IoT and Machine Learning Based Prediction of Smart Building Indoor Temperature

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IoT and Machine Learning Based Prediction of Smart Building Indoor Temperature

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***Abstract*—The demand for useful energy has increased astronomically over the past few decades, especially in building sector, due to rapid development and enhanced lifestyle. The energy performance of the building is reliant on several parameters like surrounding weather variables, building characteristics and energy usage pattern. This literature highlights a mechanism integrating the Internet of Things (IoT) and some widely used machine learning algorithms to create a predictive model that can be used for forecasting of smart building indoor temperature. This predictive model has been trained with on-line learning methodology for developing viability to a completely unfamiliar dataset. The paper carries out a Machine Learning based experimentation on recorded real sensor data[1] to validate the approach. Following that, the paper suggests integration of following strategy into an Edge Computing based IoT architecture for enabling the building to work in an energy-efficient fashion.**

***Keywords*-Predictive model; IoT; On-line Learning; Multi-Variate Forecasting models, Smart Building; Edge Computing.**

I. Introduction

Globally, the energy consumption at the commercial and residential buildings share a staggering one-third amount of the useful energy demand which is accelerating at an astronomical rate which is partially utilised by HVAC systems. For addressing the concerns of global climate change and reduction of energy wastage, household energy conservation has piqued interest. Finite nature and scarcity of energy enforce it to be shared. Heating, ventilation and cooling requirements, i.e. the loads, in turn, determine the heating and cooling equipment design specification to maintain the thermal comforts inside the conditioned space[2]. The power rating and the usage pattern of the energy appliances mainly decide the quantity of the energy which is dictated by the overwhelmingly complex and difficult to comprehend interaction between the occupant and building system[3]. The main challenge lies to analyse or predict this, is the dynamical behaviour of the building system. Complex and intricate energy simulation tools like OpenStudio, EnergyPlus, Autodesk Revit are extensively employed to have an estimation of the building energy consumption as practice has reflected the results to be trustworthy. However, the accuracy metrics of this results is highly dependent on the complexity and spread of the dataset varying with the influential building parameters and consumes a lot of time with a requirement of domain-specific expertise.

Machine learning has revolutionized the way we use to experience the web[4]. With a well-diversified repertoire of real-life implications, ranging from web search recommendation to financial predictions, it hasnt left any stone unturned. In this aspect, machine learning can facilitate to develop a holistic apprehension of the cost-effective and energy-saving building, using a quantitative, data-driven approach. Understanding the occupants behaviour (OB) is of paramount importance for the indoor room temperature prediction leading towards the consumption of energy, regardless of the buildings construction.The determining part of OB depends on an enormous variance in the energy usage cycle and the thermal comfort requirement varying as per person, which is mainly affected by the occupants interaction with the thermal control systems (Thermostat and HVAC setting parameters), building components (fenestrations, drapes, roof styling) and energy appliance usage. Several studies have also revealed that the net consumption of the building severely depending on the work-style approach taken by the occupants. In reality, off-peak hours account more wastage of energy than the genuine consumption during the peak hours caused by a wasteful approach to energy usage rather than an austere one. Hence, it is imperative to research in the idea of energy efficient home-based systems, perfectly poising at a balance between comfort versus consumption curve. The attenuation of various thermal systems depends on a straightforward relationship with the concept of individual's comfort; which leads to indoor room temperature forecasting.

The present literature has emphasised on multiple variable predictions of indoor temperature utilising various weather parameters as the input points, like the amount of solar irradiation available at the geographical location of consideration during different previous time periods, the outdoor ambient temperature and the velocity of the wind. The prediction of the temperature of the conditioned space is calculated implementing time series solution with the aid of some traditional machine learning algorithms like Neural Networks, Random Forest and Support Vector Machine (SVM).

II. State-of-the-Art

There has been a growing interest among the researchers for the building energy consumption profiling in the past few decades. According to a survey report published by International Energy Agency (IEA), by the end of 2050, the global energy consumption from HVAC components are going to be tripled which is almost the energy demand of USA, EU and Japan by today. Hai-xiang Zhao and Fredric Magouls [5] has reviewed the contemporary works in the sector of building energy consumption analysis mainly sub-divided under the categories of collaborative physical engineering models, statistical regression models and artificial intelligence methods like neural networks and SVM; provided a holistic understanding and comparative insights about their respective prediction efficiency, model creation complexity and dependence on the window of inputs collected. A.S.Ahmad, M.P.Abdullah et al. [6] has focused on the detailed analysis of various artificial intelligence methods like General Regression neural network(GRNN), radial basis neural network(RBNN), Group method of data handling(GMDH), uni-variable and multi-variable SVM, Least Square SVM(LSSVM) and hybrid models. They also discussed their underlying principles, statistical performance variables and computational advantages and ranges of efficiency depending on the climate zone and time horizon required for the prediction studies. Nelson Fumo [7] abridged the systematization of various forecasting techniques collaborated by other literature reviews and emphasised on the effect of model tuning(calibration) for attenuating the simulation results generated from an existing model to the expected outcomes and influencing weather parameters for energy consumption prediction. Zhengwei Li, Yanmin Han and Peng Xu [8] has reviewed twelve energy benchmarking meth-ods under the classification of Black-Box, Gray and White-Box method. They proposed a selection method on a flow-chart for choosing the best method based on the requirement of input and training data, calibration effort and modeller's efficiency. Richard E.Edwards [9] et al. has presented an approach of reviewing the effectiveness of seven machine learning methodologies on a building dataset of energy consumption at every 15 minute interval, measured by sensors, to find the most effective one for hour-ahead prediction which is also compared with ASHRAE Great Energy Prediction Shootout. The result has expressed the dominance of neural networks commercial building domain whereas Least Square SVM works better for the residential sector. Wei Tian [10] discussed in his paper about the imperativeness of sensitivity analysis to correlate the building thermal energy performance along with the prerequisite steps necessary to perform the analysis with some real-world case studies. The reviewing method obtained from this analysis is mainly based on the range and quantity of input variables, computational complexity and purpose for research.

III. Contemporary prediction methods

The current practices to predict building energy load can be categorized into mainly three main groups: physical engineering or white-box methods, statistical regression or data-driven models and hybrid approach or grey-box models. Engineering methods utilize physical modelling for building energy con-sumption by simulating the governing laws of thermodynamics using extensive building level data. Physical modelling is con-strained mainly due to its vastness of data and computational demands. Statistical learning methods for estimating building energy consumption aim to directly regress energy consumption values on associated building and climate parameters. Hybrid methods implement a combination of both engineering and statistical models and feed the output from engineering models as an input to statistical models. The purpose of these later two models is to offset some of the constraints involved with physical modelling likewise the inability to model every respective type and sizes of building, which leads to a higher cost, with the flexibility of statistical approaches. Machine learning models are statistically proven to be better suited for modelling the complex relationships between building-level characteristics and energy consumption since such models have fewer constraints on the statistical relationships among variables. There are mainly four steps for creating a statistical model: data assembling, data pretreatment, training and testing of model. For data gathering step of developing black-box models historical/statistical data like weather condition and energy consumption are stacked, from numerous governmen-tal or privately-owned organizations open-sourced database. Model testing aims to evaluate the selected model's efficiency using standard evaluation metrics.

IV. Methodology

A. Description of the dataset

For this project, a residential building in Granada, Spain, equipped with a complex monitoring system, is used for constituting a dataset with multiple building parameters. It corresponds to one month of data sample collected from the monitor, spanning from 14^{th} March 2013 through 12^{th} April of the same year. The paper utilizes time series prediction technique where the series is spaced after every 15^{th} minutes where every data point is the average of the last quarter.

B. Time series forecasting

The time series forecasting could be easily integrated into a predictive control systems where the data points may be following a linear or non-linear trend, a cyclic variation, or a seasonal pattern over a long period of time, like a year. A time series is a collection of data sampled in an orderly sequence of uniform time interval at succession. The data points normally follow a trend, linear or non-linear along with a pattern which could be comprehended by statistical learning methods.

A time series forecasting depends on the type of input data samples; where the past values are analysed to predict the future values are relying on the assumption that it will follow the similar trend as of the past one. The forecasting models mostly depend on the number of past data samples collected, the time duration needed in future for prediction. This prediction is mainly classified into two types, single-step ahead where only next time interval is predicted while in multi-step ahead iterative forecasting follows forecasting one future data point using an iterative process and multi-step ahead direct forecasting spans its prediction timeline.

C. Target and features selection

TABLE I
DATA VARIABLES AND DESCRIPTIONS

Attributes	Units
Date of record	UTC
Time stamp	UTC
Dining room indoor temperature	°C
Room indoor temperature	°C
Forecast weather temperature	°C
Dining room CO_2	ppm
Room CO_2	ppm
Dining room RH	%
Room RH	%
Dinning room lighting	Lux
Room lighting	Lux
Rain, in the last 15 minutes where rain was detected [0 or 1]	
Wind velocity	m/s
West facade illuminance	Lux
East facade illuminance	Lux
South facade illuminance	Lux
Solar irradiance	W/m^2
Outdoor temperature	°C
Outdoor RH	%
Day of the week (computed from the date), 1=Monday, 7=Sunday	

In this literature, our objective forecast variable is Indoor temperature (room) in °C, which we denote as **'Target'**. For the prediction or forecasting of this building attributes, which has paramount importance on the building energy load distribution, we first visualize which other co-variates has a profound impact on room temperature. Initially, we made Outdoor temperature, Sun irradiance, Lighting (room), Outdoor relative humidity, Day of week as our targeted guess for co-variates, which we called **'Features'**. We noticed some interesting patterns between the correlation of this target and features, such as:

- The indoor room temperature depends on the outdoor temperature at that same time stamp, but Sun irradiance takes time to heat up the room.
- At some instances, Sun irradiance is irregular, which can be assumed as an effect of rainy/cloudy environment.
- During night time, Sun irradiance is zero, which sometimes measured as negative values due to machine inaccuracy.
- Indoor room temperature at a particular time instance is affected severely by the data points measured during each 15 minutes time interval of the previous hour.
- Lighting of the room and outdoor relative humidity did not contribute to the variation of indoor room temperature at all.

From these correlations, it is evident to create '**Lagged**' and '**Time-related**' features for the complete features, required for correlating with the target attribute.

For this purpose, we create a functionality which returns the lagged values of several co-variates and target itself of each of the particular time stamps. The created lagged values are the data points of sun irradiance at the previous 3^{rd} to 6^{th} hours, outdoor temperature at the previous 1^{st} to 4^{th} hours, and the indoor room temperature at the previous 30^{th} to 60^{th} minutes. We also created another functionality to generate time-related features like hour, day of week, month, day or night, weekend detector (day of week is either 5 or 6). We created a heat-map implementing Seaborn library for providing insight about the correlational strength between the target attribute and all selected variables or features in the Fig 22. A heat-map is a pictorial representation where data is stored in a two dimensional or matrix form where an array of colour-coding is utilized to represent different values[11].It mostly reflects a data table from above which is of importance for a generic view of the numeric data. Before using this functionality, we normalized our provided dataset matrix choose a relevant colour palette using cluster analysis which permutes the rows and the columns of the matrix to place similar values near each other according to the clustering. Here co-relational strength varies from -1 to +1, where the higher value (darker maroon colour) indicates higher correlation as well as lower value(darker blue colour) indicates a poor connection.

D. On-line learning methodology

The entire dataset, combined with target and features, was split in training and testing validation randomly, created by CARET's data partition function implemented in Python machine learning library Scikit-Learn. 80% of the data is used for training of the machine learning models where the rest is used for testing the efficiency of the model. In this present literature On-line learning methodology has been adopted instead of batch model where the entire dataset is provided at the beginning. On-line learning model initiates with a preliminary guess model and then tests it's predicted values collecting one of the available set of training values in first epoch.In each iteration, the algorithm recalibrates the parametric weight of the input for better prediction and adapts the changes to a newly evolved model. On-line learning algorithm has been advantageous over the conventional batch model due to it's lesser computational complexity and the requirement for entire dataset availability in the initial phase. For any real-time scenario where the entire dataset is unavailable in the initial design phase, this methodology is particularly useful. The main challenge to implement this algorithm to lessen the amount of '**regret**', which is the difference between the accuracy of the prediction obtained in the on-line methodology and the accuracy achieved in off-line method, i.e., where the entire dataset is available for prediction in the initial phase.

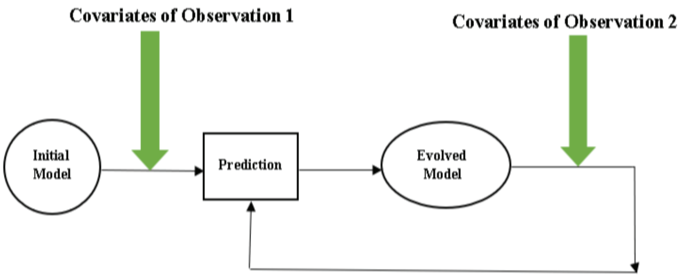

Fig. 1. On-line learning methodology

E. Experiments

The machine learning models are implemented in Python 2.7, integrated with Canopy environment, using the Scikit-Learn library along with other scientific libraries; such as Numpy, Pandas, Scipy. If not otherwise stated, default settings are used, i.e. no settings are overridden. To predict the indoor room temperature, a data-frame created by Pandas spanning ten days after addition of proper features, has been used as input. For the visualization of the predicted result's efficiency, Matplotlib and Seaborn libraries are used.

F. Performance of the regression models

All the regression models are trained with k-fold cross validation to select the best result. The supervised machine learning models' performance is quantified using a variety of standard metrics [12]. In this literature, four popular metrics have been used to evaluate the efficiency of the models, namely the Coefficient of Variance(**CV**), Mean Bias Error (**MBE**), Mean Absolute Percentage Error (**MAPE**) and Coefficient of Determination or R-squared, R^2.

Statistically, Coefficient of Variance(CV) is a standardized measurement for relative variability which determines the variance of overall prediction percentage error concerning target feature's mean value over the period. CV is defined as follows;

$$CV = \frac{\sqrt{\frac{1}{(N-1)}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}}{\bar{x}_i} \times 100 \tag{1}$$

where $\hat{x}_i$ is the predicted indoor temperature, x_i is the actual indoor temperature and $\bar{x}_i$ is the mean room temperature.

Mean Bias Error(MBE) is a measure of average errors of the prediction when the sign of the errors are also considered which also indicates how a model falters in estimation. MBE is defined as follows;

$$MBE = \frac{1}{(N-1)} \frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)}{\bar{x}_i} \times 100 \tag{2}$$

Coefficient of Determination or R^2 is a statistical measure of how close the data are to the fitted regression line. The value of R^2 varies from 0 to 1. It is a quite good apparent measure of the predictive model's accuaracy based on the feautre's aggregation untill overfitting, i.e, model memorizes data instead of learning, starts.

$$R^2 \equiv 1 - \frac{SS_{res}}{SS_{tot}} \qquad where$$

Residual sum of squares,

$$SS_{res} = \sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2 \tag{3}$$

Total sum of squares,

$$SS_{tot} = \sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2 \tag{4}$$

V. Results

A. General overview of the dataset

To assess the performance scope of the prediction models, the employed dataset has been reviewed from the feature and target selection point of view. Initially, the real-time values of the variate parameters, measured by various sensors have been collected for further assessment.

The measured readings from multiple sensors were collected from the Building Energy dataset of a Low-Energy Spanish building spanning over 30 days.

TABLE II
Actual measured values (from Sensors) of multiple attributes

	Indoor Temp.	Outdoor Temp.	Outdoor Temp.	Solar Rad.	Outdoor Humidity	Indoor Lighting
Count	2880	2880	2880	2880	2880	2880
Max	24.944	26.000	29.150	874.539	70.632	143.280
Min	11.076	5.000	9.223	-4.100	25.517	11.670
Mean	18.545	13.570	16.767	232.912	52.619	43.071
Std	2.975	4.935	4.121	304.359	10.417	45.415

The Table II presents an overview about the range of input data points of total 2880 rows in form of maximum, minimum, mean and standard deviation of the collected data inputs for target and features.

The heat-map in Fig. 2 provides insight into the correlation between the target and the selected features.

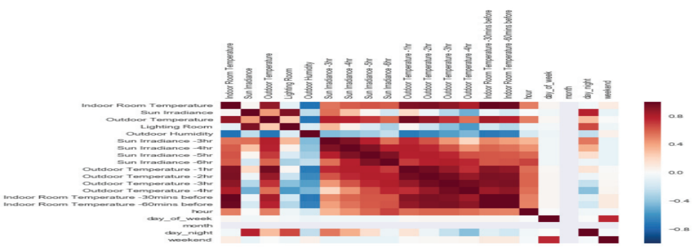

Fig. 2. Correlation between Target and Features using Heat-map functionality

The targeted dataset has been normalized and plotted for a better understanding of the features and target in Fig. 3.

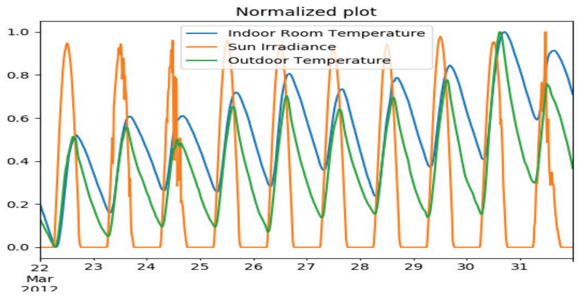

Fig. 3. Normalized plot

B. Discussion of the results

Three different supervised machine learning algorithms have been employed on the normalized dataset and their accuracy metrics are also evaluated in the Table III

TABLE III
ACCURACY METRICS FOR THE PREDICTION METHODS

Methods	MBE(10^{-8})	Coefficient of Variance(10^{-8})	R^2 Score(10^{-8})
Ensemble Random Forest	90444484	08399923	98545907
SVM	1006099800	13667716	88209488
Neural Networks	65649325	11051221	92097827

Overfitting of a model occurs in supervised machine learning when the model reads the training dataset more than expectation, i.e. it could not differentiate between the '**signal**' and '**noise**'. Noise or random fluctuations d ue to some uncertain events are picked up by the model as the part of learning process instead of treating them as an anomaly which in turn negatively impacts the future performance of the model to efficiently work on a new dataset. **Underfitting** is a phenomenon which happens only if the machine learning model has poor learning technique and insufficient amount of data. To find a good fit for the model it is best suitable to find a middle ground between them, ideally it is found when the error starts to increase when after a certain amount of time or training of the dataset. For our literature to avoid overfitting of our model, we used k-fold cross validation method, along with '**Random subsampling**' method which allows our model to tune the parameters with original training set keeping the test datasets unseen initially splitting them into k no of subsets. Also in addition we kept a validation dataset, which was introduced to the model before the final assessment, for utilising after the overall tuning of the algorithms.

The predicted and real-time values are plotted in following figures describing the efficiency of the prediction models.

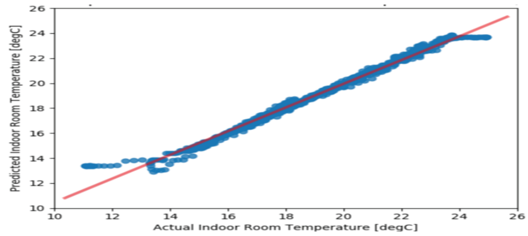

Fig. 4. Predicted vs Actual results for Random Forest

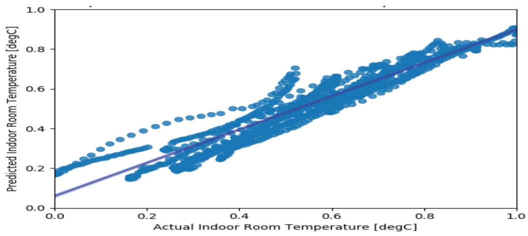

Fig. 5. Predicted v/s Actual results for SVM method

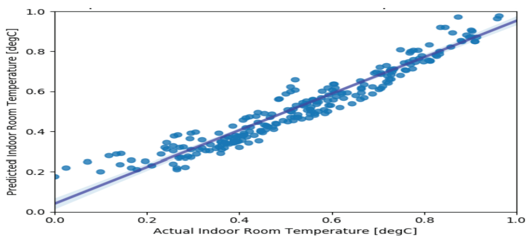

Fig. 6. Predicted v/s Actual results for Neural Networks

VI. IoT and Edge Computing Architecture

We present a novel IoT architecture for energy consumption prediction in a smart building. The architecture exploits the concepts of Edge Computing (EC), Virtual IoT Devices (VID) and Internet of Things (IoT). It provides harmonized, interoperable, light weight and secure solution for predicting the energy consumption in a smart building. The architecture is presented in figure 7 and its components are discussed in the subsections below. The architecture preserves interoperability in each stage by using standard web technologies and RESTful web services for data exchange.

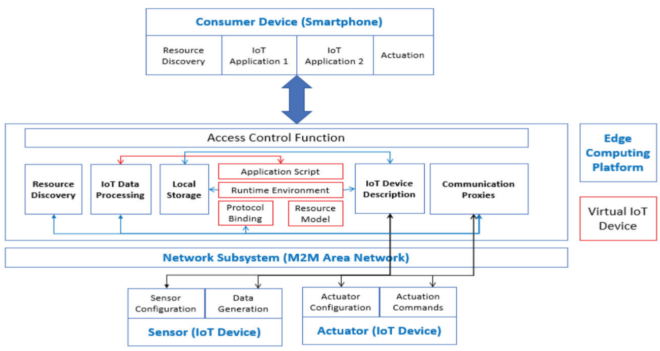

Fig. 7. Proposed IoT Architecture

A. IoT Devices

The connected devices in a smart building fall under IoT Devices. They are basically connected lights, fans, washing machines, microwave ovens, air conditioners et. They are energy consuming devices and needs a monitoring of how much energy each of them consumes for a proper energy consumption prediction of a smart building. The IoT devices have the capability to (i) actuate with proper commands (ii) provide IoT data when queried. Each IoT device has its own device description using events, properties and actuations. When these devices are connected to the Edge Computing Platform they are required to provide their description to the platform which helps in resource discovery and management of the IoT devices.

B. Edge Computing Platform

The Edge Computing Platform is the computational node of the proposed architecture the energy prediction of the devices is performed in this node. The main functional units of this node are (i) Communication Proxies (ii) IoT Device Description (iii) Resource Discovery (iv) Local Storage (v) Data Processing and Energy Prediction (vi) Virtual IoT Devices as described in [13] and [14].

Sensor Data Processing: This layer is responsible for the main data processing and energy prediction task. The layer performs (i) Sensor Data Validation (ii) Creating Meta data (iii) Energy prediction of the devices (iv) Securing the data payload. First, the sensor data is checked if the data is correct or not and belongs to the output range of the sensor. Second, a meta data is generated which is Sensor Measurement List (SenML) compliant. Third, using the data and the above described procedure energy estimation of the smart building is done. Lastly, the data payload is secured using AES-256 encryption for communication between the consumer devices and the platform.

Virtual IoT Devices: A Virtual IoT Device (VID) is a virtual sensor or virtual actuator that is capable of behaving like a physical device and is capable of replacing the physical device. This component in conjunction with the data processing layer is responsible for predicting the energy consumption of the devices from before hand without the real devices being used. This will help the consumer plan his energy expenditure from before hand and run his IoT devices accordingly.

C. Consumer Devices

Consumer devices are the interface between smart devices and smart building dwellers. The consumer devices are mainly smart phones, tablets, smart watches et. They have mobile applications that help the dwellers control the smart IoT devices, see their data and functionalities. The estimated energy expenditure will be displayed in the application running in the consumer devices. An advanced prototype created in [15] is utilized in this work.

VII. CONCLUSION

We have presented an approach combining the IoT and Machine Learning mechanisms to predict smart building's indoor temperature. The prediction of indoor temperature reduces the overall energy consumption of the building accounting for heating and cooling demand, by automatically controlling these high energy consuming devices over the network. It allows the user to effectively set an indoor temperature of his own will or the algorithm learns user choices of indoor temperature and sets to that temperature automatically by our described methodology. A higher degree of automation with a safe and secure Edge Computing based IoT architecture is a novel addition to the present literature. Our experiments and results presented in this work validate our approach.

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