Energy optimization of building IoT infrastructures in a stratified way

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Abstract. The project "energy oPtimization of building Internet Of Things Infrastructures in a Stratified way" presented a holistic approach for an AI-enabled EMS for building-level energy management and maximizing the available renewable energy sources utilization. Specifically, the solution integrated a PV generation forecasting module, a building energy demand forecasting module, and an energy task scheduling and optimization component. This paper presents the methodology and preliminary results regarding the PV generation forecasting and energy task scheduling modules tested for the premises of Institute Mihajlo Pupin.

Keywords: PV generation forecasting · Energy task scheduling.

1 Introduction

According to EU sources, three out of four buildings in Europe do not consume electricity in an efficient manner, leading to energy waste and significant carbon emissions [1]. Hence, Energy Management Systems (EMS) constitute a prominent tool for optimizing the energy consumption of building facilities. Such systems provide insights regarding energy usage in buildings, however, simple monitoring does not suffice to increase energy efficiency. In many cases, a holistic EMS approach is required, that not only monitors energy parameters but also provides advanced analytics and forecasts related to building energy demand and supply, while also optimizing energy-intensive activities towards increased energy efficiency. The approach presented in this work offers a holistic EMS for stratified optimization in buildings by integrating a PV generation forecasting component and an energy task scheduling component. Namely, the PV generation forecasting module utilizes a neural network to conduct hourly solar irradiance predictions based on hourly weather forecasts. Then, the forecasted solar irradiance for a specific location is utilized to calculate the energy generation of any PV plant, based on its characteristics, regardless of its type and size. In addition, the energy task scheduling module incorporates the PV forecasts to maximize the utilization of solar generation by providing the optimal device activation schedule based on user preferences. The rest of the paper is organized as follows. In section 2 the proposed approach is presented along with the integrated components. In section 3, preliminary experiment results are presented, while in section 4 a summary of the paper is conducted.

2 Proposed approach

2.1 PV generation forecasting module

Predicting the energy generation of a solar plant is important for the smart grid ecosystem, in order to be able to match future supply and demand [2]. Therefore, it is optimal to schedule high-consumption activities when production is predicted to be high. Before predicting solar energy generation, one of its most important parameters, solar irradiance, should be predicted. In order to train a model capable of predicting this factor, various combinations of hourly input variables were examined, such as temperature, humidity, time, date, cloud cover, pressure, wind speed, and direction. The end goal is to make hourly solar irradiance predictions for a specific location based on weather forecasts, and then calculate the PV generation for a specific PV plant based on its characteristics: s (tilt angle of the solar panels installed), b_{pv} (temperature coefficient for the solar cell - %/°C), a (total area covered from the solar panels in squared meters), h_0 (total conversion efficiency of the photovoltaic cell at the reference temperature - %), $noct$ (Nominal Operating Cell Temperature). For that reason, the following equations are used to calculate the PV generation r_t:

$$c_f = 1 - (1.17 \times 10^{-4}) \times (s_m - s)^2, \tag{1}$$

$$t_c = t_{amb} + c_f \times (218 + 823k_t) \times \frac{noct - 20}{800}, \tag{2}$$

$$h_{pv} = h_0 \times (1 - b_{pv} \times |t_0 - t_c|)\,, \tag{3}$$

$$r_t = h_{pv} \times area \times g_t, \tag{4}$$

where t_0 is the reference temperature (25°C), s_m is the optimal panel titl angle for the location, t_{amb} is the ambient temperature, k_t is the monthly clearness index for the location, and g_t is the forecasted solar irradiance from the neural network for time slot t.

2.2 Energy task scheduling module

The objective of the energy task scheduling component is to optimize the building's energy usage by modifying the activity schedule towards maximizing the renewable energy utilization from the installed PV panels. The module takes as an input the task schedule from the user (e.g. building manager), which includes the device id, the earliest hour that the device must start, the latest hour that the device must start, the duration (hours) that the device should be active, and its consumption (in kW). In addition, the system takes as an input the hourly forecasted energy supply r_t of the building's PV panels from the PV generation forecasting module. The overall goal of the module is to reschedule the user's tasks in order to minimize the renewable energy left when an activity is placed in a certain time slot, hence smoothing out the building energy consumption. The problem is formulated as:

$$\min_{X_{t,d}} \sum_{t=1}^{T}(r_t - \sum_{d=1}^{D}(X_{t,d}P_d\kappa)), \quad \forall t \in \{1,\ldots,T\}, \tag{5}$$

subject to:

$$r_t - \sum_{d=1}^{D}(X_{t,d}P_d\kappa) \geq 0, \tag{6}$$

$$X_{t,d} = 0 \quad \text{for } t < e_d \text{ and } t > l_d \ \forall d \in \{1,\ldots,D\}, \tag{7}$$

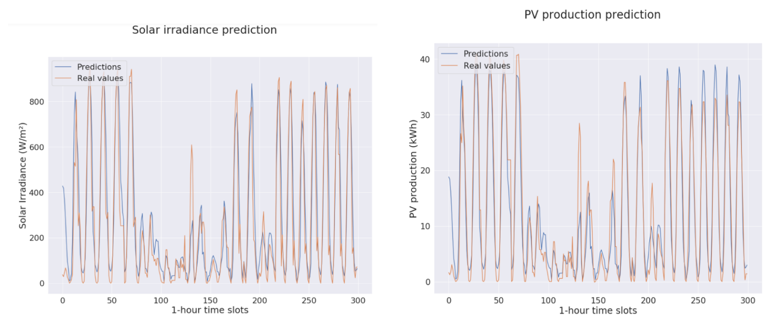
$$\sum_{t=1}^{T} X_{t,d} \leq D_d \quad \forall d \in \{1,\ldots,D\}, \tag{8}$$

$$X_{t,d} - X_{t-1,d} + X_{t-2,d} \leq 1 \quad \forall t \in \{1,\ldots,T\}, \forall d \in \{1,\ldots,D\}, \tag{9}$$

where T is the time horizon, D is the number of devices, $X_{t,d} \in \{0,1\}$ is the decision variable that determines if device d is ON (1) or OFF (0) at time slot t, r_t is the forecasted renewable energy generation (in kWh) for time slot t with $r_t \geq 0 \ \forall t \in \{1,\ldots,T\}$, P_d is the power consumption (in kW) of device d with $P_d \geq 0 \ \forall d \in \{1,\ldots,D\}$, κ is the duration of time step in hours (1 in our case), e_d is the earliest start time for a device d set by the user, l_d is the latest start time for a device d set by the user, $D_d \in \mathbb{N}$ is the duration of device d in hours.

3 Preliminary results

The PV forecasting module was validated using PV generation and weather data provided by Institut Mihajlo Pupin, one of the pilots of the PLATOON project. Specifically, PV production data were provided regarding 180 rooftop solar panels from one of Institut Mihajlo Pupin's buildings, along with weather data from a PV weather station. The neural network architecture that resulted in the lowest errors is a multilayer perceptron consisting of 3 hidden layers with 100, 50 and 10 neurons each. Additionally, a 80-20 train-test split is used, while also early stopping was utilized with 10% of the training set as the validation set. The loss function used is the Mean Squared Error(MSE): $MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2$, where Y_i refer to real/target values and $\hat{Y}_i$ are the model predictions. For



(a) Solar Radiation predictions (b) Energy supply predictions

Fig. 1: Forecasts evaluation

further evaluation, Mean Absolute Error (MAE) and R^2 were utilized: $MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|$, $R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \frac{1}{n}\sum_{i=1}^{n} Y_i)^2}$.

After training, the model was tested on the held-out test set, achieving $R^2 =$ 84%, MSE = 15986.93, and MAE = 83.39 Watt$/m^2$ for hourly solar irradiance forecasting. In Fig. 1a, the trained model solar irradiance forecasts are compared with the real values for 300 hourly time slots, while in Fig. 1b the respective PV generation forecasts are compared against the actual measurements.

4 Conclusion

In this work, a subset of the results of the project "energy oPtimization of building Internet Of Things Infrastructures in a Stratified way" is presented. Specifically, the approach behind the PV generation forecasting and the energy task scheduling modules is discussed and preliminary experiments are presented. The results show that the trained model can accurately predict the energy generation of the PV panels installed at the premises of Institut Mihajlo Pupin.

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