POWER CONSUMPTION FORECASTING IN THE PRESENCE OF DISTRIBUTED GENERATION AND STORAGE IN SMART HOME

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ABSTRACT

Energy modeling and energy forecasting play an important role in Energy management systems. Since residential consumptions have a large share in load consumption, an accurate load prediction can avoid most of failures in power grid. Furthermore, new players (Electric Vehicle, Renewable Energy) have emerged in the electrical systems that have caused demand forecasting to gain special interest. So, apart from demand forecasting, power generation and power saving forecasting models have also received increasing attention, especially. In this paper we propose a comprehensive model for electricity load prediction in smart home. We cover all sources of electricity consumption, generation and storage in this model to achieve a prediction with high accuracy (e.g. user power consumption behaviors, electric vehicles, renewable energies and etc.). In the other words, our model consists of three sub models: user electricity consumption sub model, renewable energies sub model (solar cells and wind turbines) and EVs power consumption and storage sub model. All these sub models together build an accurate model that provides low error predictions for EMSs. We use statistical models for power consumption/generation forecasting; also we considered preprocessing algorithms for preparing raw historical data. These preprocessing algorithms are helping us to smooth and omit unusable data that are collected during some transient events.

INTRODUCTION

According to common classifications [1], demand forecasting models are classified based on two different criteria: the forecasting horizon and the aim of the forecast, also we can divide them into linear and non-linear models and a third group consists of models that use a combination of both. In general we have three categories in forecasting horizon: Very Short-Term Load Forecasting (VSTLF), Short-Term Load Forecasting (STLF) and Medium-Term and Long-Term Load Forecasting (MTLF and LTLF). The most important forecasting horizons are weekly, daily and hourly. The main difference among the three is the scope of the variables used. Also, we can classify forecasting models based on the number of values to predict (aim of the forecast). Two main groups exist: the first group is formed by those that forecast only one value (next hour’s load, next day’s peak load, next day’s total load, etc.); the second group consists of forecasts with multiples values, such as next hours, peak load plus terms, etc.

SYSTEM MODEL

We consider the smart home with two renewable energy generators (e.g. photovoltaic solar panels and wind turbines), a set of home appliances, a set of Electric Vehicles (EVs) and a home central controller. Fig. 1 shows the smart home structure in the presence of distributed generators and storage. EVs can play both power consumer and storage roles in the smart home. The central controller of the smart home is responsible for aggregating consumption and generation data from renewable energy generators, EVs and home appliances for scheduling and forecasting the smart home power consumption. In the following subsections, we discuss each component of the system model.

Household Consumption

We suppose each appliance is scheduled to consume electricity or remain idle in an hour $h$ during the day. Each
A home appliance may have different load levels.

Let $c_a$ be the number of home appliances (e.g., washer, dryer, refrigerator and etc.), $E_k^l$ the mean electricity consumption of $k^{th}$ home appliance during one hour in $l^{th}$ load level, $S_k^l(h)$ the appliance state in an hour $h$ (e.g. off or on in specific load levels) and $c_f$ the appliances predefined load levels. Then, the total electric energy consumed by home appliances in an hour $h$ is given by:

$$E_c(h) = \sum_{k=1}^{c_a} E_k^l \cdot S_k^l(h)$$  \hspace{1cm} (1)

where for each $k \in \{1,2,\ldots, c_a\}$, the following constraint must be satisfied:

$$\sum_{n=1}^{c_f} S_k^n(h) = 1 \quad \forall h \in \{1,2,\ldots, 24\}$$ \hspace{1cm} (2)

**Renewable Energy Sources**

We consider a smart home with $g_s$ photovoltaic solar panels and $g_w$ wind turbines. The total electricity generated in an hour $h$ is given by:

$$E_g(h) = \sum_{i=1}^{g_s} E_i(h) + \sum_{j=1}^{g_w} E_j(h)$$ \hspace{1cm} (3)

**Solar Power**

Photovoltaic solar cells have high variability. In addition to their deterministic variable nature due to day and night cycles, there is a randomly variable component due to weather conditions, e.g., clouds. In order to overcome power generation variability, energy storage can then be used to make the PV generation profile more dispatchable by increasing its availability [2]. So PVs and their rechargeable batteries can provide a reliable power generation and storage source, particularly in the situations where PVs are the only source of power in a power grid. Since the battery capacity plays an important role in PV power generation system reliability and it would depend on the environmental conditions and the time of the day, choosing an optimal battery size can be still critical [3], [4] and [5] discussed about PV battery sizing in smart grids. We consider the solar power as a subsidiary power source. Battery sizing is out of the scope of this paper. The electricity generated by the $i^{th}$ photovoltaic (PV) panel can be calculated as follows [6]:

$$E_i(h) = \frac{e}{K} \cdot R_i^2 \cdot \frac{R_h}{R_h} \quad 0 < R_h < K$$

$$E_i(h) = \frac{e}{K} \cdot R_i^2 \cdot R_h \quad R_h > K$$ \hspace{1cm} (4)

where $e$, $K$ and $R_h$ represent the number of photovoltaic cells in the PV panel, the corresponding efficiency, critical radiation point in W/m$^2$ and solar radiation respectively.

**Wind Turbines**

The renewable energy sources are naturally stochastic, wind is a highly unstable energy source that cannot be fully described by any stochastic model. Wind speed at every hour is correlated with the speed at previous hours [6]. Increasing order of the statistical model can improve the wind speed forecast. The electricity generated from $j^{th}$ wind turbine in an hour $h$ is given by:

$$E_j(h) = \frac{1}{2} \cdot \rho \cdot A \cdot V(h) \cdot C_p$$ \hspace{1cm} (5)

where $(h)$, $\rho$, $A$ and $C_p$ represent the wind speed in hour $h$, the air density in kg/m$^3$, swap area of the turbine and Betz limit, respectively.

**Electric Vehicles**

Due to environmental and economic factors, the use of electric vehicles (EV) and plug-in hybrid EVs (PHEV) is expected to rise considerably in the near future [7]. EVs charging load have an important impact on smart grids, especially in large scales [8]. Although EVs charging load in absence of a proper grid demand management can be a notable threat for grid availability, its ability in storing electricity can provide home power demands in grid failure or peak times. Let $c_e$ the number of EVs, $E_m$ the mean electricity consumption of $m^{th}$ electric vehicle during one hour and $S_m(h)$ the EV state in an hour $h$ (e.g. charging, discharging, or remaining idle), then we have:

$$E_{ev}(h) = \sum_{m=1}^{c_e} E_m \cdot S_m(h)$$ \hspace{1cm} (6)

**Power Storage Resources**
We consider two resources for storing electric power, renewable energy storage and electric vehicles batteries. We provide a proper combination of EVs power consumption and generation (e.g. discharging) in equ.(6). The total stored electric power for renewable energy batteries in an hour \( h \) is given by:

\[
E_b(h) = E_b(h-1) + \sum_{i=1}^{\theta_s} \alpha (E_i(h) - PC_i(h)) + \sum_{j=1}^{\theta_w} \beta (E_j(h) - PC_j(h))
\]  

where \( \alpha \) and \( \beta \) represent the solar cells and wind turbines batteries efficiency respectively and \( PC(h) \) is the instantaneous current power consumed by the home in an hour \( h \).

**EXPERIMENTAL RESULTS**

To evaluate the performance of our proposed model, we collect required raw data from UCI and Umass repositories. Also we use the Iowa Environmental Mesonet (IEM) datasets [9] for cloud cover and wind speed forecasting for the Toronto city in Canada during year 2015. These repositories provide home hourly power consumption and weather condition. Before injecting these data to our proposed model, we apply some refinements to datasets. These refinements contain lack of data fixing, noise removing and etc. We chose Normalized Least Mean Square (NLMS) adaptive predictor for forecasting power consumption/generation based on historical data. NLMS predictor is a statistical method that uses previous value of a time series in order to predict future values. We use 10\% of data for training our model; amount and scale of training data have straight impact on forecast accuracy.

We use Mean Absolute Error (MAE) for evaluating accuracy of proposed model as follows:

\[
MAE = \frac{1}{n} \sum_{e=1}^{n} |f_e - y_e| 
\]  

Fig. 2 depicts predicted cloud cover in comparison to real cloud cover for a year with \( \mu = 0.0004 \), train ratio\(=0.1 \) (in other words, we use 10\% of data for training) and order\(=10 \). As shown in Fig. 2, the value of MAE is almost 0.223. Fig. 3 for two different historical records size equal to 8760 and 50256, depicts predicted power consumption in comparison to home real power consumption with \( \mu = 0.0004 \), train ratio\(=0.1 \) and order\(=10 \). As shown in Fig. 3, predictor parameters (e.g. \( \mu \), order and train ratio) and dataset records count have important impact on the predictor accuracy. The value of MAE for 50256 historical records is 1.8272e-009.

Fig. 4 also shows comparison of predicted and real wind speed with \( \mu = 0.0004 \), train ratio\(=0.1 \) and order\(=10 \) and \( \mu = 0.009 \), train ratio\(=0.2 \) and order\(=10 \). Wind speed prediction error for each set of predictor parameters are shown in Fig. 4. Results show that power consumption is more predictable in comparison to the cloud cover and wind speed, in other words statistical predictor can better follow the pattern of power consumption than cloud cover.
and wind speed because of renewable energies instability. Also as mentioned before; dataset scale decreasing make predictions more accurate by preparing preferable predictor training data.

Fig. 4. Wind speed prediction

CONCLUSION

This paper provides a power consumption forecasting model for smart homes. Proposed model consist of three main sub models including: user electricity consumption sub model, renewable energies sub model (solar cells and wind turbines) and EVs power consumption and storage sub model. Our prediction method is based on statistical models. Before injecting historical data into the model, some refinements such as lack of data fixing, noise removing, digitizing were applied to datasets. Evaluation results confirmed that the proposed model is able to predict home power consumption with acceptable mean absolute error.

REFERENCES


