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

Mohammad YAGHMAEE, MEEDC-Iran, yaghmaee@ieee.org
Mohammad Ali FARAHNAKIAN, Tavanir-Iran
Reyhaneh HAJIMAHDIZADEH, MEEDC-Iran, reihaneh_mahdizadeh@yahoo.com
Mohsen ZABIHI, MEEDC-Iran, m.zabihi@meedc.net

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 another parameter (for example, aggregated load) or even next day's hourly forecast- the so-called load profile. As we mentioned, there is another classification that is based on type of models (linear and non-linear models). In the 1940s, linear models started to be used to forecast demand, and these evolved into the ARMA model and its variations. From 1985 on, researchers started to realize that non-linear models accurately described the relation between periodical and residual components, non-linear models (based on artificial neural networks (ANNs)) have gained more and more attention since the second half of the 80's. This evolution is due to the fact that certain researchers achieved great advances on ANNs. Although most of the works on demand forecasting published since 2000 have focused on non-linear models, the ANNs cannot guarantee generating an optimal global solution, also their performance and reliability within an EMS running system cannot be guaranteed. Furthermore, most of the ANN prediction methods have associated the input electricity load profile with outdoor temperature, indoor temperature, or motion sensors within the household, so that ANN can correlate the electricity load profile along with these data. Collecting massive amount of information about the user and the surrounding environment increases prediction method overload and it is impossible in some situations. It is also noticeable that most of predictors are using historical data to train their models, so predictor performance is under the influence of recorded data, in the other words; resolution of historical data has an important effect on model accuracy. As we mentioned, there is a tradeoff in the use of linear/nonlinear models, for electricity load prediction.

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 home appliance may have different load levels.

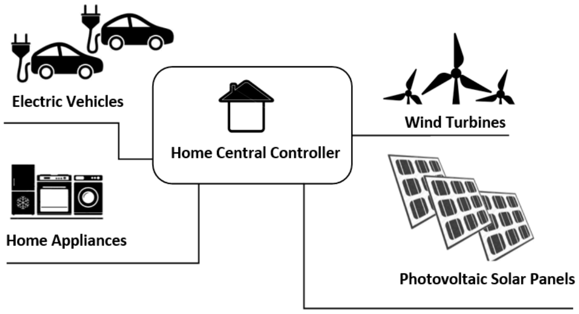

Fig. 1. Smart Home Structure

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, $S_k(h)$ the appliance state in an hour h (e.g. off or on in specific load levels) and c_l the appliances predefined load levels. Then, the total electric energy consumed by home appliances in an hour h is given by:

$$E_c(h) = \sum_{k=1}^{c_a} E_k^l . S_k^l(h) \tag{1}$$

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

$$\sum_{n=1}^{c_l} S_k^n(h) = 1 \qquad \forall\, h \in \{1,2,\ldots,24\} \tag{2}$$

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:

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

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]:

$$E_i(h) = c.\begin{cases} \frac{e}{K}.R_h^2 & 0 < R_h < K \\ e.R_h & R_h > K \end{cases} \tag{4}$$

where c, 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:

$$E_j(h) = \frac{1}{2}.\rho\,.A.V(h)^3.C_p \tag{5}$$

where $(h), \rho$, A and C_p represent the wind speed in hour h, the air density in kg/m^2, 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:

$$E_{ev}(h) = \sum_{m=1}^{c_e} E_m . S_m(h) \tag{6}$$

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:

$$E_b(h) = E_b(h-1) + \sum_{i=1}^{g_s} \alpha(E_i(h) - PC_i(h)) + \sum_{j=1}^{g_w} \beta(E_j(h) - PC_j(h)) \quad (7)$$

where α and β 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*.

EXPRIMENTAL 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:

$$MAE = \frac{1}{n}\sum_{e=1}^{n} |f_e - y_e| \quad (8)$$

Fig. 2 depicts predicted cloud cover in comparison to real cloud cover for a year with μ = 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 μ = 0.0004, train ratio=0.1 and order=10. As shown in Fig. 3, predictor parameters (e.g. μ, 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.

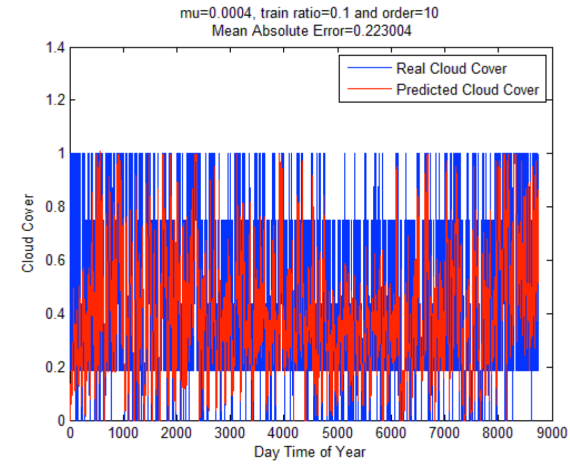

Fig. 2. Cloud cover prediction

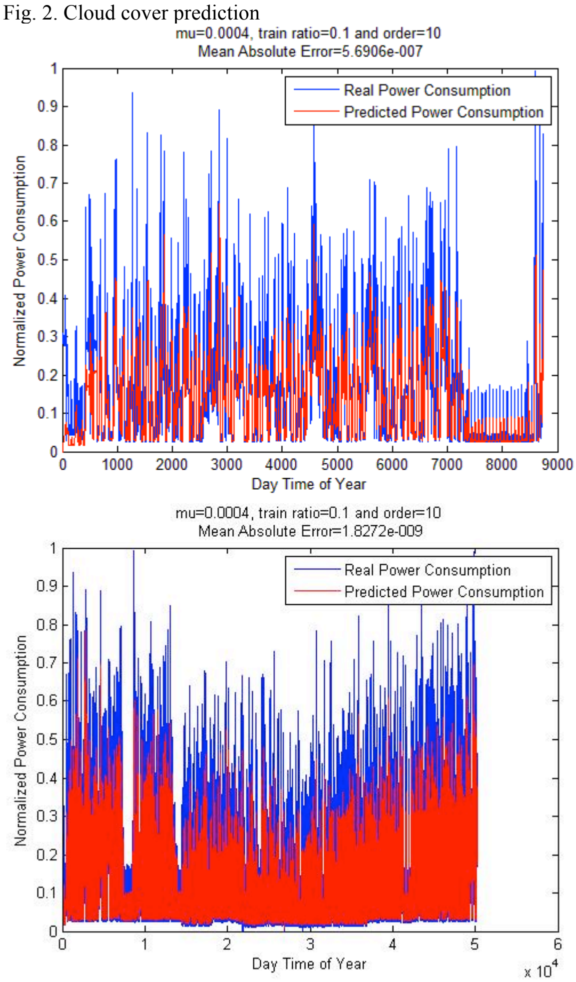

Fig. 3. Power consumption prediction

Fig. 4 also shows comparison of predicted and real wind speed with μ = 0.0004, train ratio=0.1 and order=10 and μ = 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.

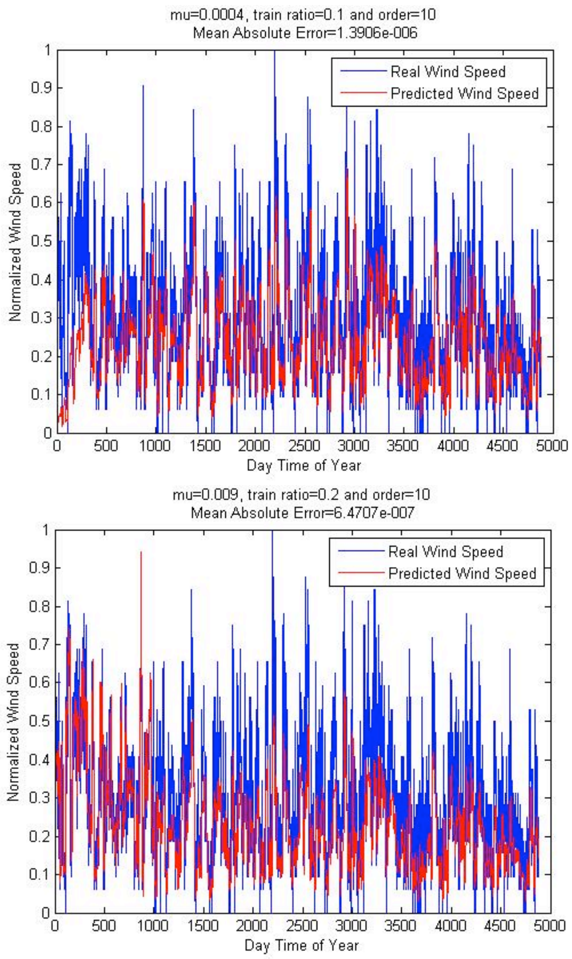

Fig. 4. Wind speed prediction

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

[1] L. Hernandez, C. Baladron, J. M. Aguiar, B. Carro, A. J. Sanchez-Esguevillas, J. Lloret and Joaquim Massana, “A Survey on Electric Power Demand Forecasting: Future Trends in Smart Grids, Microgrids and Smart Buildings,” IEEE Communications Surveys & Tutorials, pp. 1460-1495, Third Quarter 2014.

[2] J. Song, V. Krishnamurthy, A. Kwasinski and R. Sharma, “Development of a Markov-Chain-Based Energy Storage Model for Power Supply Availability Assessment of Photovoltaic Generation Plants,” IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, pp. 491-500, Apr. 2013.

[3] D. Niyato, E. Hossain and A. Fallahi, “Sleep and Wakeup Strategies in Solar-Powered Wireless Sensor/Mesh Networks: Performance Analysis and Optimization,” IEEE TRANSACTIONS ON MOBILE COMPUTING, pp. 221-236, Feb. 2007.

[4] V. Chamola and B. Sikdar, “A Multistate Markov Model for Dimensioning Solar Powered Cellular Base Stations,” IEEE TRANSACTIONS ON SUSTAINABLE ENERGY, pp. 1650-1652, Oct. 2015.

[5] M. A. Murtaza and M. Tahir, “Optimal Data Transmission and Battery Charging Policies for Solar Powered Sensor Networks using Markov Decision Process,” IEEE Wireless communication and Networking Conference, 2013.

[6] M. H. K. Tushar, C. Assi, M. Maier and M. F. Uddin, “Smart Microgrids: Optimal Joint Scheduling for Electric Vehicles and Home Appliances,” IEEE TRANSACTIONS ON SMART GRID, pp. 239-250, Jan. 2014.

[7] M. Alizadeh, A. Scaglione, J. Davies and K. S. Kurani, “A Scalable Stochastic Model for the Electricity Demand of Electric and Plug-In Hybrid Vehicles,” IEEE TRANSACTIONS ON SMART GRID, pp. 848-860, Mar. 2014.

[8] A. Ashtari, E. Bibeau, S. Shahidinejad, and T. Molinski, “PEV Charging Profile Prediction and Analysis Based on Vehicle Usage Data,” IEEE TRANSACTIONS ON SMART GRID, pp. 341-350, Mar. 2012.

[9] IEM, " Iowa Environmental Mesonet (IEM)”, 2016 [Online]. Available: https://mesonet.agron.iastate.edu