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Management of Smart Energy Systems with IoT-based Predictive Analytics for More Efficient Energy Consumption

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ABSTRACT

Smart energy solutions and related systems like smart homes, smart cities are growing and stay the essential part of the whole ecosystem that we use to optimize the energy consumption. Modern Smart Energy systems can be highly successful, but they require intensive monitoring, control and management. Predictive analytics is one of the most important functionalities, required for modern intelligent systems, related to management of the energy consumption. There are two different aspects:

- Prediction of the energy price and availability
- Prediction of possible failures of the smart energy system equipment

In the past predictive analytics was quite expensive feature, because statistical algorithms require more computing power. With cloud-based IoT-based Predictive Analytics is easier, cheaper and more easily accessible for design, implementation and maintenance. This research has a goal to propose target solution design and appropriate models for Predictive Analytics in Smart Energy systems, based on Microsoft Azure.

Keywords: smart energy, IoT, predictive maintenance, machine learning, Microsoft Azure.

Acknowledgments: Special thanks to my family for the support and Microsoft for the Azure resources, which made possible this research.

Introduction

The energy consumption in different types of buildings has significantly increased in the last years. Energy is a very important part of our lives and almost all things in some way are associated with electricity [1, 2]. In accordance with the report issued by the US Energy Information Administration (EIA), it is expected 28% growth in global energy demand until 2040 [3]. Due to not optimal usage, a huge amount of energy is wasted annually. This situation crates a case energy wastage, which could be avoided by efficient utilization of energy. New smart energy consumption solutions are required to optimize the proper use of energy [4]. An energy consumption prediction is a very important component in the new solutions for smart energy management to achieve efficient energy maintenance and reduce environmental effect [6]. This case is actual for all kind of buildings, but is a little more challenging in residential buildings, because there are many types of buildings and different forms of energy. Also many factors are involved to influence the energy behavior of the building structures, such as weather circumstances, the physical material used in the building construction, company behavior, sub-level systems, i.e., lighting, heating, ventilating, and air-conditioning (HVAC) systems, and the execution and routines of the sub-level components [5].

IoT and Smart Energy

Technologies based on the Internet of Things (IoT) are very significant to comprehend the notion of smart homes. Many solutions for managing energy consumption predictions in buildings based on the IoT can be found in the literature [7].

After the growing of the new advances and techniques on Information and Communications Technologies (ICT), every place, everything and everyone can be impacted by embedded technologies allowing connection and communication between them in a non-intrusive and efficient way. This is the technological basis promoted by the so popular Internet of Things (IoT) [8].

The high volume of data that can be generated nowadays in urban environments, coming from different data sources, provides a great scenario to achieve intelligent and efficient management systems of energy consumption based on IoT. Big data analytics helps us to leverage the huge amounts of data provided by IoT-based ecosystems in order to reveal insights that help explain, expose and predict knowledge from them [9].

Methodology

The current research has two parts:

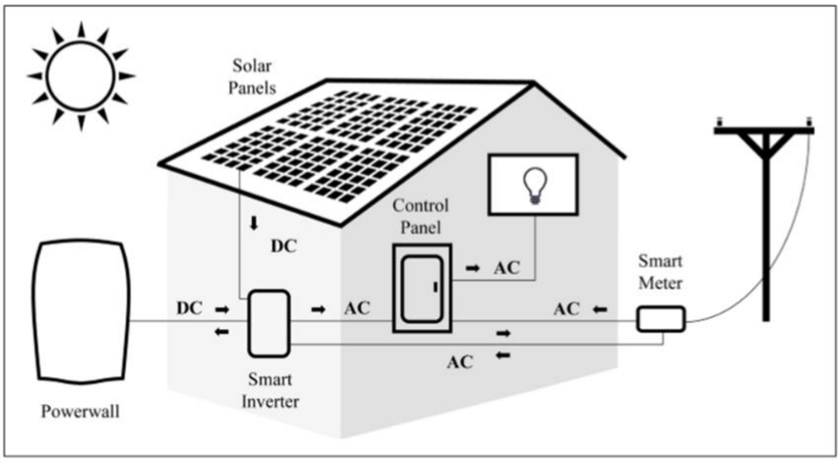
1. Classification and Regression Analysis using Decision Trees in Power BI, based on data, received from [13].

2. Energy consumption prediction, based on IoT Solution, collecting data in real time and using Machine Learning.

Power BI contains the functionality, needed to classify and analyze data from existing datasets.

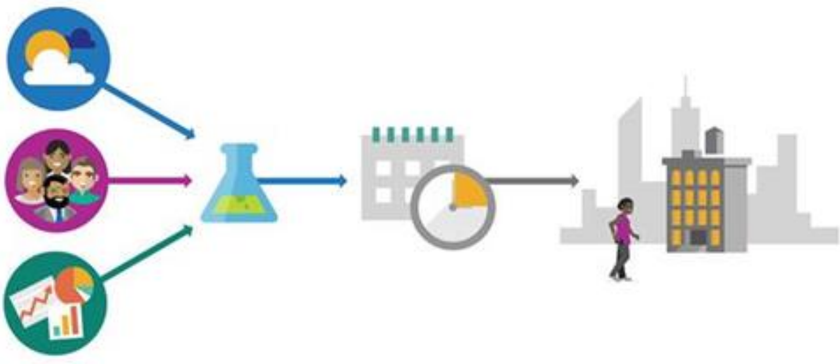
The IoT solution can be considered as part of real-life smart energy solutions, which are used to predict the energy consumption and to propose excluding of some power consumers when the consumption is too high

Figure 1. *Sample Real-Life Smart Energy System*



The current research includes data for energy consumption, based on HVAC (Heating, ventilation, and air conditioning) and energy consumers with general purpose: fridges, washing machines etc.

Figure 2. *Using Weather, Occupancy, and System Data with Machine Learning to Improve HVAC Scheduling*



Source: Microsoft Corporation.

Datasets that are used include the total electrical energy consumption, the heating and cooling energy consumption, and the outdoor and indoor environmental data such as temperature and humidity. The heating and cooling parts are deemed as the HVAC consumption, while the total electricity consumption covers a wider range of loads in the building. Although separate lighting data may be useful, such data are not currently available. Moreover, in the research are unified the semi-hourly or hourly logged data to an hourly basis for uniform analysis.

Proposed Energy Consumption Prediction Methodology

Energy consumption methodology, used in the research is based on regression algorithm:

Regression: Predict the Remaining Useful Life (RUL), or Time to Failure (TTF). In the current context, prediction is for remaining time with non-pick energy consumption values and the expected time to the next energy consumption pic.
Binary classification: Predict if an asset will fail within certain period (e.g. hours).

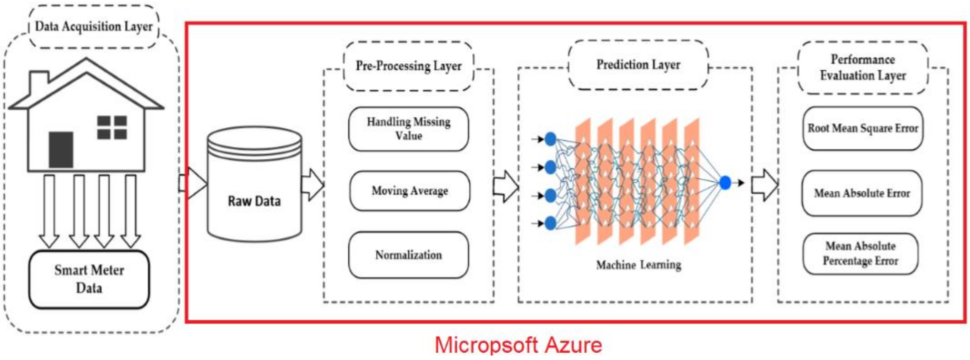
Sample data is generated synthetically from of datasets, received from [13]. Sample data is generated real time using historical dataset, based on variations of the data.

IoT Predictive Analysis Solution Overview Design

The solution contains the following parts:

- Sensors + field gateway / smart data meter
- Cloud gateway (IoT Hub)
- Data Storage (Azure Blob Storage)
- Databases (Azure SQL Database, Cosmos DB)
- Preprocessing Layer (Azure Stream Analytics)
- Prediction Layer (Azure ML)
- Performance Evaluation & Visualization (Power BI)

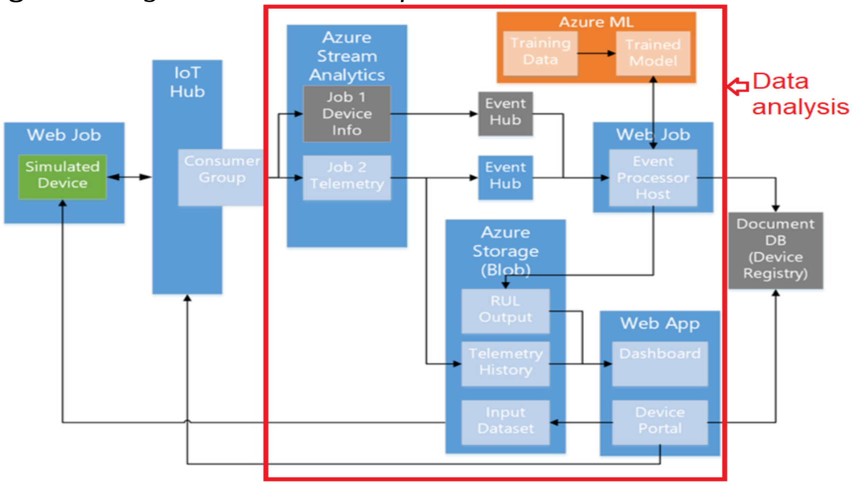
Figure 3. *Detailed Processing Diagram for the Proposed Energy Consumption Prediction Approach*



Logical Architecture

Logical architecture shows used components in the solution and demonstrates data flows:

Figure 4. *Logical Architecture of the Test Solution*



Azure provides advanced big-data management tools and has the capability to host a flexible, cost-effective solution in the cloud. In the solution are used the following components:

We identified the following as our primary solution components:

- Azure Machine Learning Studio. This fully managed cloud service enables you to easily build, deploy, and share predictive analytics solutions. It is designed for applied machine learning and it provides simple and easy deployment of machine learning algorithms.
- Microsoft Azure Stream Analytics is a server-less scalable complex event-processing engine by Microsoft that enables users to develop and run real-time analytics on multiple streams of data from sources such as devices, sensors, web sites, social media, and other applications. Stream Analytics supports three different types of input sources - Azure Event Hubs, Azure IoT Hubs, and Azure Blob Storage.
- Microsoft Power BI. A business analytics solution, Power BI enables data visualization and presentation, to help you further explore and analyze your data. Power BI uses a wide range of visuals and reports to deliver business intelligence insights and share them on a cloud-based platform.
- Azure Event Hubs is a Big Data streaming platform and event ingestion service, capable of receiving and processing millions of events per second. Event Hubs can process and store events, data, or telemetry produced by distributed software and devices. Data sent to an event hub can be transformed and stored by using any real-time analytics provider or batching/storage adapters.

Documentdb – A Multi-Model Nosql Database, Used for Processed Data

- Azure SQL Database, used for configuration data
- Azure Blob Storage, used for raw data
- IoT Hub – the Microsoft Azure cloud gateway service, which communications with devices. IoT Hub is configurable and supports automatic device provisioning

The Azure ML team has published a Predictive Maintenance template showing techniques used to predict when an in-service machine would fail, so the maintenance could be planned. If one follows step-by-step instructions provided by the template at the end you will get a trained model and a published Web Service that would accept some input data and produce a prediction based on it, but the template is missing any information how to collect data from devices (energy consumers), pass it to the model, and utilize the output.

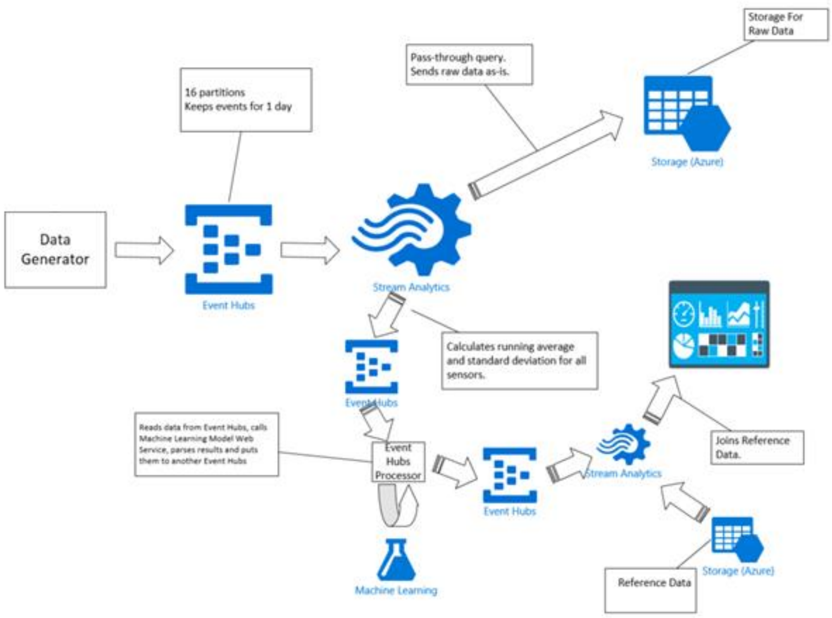
Experimental Setup

Experimental part, which needs to prove the correction of the analysis, does not need to have the real devices and communication via IoT Hub.

In the experimental solution is used generator, which generates variation of the data, based on the sample datasets.

This generator sends data to Azure Event Hub, and from there data is processed via Azure Stream Analytics. All the rest components are identical with real life IoT Solutions.

Figure 5. *High-Level Architecture View of the Experimental Setup*



Source: Microsoft Corporation.

Predictive Maintenance Template

Predictive Maintenance Template, used in Azure Machine Learning Studio is a modified template, which is offered in Microsoft Azure for general predictive maintenance tasks. In the current study, predictive maintenance template is used for prediction when the energy consumption is too high and there should be started activities to prevent the huge amount of energy consumption:

- Stop some energy consumptions
- Use alternative sources (batteries)

Predictive maintenance encompasses a variety of topics, including but not limited to: failure prediction, failure diagnosis (root cause analysis), failure detection, failure type classification, and recommendation of mitigation or maintenance actions after failure. As part of the Azure Machine Learning offering, Microsoft provides a template that helps data scientists easily build and deploy a predictive maintenance solution. This predictive maintenance template focuses on the techniques used to predict when an in-service machine will fail, so that maintenance can be planned. The template includes a collection of pre-configured machine learning modules, as well as custom R scripts in the Execute R Script module, to enable an end-to-end solution from data processing to deploying of the machine-learning model.

Three modeling solutions are provided in this template to accomplish the following tasks.

- Regression: Predict the Remaining Useful Life (RUL), or Time to Failure (TTF).
- Binary classification: Predict if an asset will fail within certain period (e.g. days).
- Multi-class classification: Predict if an asset will fail in different time windows: E.g., fails in window [1, w0] days; fails in the window [w0+1,w1] days; not fail within w1 days.

The time units mentioned above can be replaced by working hours, cycles, mileage, transactions, etc. based on the actual scenario.

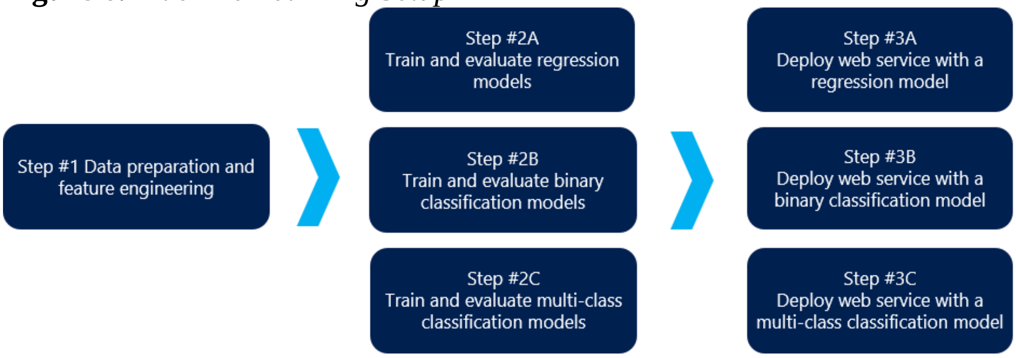
This template uses the example of simulated aircraft engine run-to-failure events to demonstrate the predictive maintenance modeling process. The implicit assumption of modeling data as done below is that the asset of interest has a progressing degradation pattern, which is reflected in the asset's sensor measurements. By examining the asset's sensor values over time, the machine-learning algorithm can learn the relationship between the sensor values and changes in sensor values to the historical failures in order to predict failures in the future. We suggest examining the data format and going through all three steps of the template before replacing the data with your own.

The template is divided into 3 separate steps with 7 experiments in total, where the first step has 1 experiment, and the other two steps each contains 3 experiments each addressing one of the modeling solutions.

Machine learning setup:

- Step 1: Data preparation and feature engineering
- Step 2: Train and evaluate model
- Step 3: Deploy as web service

Figure 6. *Machine Learning Setup*



Source: Microsoft Corporation.

Findings/Results

The research is summarized into four sequential key aspects:

1) Energy monitoring: Through communication networks, the consumption and generation of energy are monitored and logged in different granularities including the whole building, floors, departments, labs, rooms, and even occupants.
2) Energy modeling and evaluation: Through offline modeling and evaluation, the energy consumption patterns and factors that may influence the consumption and the extent of their impact are identified.
3) IoT system to apply practical changes and strategy adjustments: The modeling and evaluation: real-time results are used to identify the key energy components of the building, to apply adjustments, and to devise strategies to reduce energy consumption. IoT-based system is designed and prototyped using Azure IoT Component and Azure Machine Learning Studio to realize the strategies and achieve the goal.
4) IoT solution is used to predict energy consumption based on the sample dataset.

Detailed Evaluation and Analysis

In this section is presented a detailed modeling and evaluation results and the corresponding analysis.

For the research are used sample datasets from [13], representing energy consumption in US and worldwide.

The following analysis is provided:

1) Environmental Impacts Analysis: Here, the focus is on temperature and humidity, and study their impacts on the total electrical and HVAC energy consumption.
   a) Short period basic trend and correlation analysis: In the setup are put two groups of factors together:
      i) group 1 made of electric consumption, heating energy, and cooling energy and
      ii) group 2 containing temperature and humidity. We want to see if there is any straightforward connection. Figure 7 shows the relationship between electrical energy. Consumption and temperature. It shows almost no correlation.

During the research is sorted out the most useful measured data by analyzing the relationships among various parameters. Based on it, the data points that is used include the total electrical energy consumption, the heating and cooling energy consumption, and the outdoor and indoor environmental data such as temperature and humidity. The heating and cooling parts are deemed as the HVAC consumption, while the total electricity consumption covers a wider range of loads in the building. Although separate lighting data may be useful, such data are not currently available. Moreover, we unify the semi-hourly or hourly-logged data to an hourly basis for uniform analysis.

Regression Modeling and Analysis

In the research are used regression models to analyze the relationship among multiple factors and use the statistical approaches to examine whether they can justify our findings. Both MPR and MLR models, are used and there is comparison the two results.

Figure 7. *Total Electrical Energy Consumption with Temperature*

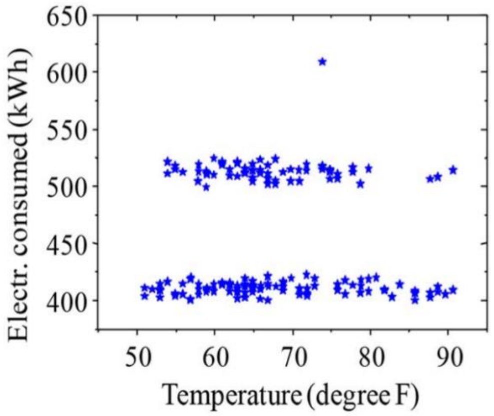


Figure 8. *Correlations among Heating Energy(H), Temperature (X), and Humidity (Y)*

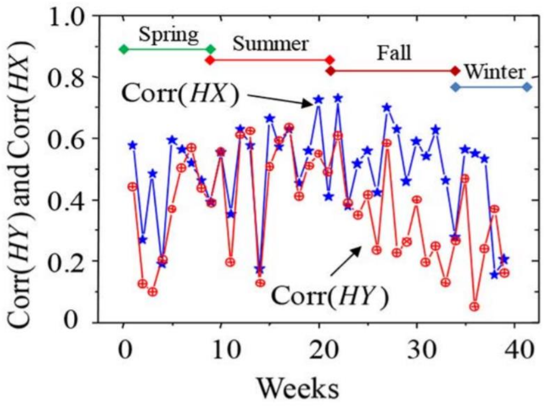


Figure 9. *Daily Electrical Energy Consumption Comparison between Summer and Fall*

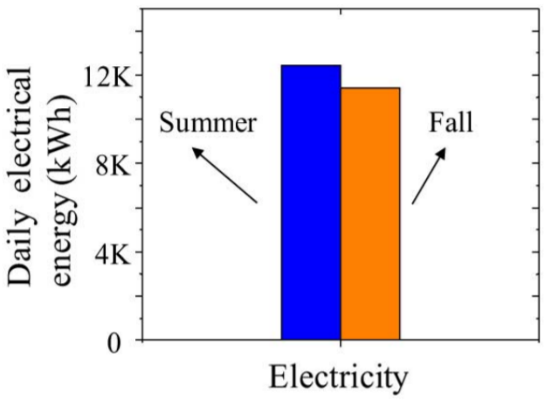


Figure 10. *Daily Energy Consumption Comparison between Summer and Fall, Considering After Hours and Office Hours*

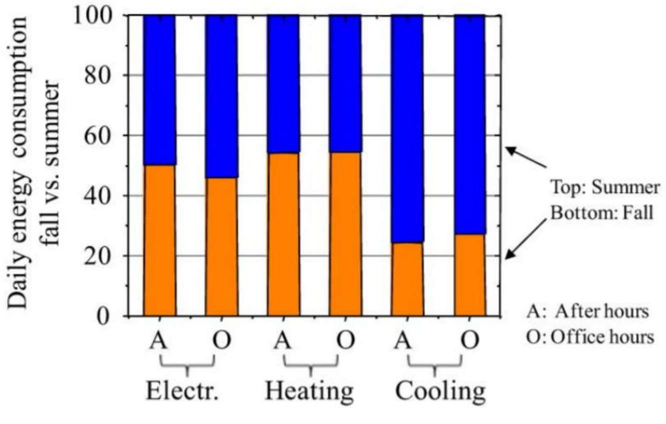


Figure 11. *Actual vs. ML Predicted Results for One-Week Energy Consumption*

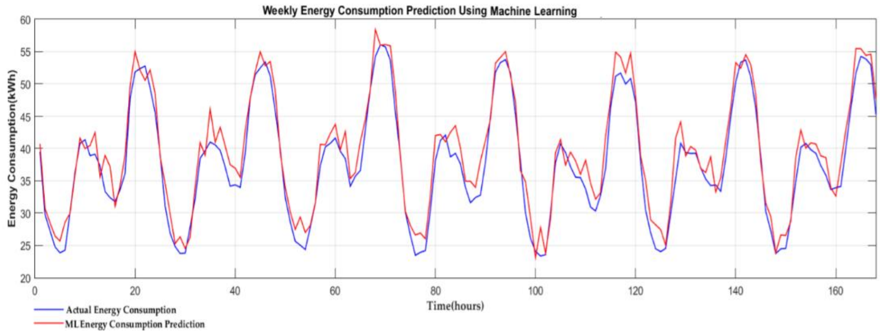
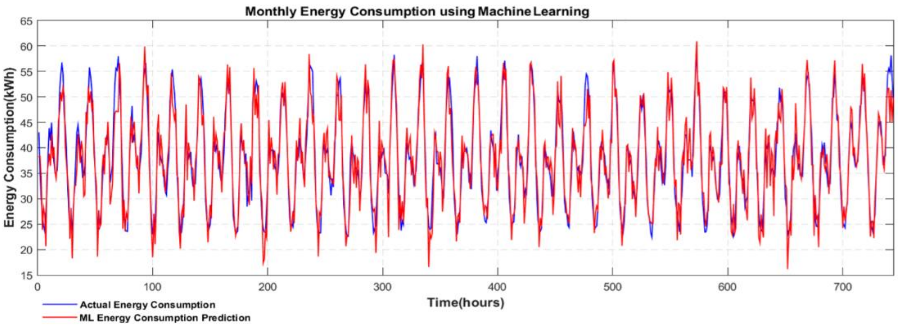


Figure 12. *Actual vs. ML Predicted Results for One-Month Energy Consumption*



Model Validation with MATLAB

Figure 13. *Actual vs. MATLAB Predicted Results for One-Week Energy Consumption*

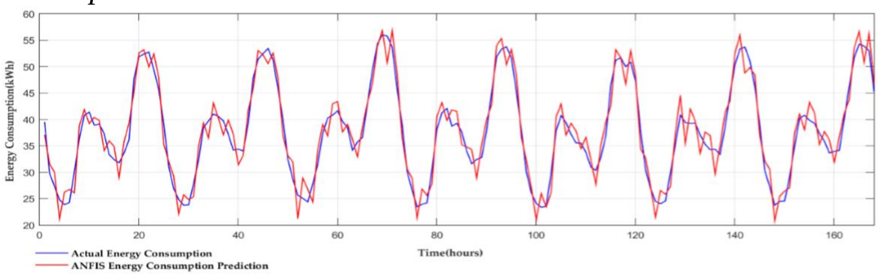
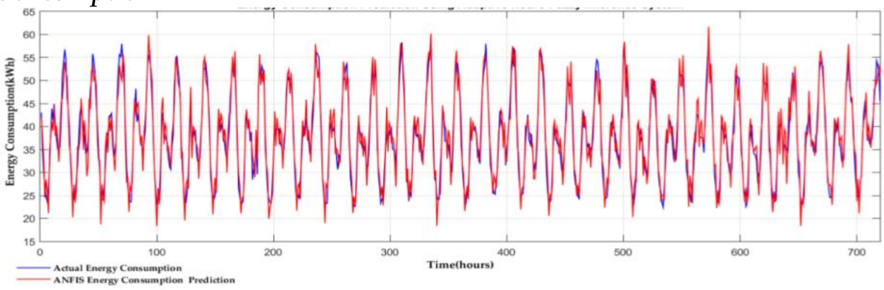


Figure 14. *Actual vs. MATLAB Predicted Results for One-Month Energy Consumption*



Conclusions

In this paper, there are added new contributions besides summarizing the work on energy consumption analysis regarding the IoT framework for smart energy (energy prediction) in buildings. The work includes:

1) Energy consumption data analysis of the green building testbed;
2) New smart automated energy control framework designs;
3) Experimental prototype that applies IoT networking and computing technologies to improve the energy efficiency in buildings.

These steps compile a complete three-step research and added significant new contributions proving the ideas and concepts we proposed. By building this IoT framework in smart homes or offices, the research aim to enable not only multiscale energy proportionality, but also create an intelligent home space, which is an important part of the future smart world. The idea for smart energy IoT solutions, which can predict and optimize energy consumption, will provide not only significant economic benefits but also huge social benefits in terms of global sustainability

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