Urban Sensing and Smart Home Energy Optimisations: A Machine Learning Approach

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ABSTRACT

Energy efficiency for smart home applications is proposed using urban sensing data with machine learning techniques. We exploit Internet of Things (IoTs) enabled environmental and energy panel sensor data, smart home sensing data and opportunistic crowd-sourced data for energy efficient applications in a smart urban home. We present some applications where data from the IoT enabled sensors can be utilised using machine learning techniques. Prediction of small scale renewable energy using solar photovoltaic panels and environmental sensor data is used in energy management such as water heating system. Smart meter data and motion sensor data are used in household appliance monitoring applications with machine learning techniques towards energy savings. Further event detection from environmental and traffic sensor data is proposed in planning and optimising energy usage of smart electric vehicles for a smart urban home. Initial experimental results show the applicability of developing energy efficient applications using machine learning techniques with IoT enabled sensor data.

Categories and Subject Descriptors

I.2.6 [**Computing Methodologies**]: Artificial Intelligence—*Learning*

Keywords

Urban sensing, Energy efficiency, Machine learning

1. INTRODUCTION

Urban sensor data can come from many public and private participatory sensing devices or networks [7, 5, 14]. Specifically, the rise of Internet of Things (IoTs) can facilitate data collection from urban sensors and sensor networks for many applications [6]. Sensor data can be, not limited to, environmental (e.g. temperature, rainfall, humidity, air and water quality and natural hazards), transport and logistics (e.g. traffic, vehicles, car parking and communication networks conditions), security surveillances, building and utility monitoring (e.g. energy usage and energy generation using solar photovoltaic panels, electricity, gas, water and telecommunications), government and businesses (e.g. urban vegetation monitoring and land surveying through remote sensing and earth observations). Participatory sensing data can come from personal devices such as smart phones, wearable devices for physical activity monitoring and smart cars. Besides physical sensor data, crowd sourced data from social networks, blogs and websites can also be considered.

Depending on the nature of the sensors or sensor networks in urban sensing, captured data can provide temporal or spatial-temporal properties [4, 13]. Further data can be categorised to either static and dynamic depending on the mobility of the sensors [11]. Data generated from urban sensing needs to be integrated, fused and tailored for applications. Although gathering urban data may be relatively easier, how to analyse and learn insights from diverse sources of data can be challenging. Structure of data, missing, noisy and uncertainty of data also pose additional challenges for any type of applications.

Machine learning can play significant roles in developing applications on urban sensing data through IoT enabled sensors. In this research, we focus on a problem where urban sensing data can be utilised towards household energy optimisation applications for a smart urban home concept. Specifically, we propose some energy efficient applications for a smart home using machine learning techniques on IoT enabled sensor data.

2. MACHINE LEARNING USING URBAN SENSING DATA FOR HOUSEHOLD ENERGY OPTIMISATIONS

In this section, we present our proposed approach of using machine learning for urban sensing data for household energy optimisation case studies. We present initial results of our proposed concepts.

2.1 A smart home assumption

In the scope of this research, we assume a smart urban home shown as a schematic in Fig.1. The smart home has a energy monitoring sensor, utility (e.g. water and gas) monitoring sensors, light sensors with activity detection, renewable energy sources such as wind or solar photovoltaic sensors or panels [9]. The home has access to the local weather

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and environmental sensor data, traffic and utilities sensor data provided by authorities and agencies. It has an hybrid electric car with charging options. The home occupants are assumed to have smart phones and wearable devices such as physical activity monitoring sensors. At least, this assumption provides us a rich set of urban sensing data so that we can make sense of data using machine learning techniques for household energy optimisations. We now present some tasks in our proposed approach where machine learning techniques can play significant roles.

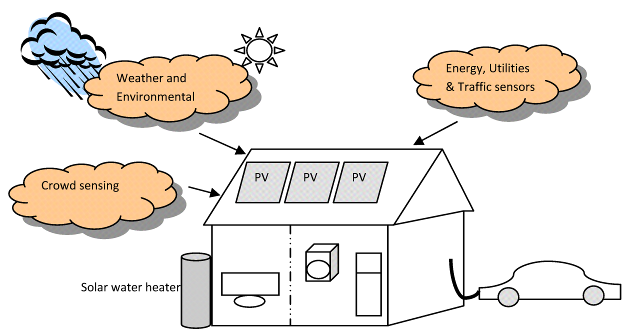

Figure 1: Schematic of a smart urban home.

2.2 Prediction of Small Scale Household Energy Sources

In this task, we consider prediction of small scale solar energy for predictive energy optimisations. We use localised environmental sensor data to predict how much solar energy from photovoltaic panels on the roofs can be generated so that we can plan our energy usage. As a proof of concepts, we use data from [1] to build machine learning models to predict solar energy. Our initial model is to predict in short-term (hourly to daily) power from small scale renewable energy sources at an urban smart home [10, 15].

We show hourly prediction of solar power for testing data using M5P (a variant of decision tree) [2] method in Fig.2. We used one year (September, 2011 to September, 2012) data of solar insolation and generated solar power data from a solar panel with every minute sampling to build the machine learning model using M5P. In dataset, 80% of data is used in training and 20% of data is used as testing. Experimental results provide about 75% accuracy in prediction for testing data.

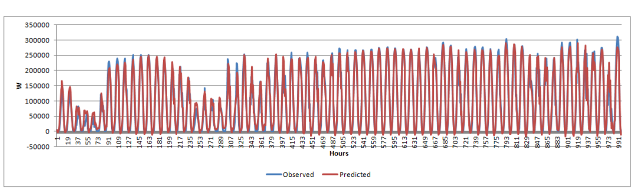

Figure 2: Prediction of hourly solar power for testing data.

2.2.1 *Solar energy prediction and solar water heater*

We are developing a prototype model of an improved solar heater with improved solar pond technology where we can use solar energy prediction and weather prediction (e.g. air temperature) using machine learning techniques to optimise energy usage at home. This application will enable energy awareness and conservation in an urban smart home such as water heating systems [12, 18].

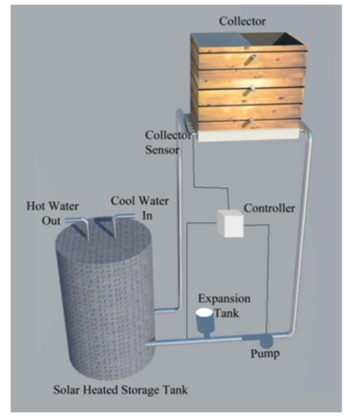

Figure 3: Schematic of a solar water heater with solar pond technology.

In Fig.3, we present the proposed model for an improved solar heater with the solar pond technology where heat from the solar energy is better utilised. The main objective of the proposed model is to increase the thermal efficiency which will be more efficient than using solar pond and solar water heater separately. We show the initial simulation results of the proposed model in Fig.4. Simulation results demonstrate that combining salinity concept of solar pond with solar heating system improves thermal efficiency.

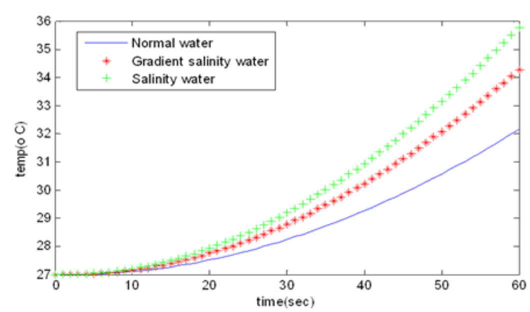

Figure 4: Performance of proposed solar water heating system.

2.3 Household Appliance Monitoring and Context Feature Generation from Sensor Data for Energy Optimisation

In this task, we investigate how aggregated smart meter energy usage data can be disaggregated so that we can identify which device is using how much energy for a smart urban home. This application has implication on saving energy costs and local smart grid energy management using IoT enabled sensor data.

We developed a machine learning model to disaggregate energy data. We used motion sensor data to generate context as features in identifying appliance usage at home [3]. The steps of energy appliance monitoring are shown in Fig. 5. We use data from [16] to perform experiments for proof of concept. Data of different appliances (dishwasher, fridge, washing machine, dryer, air conditioner(AC) in the master room, AC in the bedroom) and the motion sensor data from the bedrooms are utilized in this study. Motion sensor data from the bedrooms are used to assist in determining when the AC is turned ON.

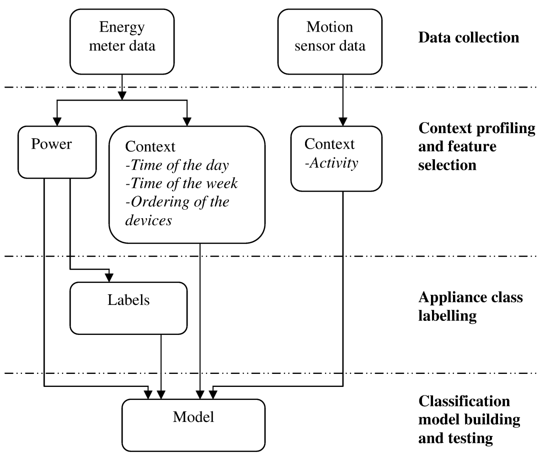

Figure 5: Appliance identification from smart meter sensor data.

In energy appliance detection using machine learning [21], besides power as features, we extract two types of features. We use temporal contexts namely the *Time of day, Day of the week and Ordering of appliances.* The temporal contexts *Time of day and Day of the week* are extracted from the time stamps of power. We extract the *Time of day and Day of the week* features data set indicating that there is a high probability of dishwasher usage in the afternoon, evening and on the weekends. The context feature *Ordering of appliances* is used when an appliance that has a high probability of running immediately after another appliance. The temporal *Ordering* of washing machine and dryer operation is used in this dataset. Motion sensor data captured from two bedrooms are used as activity context and room occupancy.

The data set used in our experiments is comprised of home appliances namely dishwasher, fridge, washing machine, dryer, AC in master, AC in bedroom. We only present here the best classifier accuracy in detecting appliance loads in Table 1. Experimental results demonstrate that the combination of power and context features improve the classification accuracy of traditional models that use power features. We found 96% accuracy in classifying appliances using additional context features on a public data [16].

Identification of appliance loads using machine learning will enable efficient energy management for an urban smart home.

Table 1: Accuracy (10-fold cross validation) of identifying appliances using different features in the classifier functional tree (FT) [8]

Classifier	Power feature	power and context
FT	85.42%	96.54%

2.4 Event Detection and Planning

In this task, we propose to use weather, traffic and incidents data from IoT enabled sensors to detect events. Event detection will be used in planning trips using optimisations techniques for electric hybrid vehicles according to the charging status of vehicles and available charging stations [20]. We also propose to use the predictions of solar photovoltaic panels described above and time of use pricing [17] to plan for charging the electric vehicles [19] at a smart home.

3. CONCLUSIONS

We proposed machine learning for integrated urban sensing data for energy optimisation applications for a smart urban home concept. Prediction of solar energy for a small scale household is used in efficient energy management. Energy appliance monitoring using smart meter data, motion sensor data and context features is investigated using machine learning approach for energy awareness. Further, event detection from environmental and crowd sensing data is proposed for energy efficient planning and charging of smart electric vehicles for a smart home. We plan to integrate all proposed approaches to a platform with user interface in future.

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