latency is defined as the time it takes for data or a request to go from the source to the destination. Latency in networks is measured in seconds.

Table 3 (a): Latency (s) in a single smart building

Controllable loads (Nos.)	ANN	ANFIS	4 layered ANN	RNN
Heating and Cooling Split Systems	0.7109	0.5274	0.3225	0.1013
Hybrid Split System	0.7111	0.5275	0.3227	0.1014
Duct Free (Mini-Split)	0.7186	0.5352	0.3306	0.1095
Window Through-the-Wall Air Conditioner and Humidifiers	0.7221	0.5388	0.3343	0.1133

Table 3(a) shows reduced latency by RNN algorithm for a commercial building with multiple devices over ANN, 4 layered NN and ANFIS. With an increasing number of devices of the same type, it shows increased latency than the reduced number of devices with the same type.

Table 3 (b): Latency (s) with more smart buildings

Uncontrollable loads (Nos.)	ANN	ANFIS	4 layered ANN	RNN
Packaged Terminal Heat Pumps	2.110	1.927	1.740	1.550
Unit Heaters	2.108	1.926	1.739	1.548
Packaged Rooftop Unit	2.107	1.924	1.737	1.546
Packaged Rooftop Heat Pump	2.105	1.923	1.736	1.545
Packaged Heating and Air	2.104	1.921	1.734	1.543
Humidifiers	2.102	1.919	1.732	1.541

Table 3 (b) shows reduced latency by RNN method for a smart building with multiple devices over ANN, ANFIS and 4 LAYERED NN. Further, it shows an increasing number of uncontrollable devices in smart commercial buildings; there is an increase in latency. It further increases with reduced bandwidth in the communication protocol used.

5. CONCLUSIONS

In this article, we show that the RNN approach will remove the need for the HVAC system to use balanced and unbalanced load. We have used an RNN model that learns how the pressure in the HVAC system has been characterised in time series so we can delete from the system the pressure sensor. We checked the model that could reliably balance the pressure determined by the device power. This way we will reduce the sensor investment costs for HVAC system service.

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