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Improving Energy Consumption of Commercial Building with IoT and Machine Learning

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Abstract

The critical requirements for devices connected to the Internet of Things (IoT) are long battery life, long coverage range, and low deployment cost. In this work, we developed a machine learning based smart controller for the HVAC of commercial building using LoRa and compared it with short range RF communication in an indoor setting. The comparison was made in terms of battery life, coverage range and memory size. The effect of changing the transmission power of LoRa on battery consumption of the sensor node was also evaluated. Results show that coverage range of LoRa was 60.4% more than short range communication inside a building. The smart controller was capable of identifying when the room was unoccupied and turning off the HVAC which reduced the energy consumption up to 19.8%.

Introduction

According to Cisco [1], 50 billion devices will be connected to the internet by 2020. Different types of devices can be connected to the internet from small devices (RFIDs, Sensors) to large devices like TVs, Cameras etc., and mobile devices like vehicles. The Internet of Things (IoT) interconnects these devices and exchanges data between these devices. Therefore, Machine to Machine (M2M) communication is required for exchange of data between devices in IoT.

Communication between devices in IoT has already been done by multi-hop short range communication (ZigBee, Bluetooth and RF communication) [2]-[4]. Short range communication (Zigbee, Bluetooth, RF communication) operates in unlicensed ISM bands centred at 2.4 GHz, 868/915 MHz. 433 MHz and 169 MHz. The coverage of these short-range communication (uni-directional or bi-directional) is usually in few meters but they can achieve high data rate. In applications where the distance between sensor nodes and base station is large, short range communication standards are not feasible.

More recently industry has been developing in low power wide area networks (LPWAN). LPWAN is introduced as a promising alternative between multi-hop short range communication which operates in unlicensed frequency band and long range cellular communication which operates in licensed frequency band. Basic requirements for LPWAN are long coverage, less power consumption, low deployment cost, low device cost, support large number of devices and easily expandable [5]. Long range (LoRa) alliance [6], Sigfox [7], and Weightless [8] are examples of LPWAN.

In our previous work [9], we implemented the smart controller for heating ventilation and cooling (HVAC) of commercial building. Random neural networks (RNN) were used for machine learning of smart controller. Multiple RNN models for estimating the occupancy, predicted mean vote (PMV) based setpoints for heating and cooling and HVAC control were integrated in the smart controller for embedding the intelligence. Communication between sensor nodes and base station was done by using fixed short range RF communication. Base station and sensor nodes communicated at 915 MHz by using RFM69HW Industry Scientific and Medical (ISM) transceiver [10]. In this work, we implemented the smart controller for Building energy management systems (BEMS) using LoRa transceiver (RFM95) [11] and compared the energy consumption of HVAC using a smart controller with simple thermostat. We have compared the power consumption of sensor nodes with LoRa transceiver and ISM transceiver, moreover we have also compared the coverage range and packet loss of LoRa transceiver with ISM transceiver inside the campus building.

Long Range IoT Communication in Unlicensed Bands

Long range LPWAN have coverage range comparable to cellular network. In rural areas, coverage of LPWAN is around 10-15 Km while in dense populated areas, coverage of LPWAN is around 2-5 Km. Unlike short range communication standards the data rate of LPWAN is low and LPWAN may not be feasible to use for data hungry applications. On the other hand, advantage of LPWAN is its long coverage range and therefore, sensor node can communicate with the base station without multi-hop link. LPWAN allows different devices to connect to the network and is feasible for applications like Smart Cities due to its long range. In this work, we have tested LoRa technology for implementing the smart controller for commercial building.

LoRa

LoRa is a spread spectrum technique which has been designed by Semtech Corporation to work in 433 MHz, 868 MHz and 915 MHz. Lora is a physical layer LPWAN solution which is derivative of Chirp Spread Spectrum (CSS) [12]. LoRa has shown resistant against Doppler effect and multipath fading.

Random Neural Networks

Gelenbe [13][14] proposed a new class of Artificial Neural Network (ANN) as Random Neural Network (RNN) in which signals are either +1 or -1. RNN is a black box learning technique which is based on concepts of probability theory applied to Markovian Queuing Theory. Applications of RNN were reported for modelling, optimization, pattern recognition and communication [15]. The details about RNN architecture and exchange of signals between the neurons are presented in [13][14].

In the RNN, signal travels in the form of impulses between the neurons. If the receiving signal has positive potential (+1) it represents excitation, and if the potential of the input signal is negative (-1) it represents inhibition to the receiving neuron. Each neuron i in the RNN has a state $k_i(t)$ which represents the potential at time t. This potential $k_i(t)$ is represented by a non-negative integer. If $k_i(t) > 0$ then neuron i is in excited state and if $k_i(t) = 0$ then neuron i is in idle state.

For a three layered network, the probability that neuron I is in excited state i.e., q_i is calculated as:

$$q_{i \in I} = \frac{\Lambda_i}{r_i + \lambda_i} \quad \text{where } I \text{ is Input Layer} \tag{9}$$

$$q_{h \in H} = \frac{\sum_{i \in I} q_i w^{+}_{(i,h)}}{r_h + \sum_{i \in I} q_i w^{-}_{(i,h)}} \quad H \text{ is hidden layer} \tag{10}$$

$$q_{o \in O} = \frac{\sum_{h \in H} q_h w^{+}_{(h,o)}}{r_h + \sum_{h \in H} q_h w^{-}_{(h,o)}} \quad O \text{ is output layer} \tag{11}$$

Where I, H and O denote the sets of Input, Hidden and Output layers respectively, and $i \in I, h \in H, o \in O$. r_i is the firing rate of neuron i, Λ_i is arrival rate of external positive signals, λ_i is arrival rate of external negative signals.

Training Algorithm for RNN: Hybird Particle Swarm Optimization with Sequential Quadratic Programming

Many researchers have used a Gradient Descent (GD) algorithm for learning the weights of an RNN model. The GD algorithm is relatively easy to implement but zigzag behaviour may cause it to be stuck near a local minimum for the problems with multiple local minima. The evolutionary algorithms are used for solving optimization problem. These techniques are better than gradient base techniques as as they do not get stuck in local minima. The Particle Swarm Optimization (PSO) algorithm performs well in finding the global minimum but it might be slow to converge to the global minimum while in the presence of multiple local minima, Sequential Quadratic Programming (SQP) optimization method usually converges to local minima. The problem of slow convergence of PSO and local minima problem of SQP optimization is addressed by the hybridization of PSO and SQP optimization algorithm [9].

Architecture of Cloud Enabled Smart Controller for HVAC

The smart controller has modular architecture and is easily expandable. The basic modules for the smart controller are: base station, environment monitoring sensor node, HVAC duct sensor node, gateway, and cloud platform for data representation, storage and RNN model training. The architecture of the cloud enabled smart controller is shown in Fig. 1.

Environment Monitoring Sensor Node

An environment monitoring sensor node monitors light intensity, temperature, humidity and CO_2 inside the room. The Environment monitoring sensor was designed to transmit the sensor's information to the base station after every 1 minute at 915 MHz using ISM transceiver and LoRa transceiver shown in Fig 2(a) and Fig 2(b).

HVAC Duct Sensor Node

An HVAC duct sensor node monitors inlet air of the HVAC coming from the HVAC duct. The sensor node monitors CO_2, temperature and humidity of the inlet air coming from the HVAC duct. The implemented HVAC duct sensor node is shown in Fig 2(c).

Base Station

A base station receives information from an environment monitoring sensor node, HVAC duct sensor node and controls actuators of the HVAC. The base station uploads the data of sensor nodes to a web portal. RNN models were trained on cloud platform and weights of trained RNN models were transferred to the base station. The control algorithm was implemented with multiple RNN models integrated on the base stations i.e. RNN occupancy estimator, RNN PMV based setpoint Estimator, RNN HVAC control model.

RNN Occupancy Estimator:

The RNN model is used for estimating the number of occupants. The RNN Occupancy estimator calculates the number of occupants inside the room by using the CO_2 and temperature values received from the environment monitoring sensor node and HVAC duct sensor node. The RNN model is trained with the dataset collected from the environment test chamber located in Glasgow Caledonian

University. The RNN model has four neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer. The inputs for the RNN model are: 1) CO_2 concentration in the room,

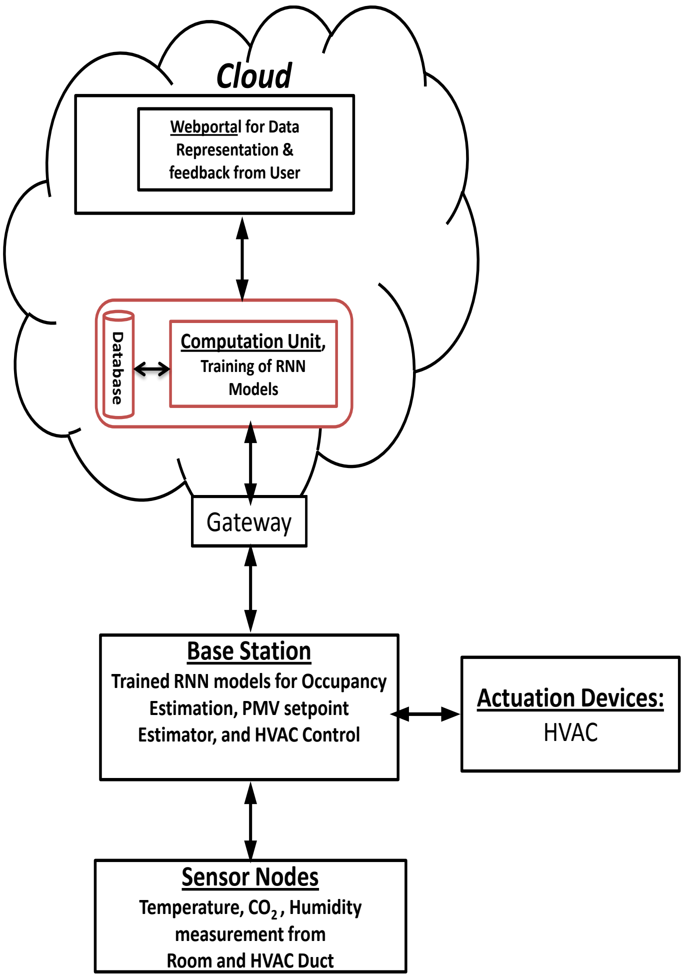

Fig. 1: Architecture of Smart Controller

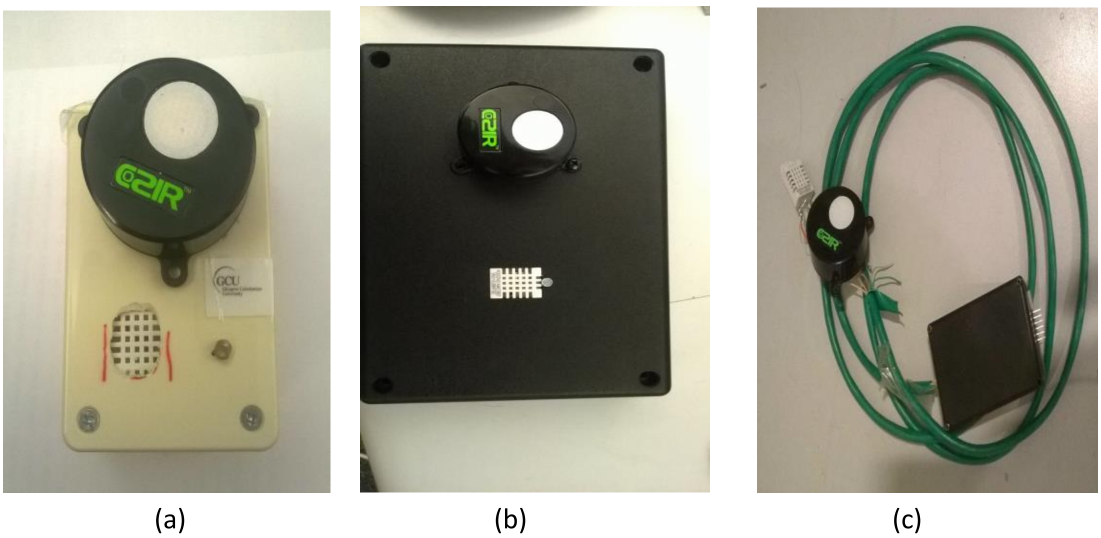

Fig 2: (a) Environment Monitoring Sensor Node with RFM 69W transceiver (b) Environment Monitoring Sensor Node with LoRa Transceiver, (c) HVAC Duct Sensor Node with RFM 69W transceiver

2) temperature of the room, 3) CO_2 concentration in the HVAC duct, 4) temperature of the air coming from the HVAC duct and output of the RNN model is the number of occupants. The RNN model is trained with the hybrid PSO-SQP and MSE is 1.28 e-02.

RNN PMV Setpoint Estimator

Fanger developed seven points index of comfort/discomfort which is dependent on six variables [16]. In this work, training data set is generated by using Fanger equation for PMV. To reduce the human interference, we assumed the typical office environment. Therefore, clothing insulation of 0.8, metabolic rate of 1.1, and air velocity of 0.15 m/s are assumed to be constant. After generating a training dataset, RNN is trained with PMV and humidity as an input and temperature as an output. A 2-4-1 RNN is trained with hybrid PSO-SQP training algorithm. In this work, PMV of -0.1,-0.3,-0.5 is tested for heating setpoint and PMV of 0.3, 0.5 and 0.7 is tested for cooling set point. The RNN PMV based setpoint estimator is implemented on the base station. The estimated setpoints from the RNN model were used by RNN HVAC control model for controlling the HVAC. In this work, when a PMV value of -0.5 was selected the estimated setpoints for temperature were varied between 22.34^{o}C and 22.47^{o}C.

Cloud Services

The base station of the WSN was interfaced with the cloud platform. Training of RNN models was done on a cloud platform and trained weights of RNN were transferred to the base station. For each sensor node, the web portal (http://sensors.traceallglobal.com/) displayed Node ID, upload time in milli seconds (the time sensor node was powered), light intensity, CO_2 concentrations, temperature, humidity, dewpoint temperature, data receiving time, motion sensor, heating setpoint, cooling setpoint, heating output for HVAC, cooling output for HVAC, ventilation output for HVAC, and number of occupants in the room.

Results

The smart controller maintained comfortable indoor environment in a building by maintaining PMV based setpoints for heating/cooling, by controlling ventilation and reduced energy consumption by estimating occupancy in a building. If room was unoccupied, the smart controller turned off the the HVAC thereby reducing energy consumption. The smart controller used RNN occupancy estimator for estimating number of occupants, RNN PMV based Setpoint Estimator for estimating PMV based setpoints for heating and cooling. The RNN HVAC control model was used for controlling the HVAC. The performance of the LoRa transceiver was compared in term of energy consumption, memory consumption, packet loss and coverage. In this work, the performance of the smart controller was evaluated in an environment chamber located in Glasgow Caledonian University, UK. Details of the environment test chamber are shown in [9]. The training dataset for RNN models was collected from the environment test chamber controlled with a simple thermostat.

Occupancy Estimation with RNN

CO_2 concentration increases in the environment chamber when the chamber is occupied but CO_2 concentration drops slowly when the occupant leaves the room. Due to this non-linear behaviour the occupancy estimation is a very challenging task. The occupancy estimation with RNN model was tested in an environment chamber for five days between 10:00 AM to 6:00 PM. The environment test chamber was occupied up to 3 persons during the test. The ground truth values for number of occupants were recorded manually to calculate the accuracy. The experiment results are shown in Fig. 3. Accuracy of the occupancy estimation with RNN model was 78.5% (i.e. when occupancy estimation with RNN was equal to the actual occupancy inside the test chamber).

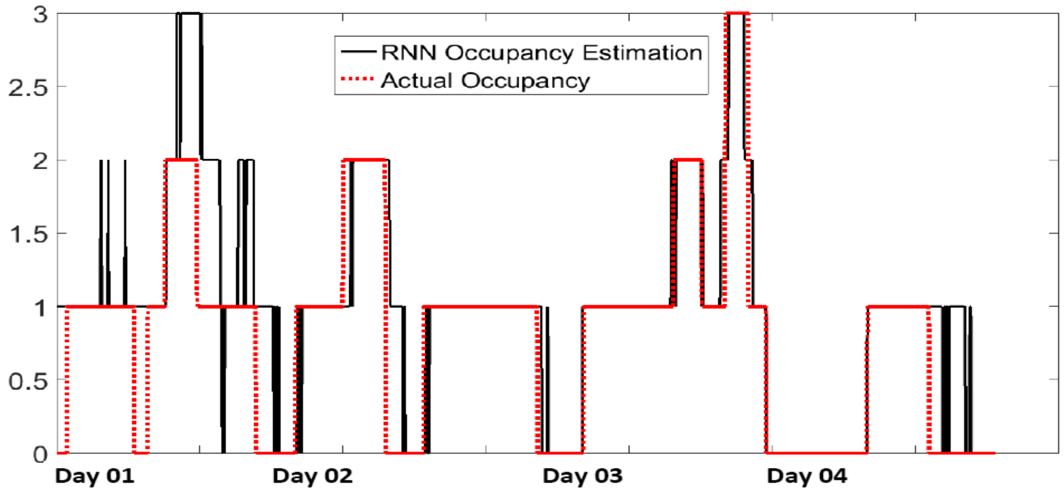

Fig. 3: Occupancy Estimation by Smart Controller

HVAC Control

The smart controller can maintain the PMV based heating/cooling setpoints and user defined heating/cooling setpoints. The upper threshold for heating setpoint and lower threshold for heating setpoint were implemented. The HVAC turned on the heating to reach the upper threshold of the heating setpoint for test chamber and the heating remains turned off until reaching the lower threshold for the heating setpoint (i.e. heating setpoint -1°C). The performance of the smart controller was evaluated for maintaining the PMV based heating setpoints in an environment test chamber.

Comparison of Energy Consumption

The energy consumption of HVAC with RNN based smart controller was compared with the energy consumption a simple thermostat. The smart controller maintained the heating/cooling setpoint if smart controller detected the occupancy using RNN occupancy estimator. During the test the setpoint for heating was 23 °C and for cooling was 26 °C. The occupancy pattern was kept same both for both the smart controller and the simple thermostat. The indoor air temperature of the test chamber is shown in Fig 4.

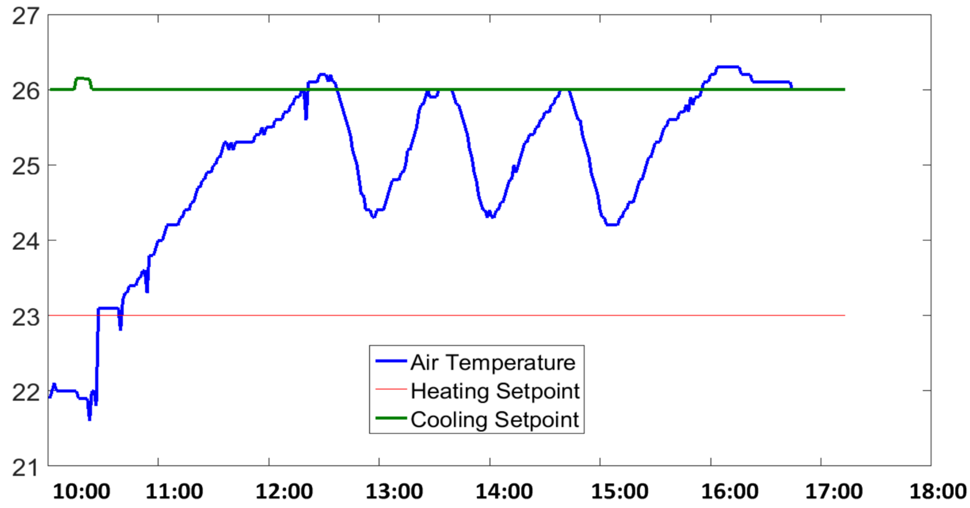

Fig. 4: Indoor air temperature of an environment chamber maintained by Smart Controller

The energy consumption using the smart controller was 30.16 KWh, while the energy consumption using the simple thermostat was 36.12 KWh. Using the smart controller, HVAC consumed 19.76% less energy. The simple thermostat maintained the air temperature between the heating and cooling setpoint during 10:00 hrs to 18:00 hrs whereas due to occupancy estimation algorithm, the smart controller turned on the HVAC at 10:30 AM and switched off the HVAC at 16:00 hrs.

Indoor Coverage Analysis of LoRa Transceiver

Coverage analysis of LPWAN is crucial for estimating the number of gateways during deployment. Most of the work for coverage analysis of LoRa has been done in outdoor settings [17],[18]. In this work, we have conducted experimental tests inside a building to evaluate the coverage range of both LoRa and the RFM 69HW transceiver. Experiment results were collected in George Moore Building at Glasgow Caledonian University which is an eight-floor building. A base station was placed in an office on fifth floor of George Moore Building. The coverage range of a LoRa transceiver was evaluated against different transmission powers (i.e., 13 dBM, 14dBM, 15dBM, 16 dBM and 17 dBM). Power consumption of the LoRa transceiver at different transmission power was also evaluated. The battery life of the sensor nodes of the smart controller with LoRa transceiver and ISM transceiver (RFM 69W) were compared. For comparison, the transmission period of packets was set to 1 minute. Comparison of coverage range, transmission power, battery consumption and packet loss is shown in Table 1. LoRa has low data transmission rate and for this work, transmission time of packet was 70 ms whereas for RFM 69HW transceiver, transmission time was 8 ms. Due to this, energy consumption of the LoRa transceiver was 5.87% more than RFM 69HW transceiver. Coverage analysis of LoRa transceiver was also done for checking the transmission range within different floors of building. It was found that sensor node with LoRa transceiver managed to transmit a packet from ground floor of the building to base station located on fifth floor of building at distance of 97 meters. Implementation of sensor node with LoRa transceiver consumed 30330 bytes of program memory and 1616 bytes of RAM whereas, implementation of sensor node with RFM69HW transceiver consumed 24028 bytes of program memory and 758 bytes of RAM.

Table 1: Comparison of Battery Consumption, Coverage Range and Packet Loss of LoRa transceiver and RFM 69HW transceiver

	Transmission Power (dBM)	Transceiver Current (mA)	Coverage Range (m)	Packet Loss (%)	Battery Consumption -4 AA cells (hours)
Sensor Node with LoRa transceiver	13	98.69	90	16.67	1107
Sensor Node with LoRa transceiver	14	105.21	90	11.12	1105.5
Sensor Node with LoRa transceiver	15	109.56	90	6.67	1104.7
Sensor Node with LoRa transceiver	16	111.3	90	0	1104
Sensor Node with LoRa transceiver	17	111.3	90	0	1104
Sensor Node with RFM 69HW transceiver	20	119.5	56	66.67	1172

Conclusion

In this work, a smart controller for HVAC of a commercial building was developed with LoRa. The smart controller maintained comfortable indoor air environment by maintaining PMV based setpoints for heating/cooling and reduced energy consumption by switching off the HVAC when room was unoccupied. Results showed that smart controller reduced the energy consumption of the building by 19.8%. Communication between sensor nodes and base station was done using LoRa transceiver. Information from sensors, control variables for HVAC and number of occupants was uploaded on the web portal. Performance of LoRa was evaluated in George Moore building of Glasgow Caledonian University for coverage analysis, battery consumption, and packet loss. Performance of LoRa was also compared with RFM 69HW transceiver in terms of battery consumption, coverage range and packet loss. We found that the LoRa transceiver at transmission power of 17 dBM consumed 6.15% more battery than did the RFM 69HW transceiver but had zero packet errors and a coverage range that was 60.7% more than the RFM 69HW transceiver. Due to the increased coverage range within buildings, the cost of the smart controller is reduced as a LoRa based smart controller requires fewer base stations, as a result LoRa is preferred for implementing the smart controller for commercial buildings.

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