An IOT and Cloud Computing Based Architecture for Energy Usage Prediction in Smart Homes

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Abstract: The miniaturization of sensor devices combined with advances in networking and communication technologies have given rise to Internet of Things (IoT) paradigm. Another contemporary technology is cloud computing which facilitates availability of computing platforms, databases and applications on-demand. In this paper, we present the development of a smart home system that uses IOT and cloud computing paradigms to predict household energy consumption and electricity costs. The proposed system collects a variety of data – such as electricity consumption, indoor temperature, humidity, outdoor weather information and uses cloud computing infrastructure for the data storage and prediction of energy consumption using timeseries forecasting methods. Users can monitor energy consumption, costs and predicted usage in real time through the dashboard application connected to cloud platform. We developed DHT11 and Arduino ESP8266 based IoT sensor to measure indoor temperature. We also wrote several services and functions in Google Cloud Platform (GCP) to collect and store sensor data and for the prediction energy consumption data.

Keywords: Internet of Things, Cloud Computing, Smart Home, Weather, Energy Consumption Prediction

1. Introduction

Due to the solid growth of global economy and increased demand for heating and cooling in some reasons, household energy consumption is increasing gradually worldwide. Since the amount of energy resources that we can use is fixed, saving energy has become the second most important task for us after the development of alternative energy. By checking household power consumption in real time and predicting future energy consumption and costs in advance, it can help us to save household energy consumption and costs. Furthermore, this approach can also be applied to tall buildings with relatively large energy consumption, helping to save a substantial amount of energy and money.

In this paper, we present the development of a smart home system that uses IOT and cloud computing paradigms to predict household energy consumption and electricity costs. The proposed system collects a variety of data – such as electricity consumption, indoor temperature, humidity, outdoor weather information and uses cloud computing infrastructure for the data storage and prediction of energy consumption using timeseries forecasting methods. The work in progress system also features a dashboard application with an easy user interface that allows a real-time view of current energy consumption and predicted energy consumption. For energy usage prediction, we are presently experimenting with a variety of machine learning models such as Autoregressive Integrated Moving Average (ARIMA), Vector Auto Regression (VAR) and deep learning based Recurrent Neural Network (RNN) techniques.

The cloud computing system receives data from the IOT devices which measure electricity consumption, temperature and humidity in real time and stores this data in Firestore, the DB function of Google Cloud Platform. Using Google Cloud Platform's Functions and Scheduler, the system analyzes the data and sends the user's energy consumption data and prediction to the Dashboard being developed with the C# Dot Net Framework.

In the remainder of this paper, we present related work, experiments to understand energy consumption patterns, system architecture and development followed by conclusion and future work.

Related Work

The research reported by Asare-Bediako in [1] states that as technology advances, energy optimization is very important because annual energy consumption is gradually increasing. He suggested ways to save energy through an integrated smart home energy management system. A smart Home Energy Management System (HEMS) architecture that takes into account both energy consumption and power generation is proposed by Han and Choi in [2]. The home server collects energy consumption and power generation data, analyzes it for energy estimation, and designs a system that controls the schedule of household energy use to minimize energy costs. Cottone et al. [3] proposed recognizing user daily life activities by relying on the analysis of environmental sensory data in order to minimize energy consumption by guaranteeing that peak demands do not exceed a given threshold. Mishra et al. [4] explored an intelligent charging system, called SmartCharge, and an on-site battery array to store low-cost energy for use during high-cost periods. SmartCharge's algorithm reduces electricity costs by determining when to switch the home's power supply between the grid and the battery array.

Soliman et al. [5] presented an approach for the development of Smart Home applications by integrating Internet of Things (IoT) with Web services and Cloud computing. Their multi-dimensional approach focuses on embedding intelligence into sensors and actuators using Arduino platform, networking smart things using Zigbee technology, facilitating interactions with smart things using Cloud services and improving data exchange efficiency using JSON data format. The research work by Piyare [6] presents a low cost and flexible home control and monitoring system using an embedded micro-web server, with IP connectivity for accessing and controlling devices and appliances remotely using Android based Smart phone app.

Zeynali et al. [7] implement two-stage stochastic programming in a smart home application to reduce the electricity procurement cost of an ordinary household. Sabit et al. [8] present an ambience intelligence application for smart home systems for efficient use of electricity, for enhancing comfort zone and to achieve independence of living and security. Their system integrates smart home occupant's identification, sensors-actuators deployment, a gateway hub, machine learning, and cloud computing components to realize the objectives of smart living.

2. Experiment

According to Hart et. al. [9], the energy usage of refrigerators, freezers and domestic hot water systems varies depending on the weather. All appliances showed varying degrees of weather sensitivity, which was universally stronger in the cooling season than in the heating season. This suggests that energy use varies depending on the weather. To identify the correlation between weather data and energy consumption, we used the Enertalk energy consumption dataset for 22 houses in Seoul [10] provided by Encored Company together with weather data to confirm the correlation between weather and energy consumption. We combined weather data and consumption data for 22 homes from 2016 to 2017 provided by Encored into a single data file through Python scripts.

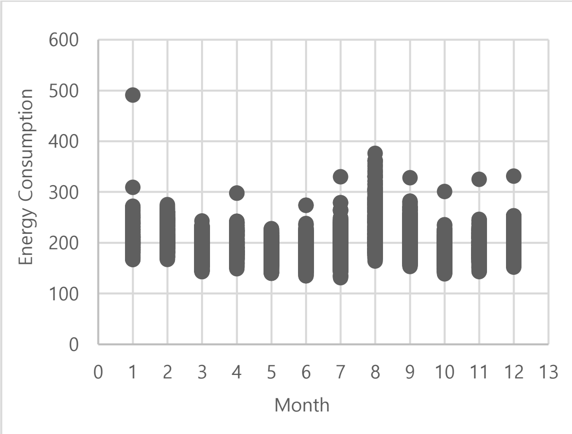

Figure 1: Energy Consumption per month (Enertalk dataset [9])

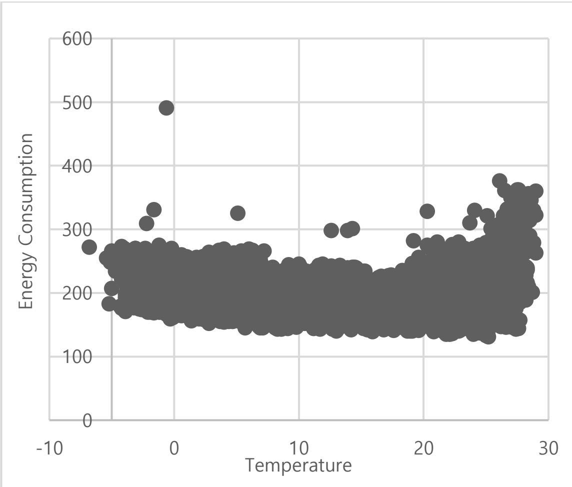

Figure 2: Energy Consumption vs. temperature (Enertalk dataset [9])

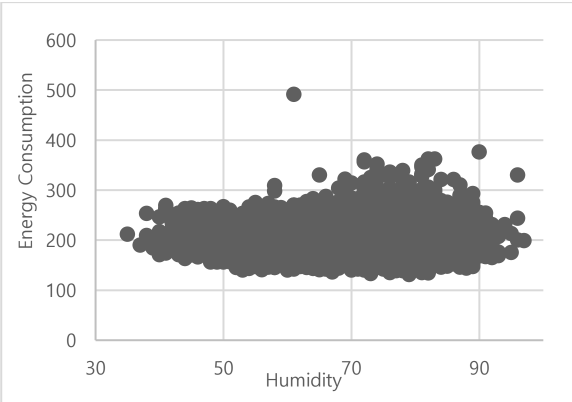

Figure 3: Energy Consumption vs humidity (Enertalk dataset [9])

The graph shown in Figure 1 shows the energy consumption in watts vs. month for these homes. We can observe through this graph that energy consumption in summer is higher compared to other months. The graph in Figure 2 shows energy consumption as compared to outdoor temperature, while the graph in Figure 3 shows energy consumption compared to indoor temperature. These graphs suggest that energy consumption increases in the summer when humidity and temperature are on the higher side. We can confirm that external weather factors affect energy consumption of residential households.

3. System Architecture

3.1 Architecture of Proposed Smart Home System

A multi-tier system architecture for smart home to predict household energy consumption is shown in Figure 4. The first tier consists of IoT enabled sensor devices that measure household electricity consumption, indoor temperature and humidity and transmit data to the cloud computing platform. The second tier consists of a cloud computing platform that provides datastore services for the storage of information provided by sensors and service for hosting energy prediction models. The cloud computing platform also provides a service to fetch real-time outdoor weather data which is used for predicting future energy consumption. The third tier consists of a Dashboard application that allows monitoring current energy consumption, predicted energy consumption and costs.

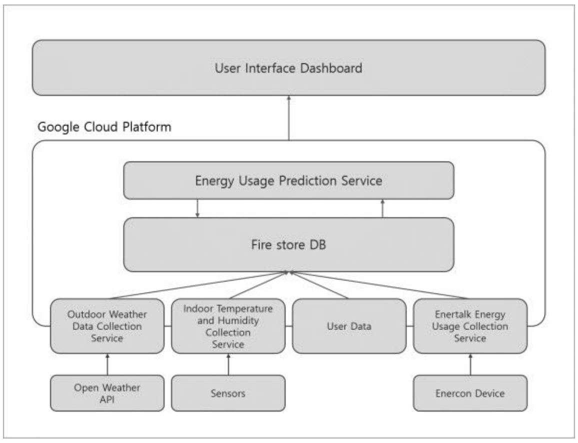

Figure 4: A multi-tier system architecture for the prediction of household energy usage

On the implementation side, we store data for each service using Firestore Database of Google Cloud Platform. We are developing a machine learning algorithm based prediction models which predict energy consumption and costs and store these predictions in the Firestore database. These values are later used by the User Interface (UI) Dashboard for users to easily check the energy consumption and prediction.

3.2 Architecture for UI Dashboard

The architecture of UI dashboard that helps users to gain easy access to electricity consumption and prediction data is shown in Figure 5. The UI dashboard is implemented using C# .net Framework, which imports the electricity consumption and other data in real time from the database hosted at the cloud computing platform and visualizes this data to the user. Users can also check the temperature and humidity inside the house in real time, and check the weather conditions outside by using UI Dashboard. The predicted energy consumption and costs data predicted by Google Cloud Platform's Functions can also be seen on the dashboard.

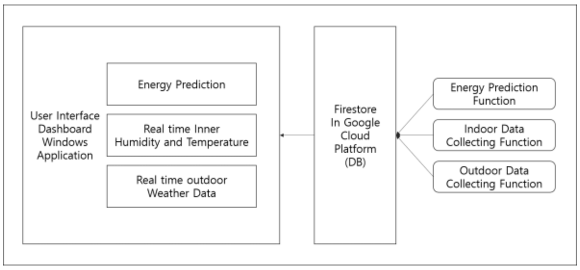

Figure 5: The architecture of UI dashboard

4. Energy Usage Prediction Methods

We collected energy consumption data of three houses during the duration 15th December 2019-3rd May 2020 using Enertalk electricity measurement device made available by Encored company. In order to predict energy consumption, we first did a comparative study of different machine learning models available in Weka software and then implemented two statistical models, AutoRegressive Integrated Moving Average (ARIMA) and Vector AutoRegression (VAR) in Python.

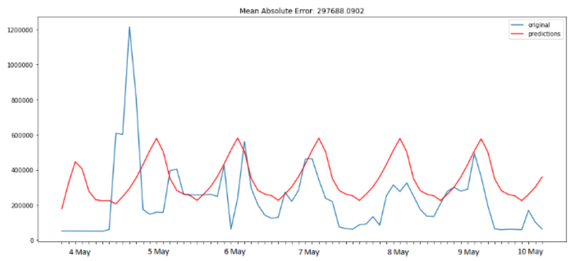

Figure 6: ARIMA Hourly Graph – MAE:297688

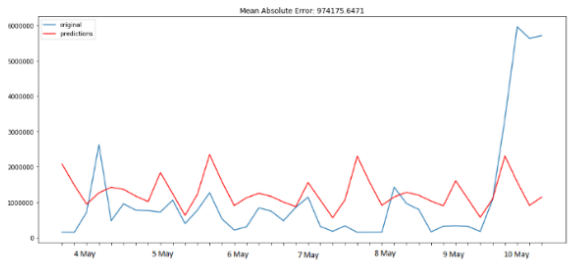

Figure 7: ARIMA 3 Hourly Graph – MAE:974175

We implemented both models using the python package `statsmodels`. The main problem we faced was that the size of the energy consumption data we collected was very short. This resulted in a sub-optional performance of developed models. To improve the accuracy of the model we tried to experiment on data with a longer interval, so we resampled data from a 15 minutes interval to 1 hour, 3 hours, 6 hours, 12 hours and daily interval. The graphs shown in Figure 4 and Figure 5 show the result of forecasting energy consumption using ARIMA. We will describe our detailed experiences with developing machine learning models for energy prediction in other research paper.

5. System Implementation

In this section, we present implementation details of our proposed system.

Google Cloud Platform

Cloud computing is the immediate delivery of system resources for virtualized computers through the cloud system. A type of Internet-based computing refers to the technology that processes work on other computers connected to the cloud, not on their own computers. Google Cloud Platform (GCP) [11] is the platform of our choice for the system implementation. GCP is Google's cloud computing service that provides hosting on the same infrastructure of Google. The cloud platform provides developer functions for the development of various services like Firebase or Scheduler.

5.1 Service for Weather Data Collection

We wrote a cloud function in GCP that collects outdoor weather data using the OpenWeatherMap API and Schedules a Cronjob (as shown in Figure 8) in GCP to collect outdoor weather data of Seoul city every 30 minutes. This data is written to Firestore (a GCP database) in JSON format.

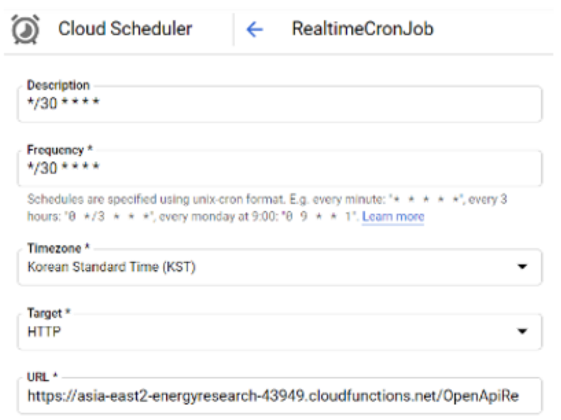

Figure 8: Using a cloud scheduler for fetching real-time weather data from OpenWeatherMap API

Data shown in Table 1 is imported in real time through the OpenWeatherMap API and is stored in the GCP Firestore database.

Table 1: Structure of outdoor weather data

Name	Contents
Outdoor Weather Data Collection (Real time Weather Data)	Date
	City
	Country
	Temperature
	Humidity
	Pressure
	Cloud
	Rain
	Snow
	Wind
	Discomfort Index

5.2. Service for Temperature and Humidity Data Collection in houses

We measure room temperature and humidity data (Table 2) using Arduino and DHT11 sensor assembly and send this data to GCP Firestore database in real time.

Table 2: Structure of indoor weather data

Name	Contents
Real time inner Temperature and Humidity Data	Date
	House ID
	Room ID
	Temperature
	Humidity

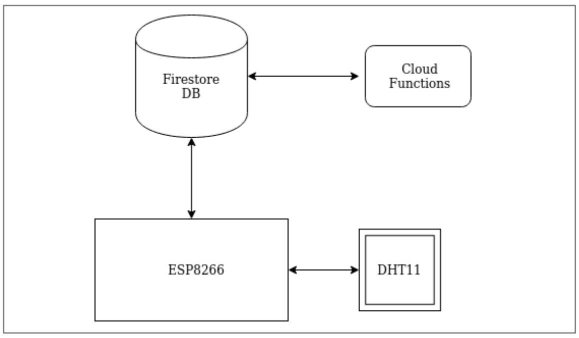

Figure 9: Architecture for collecting and storing indoor temperature and humidity data

GCP provides a vast amount of services which can be used for developing IOT devices. For this project we had to choose between using google virtual machine, Google IOT devices, Google Cloud Functions, or Firebase API to establish a connection between our sensor and the cloud database. Even though all the options were great we chose to use firebase as we found it the most straightforward and easy to learn. The architecture we used is made up of three main components that is Cloud Firestore Database, Sensor Device and Cloud functions. This basic architecture allows Arduino ESP8266 device to upload data directly to Cloud Firestore without involvement of a server. Figure 10 shows the prototype of DHT11 and ESP8266 sensor to measure indoor temperature.

DHT11: DHT11 sensor is a simple sensor which can easily be controlled by our ESP8266 micro-computer. It provides three pins for connections, the data pin, 3v3 pin and ground pin. These pins are labeled with the same names as on the ESP2866 which makes it much easier to connect.

ESP82266: The ESP8266 is used as a microcomputer to communicate with the DHT11 sensor. To connect to the sensor, we installed the DH11 Library in our Arduino IDE. The library also comes with some basic examples on how to read values. After successfully reading values from the sensor, the next thing will be to post that data to the firebase. To do this we need to install the Firebase Arduino library which helps us easily make a connection and send data. The only thing we have to do beforehand is to create a real time Firestore database on Firebase and copy the credentials to the uno code.

Firestore Database: In the Firestore database we have to set up a real-time database and copy the credentials needed for connecting from our device.

Cloud Functions: Once our data has been uploaded to the firebase, we can do anything we want with it. Firebase Cloud Functions allow us to create trigger functions that can be run upon creation as well as any functions we want to use to get, change, delete, or update our data. The functions can be written in many languages and easily deployed online.

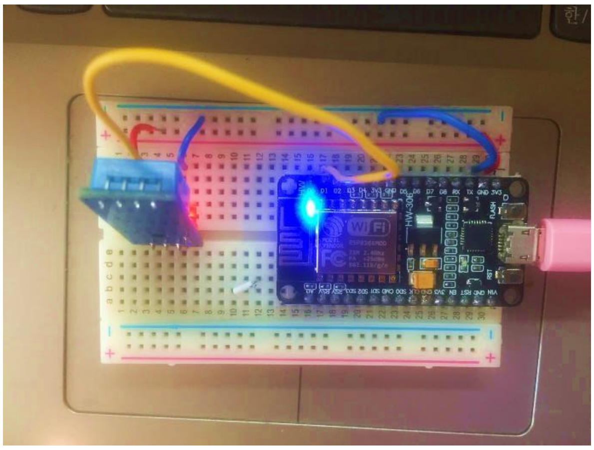

Figure 10: Sensor assembly for collecting and storing indoor temperature and humidity data

5.3. Service for Energy Usage Collection in houses

We measure household energy usage (Table 3) in real-time using Enertalk sensor. The measured data is periodically sent and stored in the Enertalk cloud. We wrote Python script to fetch electricity usage data from Enertalk cloud using Entertalk API [12] and send this data to GCP Firestore database in real time.

Table 3: Structure of energy usage data

Name	Contents
Real time energy usage and cost data	Date
	House ID
	Room ID
	Energy Usage
	Cost

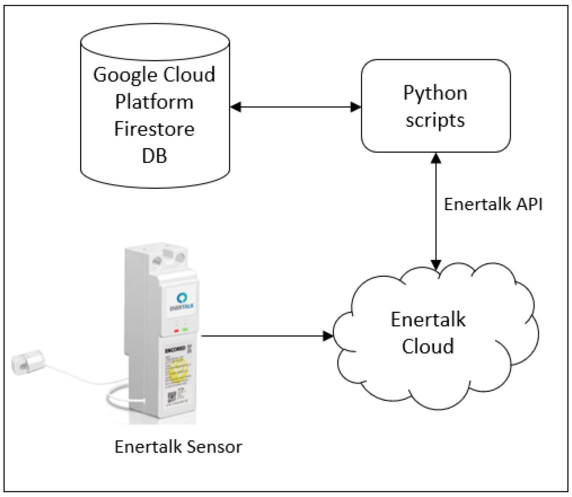

Figure 11: Architecture for collecting and storing electricity consumption data

5. Development for UI Dashboard

We are currently developing the Windows UI Dashboard Application using C# .net framework. The UI Application connects to the Firestore in Google Cloud Platform, and every second the data is retrieved from the database and updated. Users can check the data in real time.

Figure 12: Login screen of UI dashboard

We implemented the login screen (Figure 12) in the user interface. User ID and password information is stored in the Firestore database. We are currently working on various sections for visualizing data. In the Energy Usage section, UI shows the user's electricity consumption data, and users can view changes in energy usage over a specific period of time through a graph. The Energy Prediction section visualizes predicted energy usage and costs. The UI also shows the current weather data of user's city as shown in Figure 13.

Figure 12: UI showing current weather of Seoul city

6. Conclusion and Future Work

In this paper, we presented the architecture and ongoing development experience of an IoT and cloud computing-based system for the measurement and prediction of household energy consumption. We identified the factors that affect energy consumption and created a machine learning based model to predict the energy consumption of users. We developed DHT11 and Arduino ESP8266 based IoT sensor to measure indoor temperature. We also wrote several services in Google Cloud Platform (GCP) to collect and store variety of data such as real time weather data and energy consumption data. In addition, the Windows UI Dashboard application being developed allows users to see the amount of energy and costs consumed in real time. Visualization also helps users to see how much energy they will consume in the future.

While the ARIMA and VAR models developed for energy usage prediction were able to capture the trends, they were not as accurate as the amount of data so far collected in this study is small. In addition, there are also differences in people's standard of living, as well as not considering the quantity of household energy consumption data, of home appliances. In order to develop a more accurate prediction model, more data needs to be collected and data needs to be selectively learned according to living standards and the number of home appliances. As a future work, we plan to investigate use of RNN model for time series forecasting and compare performance with ARIMA and VAR models

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