Smart Energy Management System for Residential Homes Regarding Uncertainties of Photovoltaic Array and Plug-in Electric Vehicle

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***Abstract*– smart energy management approaches can improve the economy and performance of residential homes integrated with photovoltaic array (PV) and plug-in electric vehicle (PEV). The key novelty of this paper is improving the real-time operation of the smart home using advanced stochastic forecast techniques and stochastic control methods. In this paper, an optimal model predictive control is formulated for a smart home to minimize the electricity cost under time-varying electricity price signals. In addition, the PEV charging and home power demand requirements have to be satisfied in a smart and optimal way. Stochastic forecast model is developed for PV, home load demand and PEV to consider the effect of the different uncertainties on their performance. Furthermore, a fundamental trade-off between PEV lithium-ion battery aging and economic performance of the energy management system is implemented through an appropriate cost function formulation. In this paper, the PEV departure time and required energy consumption during driving are modeled by Markov chain and conditional probability. In addition, the PV performance and home load demand are modeled by PVWatt model and adaptive neuro-fuzzy inference system (ANFIS) respectively. Afterward, a Model Predictive control (MPC) is designed to minimize the cost of energy as well as make increase the lifetime of the PEV battery by avoiding unnecessary charging/discharging schemes. The results demonstrate the effectiveness and enhancement of the proposed method.**

Index Terms – Smart energy management system, Model predictive control, uncertainties, plug-in electric vehicle, photovoltaic array.

I. INTRODUCTION

Recently, the ideas of smart homes, low energy building, net-zero energy building and islanded Microgrid are promoted rapidly because these are able to address many current problems like the need for electricity, global warming, remot area economic limitation, etc [1] [2][3]. Smart home integrated with PV and PEV can reduce the electricity usage from the grid by 23% and reduce the carbon emission by 30 % [1]. In the smart home concepts, the PV array works as local electric resource and PEV battery operates as storage to save the electricity when it is cheap and inject it to the home when the electricity price is high. Formulating an optimal SEMS under the uncertainties related to load, PEV, PV power generation, and environmental condition is significantly tricky because the size of optimization problem will increase and many factors will add as constraints to the optimization problem. Consequently, researchers have focused developing effective SEMS, which consider the effects of random parameters.

Many researches has been devoted for SEMS to optimize the energy consumption of houses. In [4], rule-based energy scheduling methods were used. The problem of these kinds of methods is the lack of logical designing methodology. Therefore, other energy management approaches attracted significant interest like linear programming and mixed integer linear programming optimization methods. These methods were used often in most smart homes literature to calculate optimal control policies [5]. In these research, linear models were used for PV and battery of PEVs, but in reality, the models of batteries and PVs are nonlinear [6]. Thereby, nonlinear optimization methods are attracted more interest [7].

On the other hand, uncertainties related to PV, load demand and PEV are other critical challenges for designing a proper SEMS. PV power output varies due to air mass, weather condition, the time of the day, etc. similarly, PEV state of charge and the PEV availability time intermit due to, driving distance, driving style, etc. [8][9]. Thereby, stochastic models were obtained for PEV availability time and trip distance by Markov chain model for formulating an stochastic dynamic optimization to smartly charge the PEV [10][11]. Based on forecast models for PV and home load demand, a SEMS was derived for commercial PEV charging [12]. An SEMS was governed to dynamically schedule Household power consumption for each household units and based on which the required power demand was forecasted and reported to the grid [13]. An MPC algorithm was formulating for a home with nonlinear models of PV and battery energy storages in which house load demand was forecasted by artificial neural network [6]. In [9], radial basis function neural network was proposed to forecast electricity load consumption and PV power output due to its ability to capture nonlinear relationships between inputs and outputs and models the effect of uncertainties. Furthermore, an SDP algorithm was developed to minimize the cost of electrical energy, whereas PEV charging requirement and power demand were satisfied. In [14], an MPC was formulated

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in a multi-stage energy management system to minimize the cost of energy for a home. Three stages were considered, in the first stage, the PV and load forecasted, second an off-line optimization performed to minimize the cost of a day ahead, then MPC implemented to improve real-time operation by decreasing the error of the forecasted data and real-time data information. Only a few works like [14] and [6] can be found in the literature which actually tries to decrease the gap between forecast error and real-time system operation. In these works, the energy management was performed for the house with battery, PV and thermal devices. However, developing a SEMS for a residential house with PV and PEV to make tradeoff between the economic performance and PEV battery degradation cost has been not fully addressed yet.

The main contribution of this paper is developing a SEMS for a residential home with PV and PEV to immunize the cost of electricity and make tradeoff with PEV battery ageing . In this paper, the effect of random uncertainties is modeled for PV and PEV and home load demand. The forecast models are found by ANFIS and Markov chain. An MPC is formulated to minimize the electricity cost while satisfied PEV charging and home load requirements and increase the life time of the PEV battery.

This paper is organized as follows. The models of the PEV charging, PV and home load demand, as well as the random parameters, are explained in section II. In section III, the MPC formulation and objective function are discussed. The simulation results are displayed in section IV. The conclusion is presented in section V.

II. SMART ENERGY MANAGEMENT MODEL

In this section, the structure of the SEMS and the system variable stochastic models are introduced and developed.

A. Smart energy management configuration

Fig.1 illustrates the overall structure of the SEMS for a residential home. As it is shown in Fig.1, the SEMS is designed to collect and analyze the data from a different source of energy and devices. In addition, it is in charge to send control signals to minimize the electricity cost.

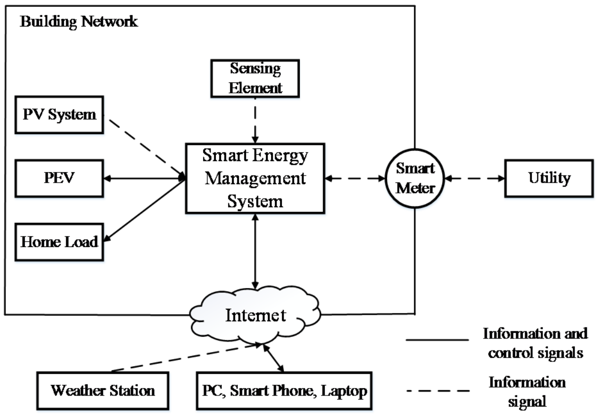


Fig. 1. The overall structure of a residential home with its SEMS. The dashed line is the information signal and the straight line is the information and control signal.

B. stochastic modeling of the system

The first step for developing a SEMS is obtaining accurate and appropriate models for the home variables. In this section, the PV model, PEV battery status model, the PEV battery's driving energy requires and home load demand are explained.

1) PV forecast model

In the PV research community, there are plenty of studies which used various approaches, like data-driven and model-based methods to find proper PV forecast models [15]. In this paper, the PVWatt model is used, which is a nonlinear function of effective Irradiance and solar cell temperature. In this model, the effect of weather condition and Irradiance variation are considered for the PV model. This model was introduced by the national renewable energy laboratory (NREL) [16]. Based on the variation of irradiance level, the power output is formulated as follows [16]:

$$\begin{cases} P_{mp,array}\left(\rho_e, T_c\right) = N_s \times N_p \times \\ \quad \left(P_{mp,s}\left(\frac{\rho_e}{\rho_s}\left[1+\gamma\left(T_c - T_s\right)\right] - k_G\frac{\rho_s-\rho_e}{\rho_s-\rho_c}\right)\right), \ \rho_e > \rho_c = 200\, W/m^2 \\ P_{mp,array}\left(\rho_e, T_c\right) = N_s \times N_p \times \\ \quad \left(P_{mp,s}\left(\frac{\rho_e}{\rho_s}\left[1+\gamma\left(T_c - T_s\right)\right] - k_G\left[1-\left(1-\frac{\rho_e}{\rho_c}\right)^4\right]\right)\right), \rho_e \le \rho_c = 200\, W/m^2 \end{cases} \tag{1}$$

where

$$k_G = \frac{P_{mp}\left(G_c, T_c\right) - P_{mp,meas}\left(G_c, T_c\right)}{P_{mp,s}} \tag{2}$$

where the variables $P_{mp,s}$ and $P_{mp,array}$ are the PV output at the maximum point of the PV module and array (KW). The variable γ is the Normalized temperature constant of peak power $(1/^{\circ}C)$. The N_s and N_p are the number of subarrays and panels respectively. The T_c ($^{\circ}C$) and ρ_e (W/m^2) are the solar cell temperature and effective solar irradiance model, for more details relate how to calculate T_c and ρ_e see [16]. The T_s ($25/^{\circ}C$) and ρ_s $(1000W/m^2)$ are the temperature and solar irradiance under standard test condition (STC). The variable ρ_c is the solar irradiance under the low light conditions $(200W/m^2)$.

Under the low light condition, the PVWatts model is more accurate. It can be parameterized from the datasheet of the PV panel as well as can be generalized to the various PV type technologies like model thin-film based PV systems.

2) PEV status model

The PEV status modeling is another stochastic parameter which has to be modeled to design an efficient SEMS. In order to show the PEV status (home or driving), a Markov chain is designed. In this paper $X_k = 0$ (driving) and $X_k = 1$ (home) denotes PEV status plugged-out and plugged-in status, respectively. The Markov chain dynamics equation is given by:

$$\begin{cases} P_{01,k} = \Pr\left[x_{k+1} = 0 \middle| x_k = 1, k\right] = D(k), \\ P_{11,k} = \Pr\left[x_{k+1} = 1 \middle| x_k = 1, k\right] = 1 - D(k), \\ P_{10,k} = \Pr\left[x_{k+1} = 1 \middle| x_k = 0, k\right] = C(k), \\ P_{00,k} = \Pr\left[x_{k+1} = 0 \middle| x_k = 0, k\right] = 1 - C(k), \end{cases} \tag{3}$$

where $C(k)$ and $D(k)$ are the amount of transient probability of plug-in and plug-out time respectively. the daily driving of 10 persons was studied over 3197 working days. Their working place was at the University office in Chengdu, China. They started their tasks from 8:30AM and finished at 5:30PM [9]. The PEV's probability temporal distribution for plug-in and plug-out status was achieved, by analyzing the statistical daily driving data. As it can be evident in Fig. 2, the plug-out probability is almost high around 7:30AM when the car leaves the house. Moreover in every time hours, the Markov transition probability matrix of PEV is plotted in Fig. 3 by the statistical data.

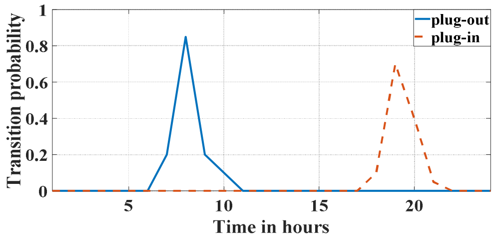


Fig. 2. Temporal distribution of the PEV plug-in and plug-out time [9].

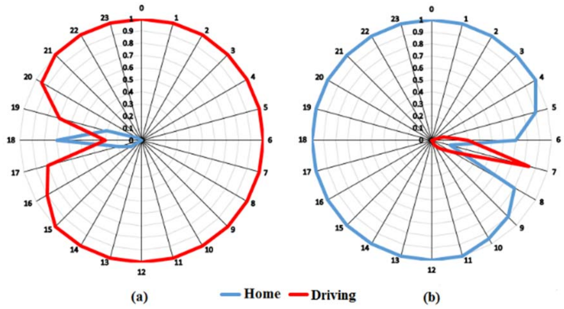


Fig. 3. The PEV transition probability matrix of the Markov chain: (a): from driving state; (b): from home state.

3) PEV battery energy at arrival time

Several factors can affect the PEV battery energy. For example, the amount of battery energy at the plug-out time, driving distance, driving styles (city/country), traffic, etc. In this study, only the effect of driving distance is assumed. The energy of the PEV battery can be calculated by the following equation [17]:

$$E_{in} = \begin{cases} E^{\min}, & if\ E_{out} - E_{cc} \times d \le E^{\min}, \\ E_{out} - E_{cc} \times d, & otherwise, \end{cases} \tag{4}$$

where the E_{in} and E_{out} are the battery energy's values at plug-in and plug-out time respectively. The variable $E^{\min}$ is the minimal energy level. The $E_{cc} = 0.159(KWh/km)$ is the energy consumption per kilometer and d is the driving distance [17]. Therefore by knowing the amount of E_{out} and *d*, conditional probability distribution of the PEV can be obtained by given:

$$M_{AB} = P\left(E_{in} = A \middle| E_{out} = B\right) = \frac{P(A \cap B)}{P(B)} \tag{5}$$

where A and B are the amounts from the feasible discretized set of the EV battery energy values $(A, B \in S)$. The amount of M_{AB} is the probability in which the energy of the battery at a plug-in time $E_{in} = A$, result in $E_{out} = B$. Thanks to the US national household travel survey where provided statistical data of daily driving distance, The probability of plug-in energy E_{in} by given E_{out} is calculated [18]. As it is shown in Fig.4, the plug-in energy is always less than the plug-out energy and the plug-out energy never have to be lower than the minimum energy $E_{\min}$.

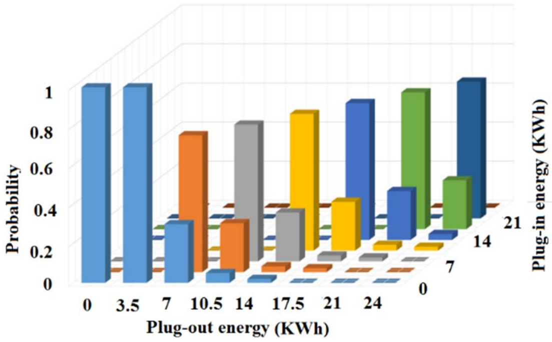


Fig. 4. The conditional probability of PEV battery during the plug-in time[18].

To sum up, the dynamic equation for PEV in a day for all points in time with incorporating statistics of the random processes is as follow [9]:

$$E_{k+1}=\begin{cases} E_k, & X_k=0\rightarrow X_{k+1}=0 \\ \mathrm{Pr}o\left[E_{in}\right]_{E^{\min}}^{E^{\max}}, & X_k=0\rightarrow X_{k+1}=1 \\ E_K+\Delta t\left(P_{ev,K}-\eta\left|P_{ev,K}\right|\right), & X_k=1\rightarrow X_{k+1}=1 \\ E_K+\Delta t\left(P_{ev,K}-\eta\left|P_{ev,K}\right|\right), & X_k=1\rightarrow X_{k+1}=0 \end{cases} \tag{6}$$

where the η , Δt are the loss of energy and time period, respectively. The variables E_k and $P_{ev,k}$ are the battery energy and the PEV charging/discharging power at time k respectively.

4) Power usage model

Another crucial factor in designing a proper and effective SEMS is Load demand forecasting. In literature, several techniques were developed to forecast home load demand. In [19], three modeling approaches were developed to forecast the electric energy consumption. In this article, an ANFIS model is trained to forecast the household energy consumption. The ANFIS is selected because of its ability to take the benefits of the artificial neural network and neuro-fuzzy inference system in one framework. The time of the day, days of the month, ambient temperature and wind speed are considered as inputs of the ANFIS. The historic power consumption data is applied as the output of the ANFIS model. In this study, 70% of the data is applied to train the ANFIS and the rest is used for validation.

5) Power conservation

In the smart home, the power conservation law has to be always held:

$$P_{grid,k} = X_k P_{ev,k} + P_{dem,k} - P_{pv,k}, \quad k = 0,\dots,N-1$$
$$X_k = \begin{cases} 0 & for\ t_a \le k \le t_b \\ 1 & otherwise, \end{cases} \tag{7}$$

where k is the time index (hour). The variables P_{pv}, P_{grid}, P_{ev} and P_{dem} are PV power, grid power, PEV (charging/discharging) power and load demand power respectively. In addition, t_a and t_b are plug-out and plug-in time respectively. Furthermore, the following constraint has to be hold at all time:

$$P_{ev}^{\min} \le P_{ev,k} \le P_{ev}^{\max} \quad k = 0,\cdots,N-1 \tag{8}$$

$$E^{\min} \le E_k \le E^{\max} \quad k = 0,\cdots,N-1 \tag{9}$$

All the above equation explain the subsystem models which will be used for the MPC. In sequence, the MPC and optimization problem is formulated.

III. Model Predictive Control and Optimization

In practice, the SEMS needs to update its control signals, due to unavoidable forecasting error of the day-ahead and PEV random parameters. Therefore, the MPC is proposed due to its ability to control multivariable constraints by taking the control signals from the online optimization solution [20]. It is a well-established method in the control industry, which first predict the behaviour of the system over a future horizon, then, optimized cost function and determine a set of control actions, afterward, the first control signal is applied to the real system. In the next step, the optimization time horizon is updated and move forward with a one-time interval. In this paper, the MPC manipulates the control variable $u_k=P_{ev}$, given the forecast weather condition, home load demand and electricity cost to minimize the cost of energy. The variables x_k, u_k, d_k and y_k are denoted as the state, control signal, disturbance and output of the system. Thereby, the system model is as follows:

$$x_{k+1}=f\left(x_k,u_k,d_k\right),\ y_k=g\left(x_k,u_k,d_k\right) \tag{10}$$

with $x_k=E_k$, $y_k=p_{grid,k}$, $u_k=p_{ev}$ and $d_k=\left[\hat{p}_{pv,k},\hat{p}_{dem,k},\hat{X}_k\ and\ \hat{E}_{in}\right]^T$, where $\hat{p}_{pv,k},\hat{p}_{dem,k},\hat{X}_k\ and\ \hat{E}_{in}$ are the forecast of PV output power, home load demand, the PEV status and the battery energy of the PEV respectively. In Fig. 5, the schematic of the MPC process is illustrated. As it is obvious, the MPC by coordinating charging/discharging schemes of the P_{ev} is able to make tradeoff between the economic performance and battery ageing cost as well as satisfy the home load and PEV charging requirements.

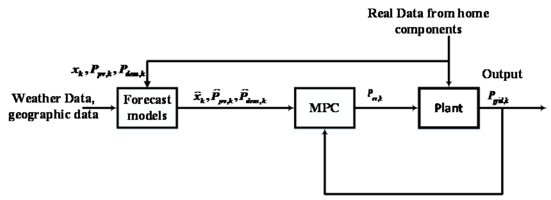


Fig. 5. MPC process structure.

In this paper the objective function is formulated as follows:

$$\min_{P_{ev,k},E_k,x_k} \sum_{k=0}^{N-1} \left(\lambda_1 C_k y_k + \lambda_2 S_k C_k^{ev}\right)^2 \tag{11}$$

where $\lambda_1, \lambda_2 \in [0 \quad 1]$ are weighting parameters, the variable C_k is the time-varying electricity price [$/kWh]. In addition C_k^{ev} and S_k are the battery degradation cost and the PEV charging/ discharging Indicator factor which determine as follows:

$$S_k = \begin{cases} 0 & if \quad P_{ev,k-1} = P_{ev,k} \\ deference\, of\ P_{ev,k} & if \quad P_{ev,k-1} \neq P_{ev,k} \end{cases} \tag{12}$$

$$C_k^{ev} = \frac{pr_{batt}^{ev}}{\xi^{ev}} \tag{13}$$

where ξ^{ev} is the total life cycle cumulative ampere- hours throughput of the PEV battery and pr_{batt}^{ev} is the PEV battery initial price. In this paper, dynamic optimization approach is used to solve the constrained nonlinear optimization problem due to the nonlinearities in the PV and PEV models. Equation (1)-(13) are the constraints of the optimization problem.

IV. Results

The four (kW) residential PV system is used for a single-family home located in Esbjerg, Denmark. The PV system has two subarrays, including 16 panels which connected in series. The Solar-edge inverter with maximum 4000 (VA) AC power output and a Nissan leaf with 24 (kWh) T-shaped lithium battery pack are utilized as well. In this section first, the home load demand forecast model is validated and compared with the real measured data. In Fig. 6, home load demand profile is exhibited. It is forecasted by trained ANFIS. As it is shown, the ANFIS is able to follow the pattern of the load practically. In order to show the accuracy of the trained ANFIS, the results are compared with a trained neural network forecast model as well. Moreover, weather forecast services can be found everywhere easily and by incorporating forecasted weather data stream in the solar cell temperature and effective irradiance model, the forecasted solar cell temperature and effective irradiance can be obtained [21]. Thereby, by knowing the forecasted amount of irradiance and solar cell temperature, the PV power generation can be forecasted by (1). Afterward, the forecasted data is applied to the MPC, the MPC make an optimal decision and determine the control actions. At the next step, the forecasted data is updated based on the real measured data and will be send to the MPC. This procedure will be continued until the end of the day. In this paper, the time step is set to 1 hour and the operation period is 24 hours, which it is from 1AM to 12 AM. Moreover, the control horizon length of the MPC set to 3 hours.

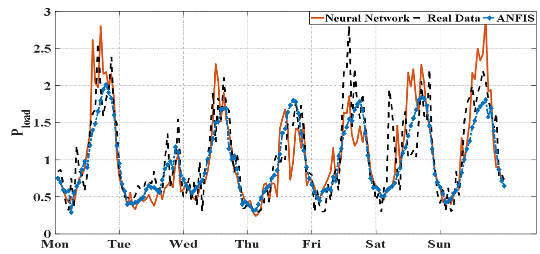
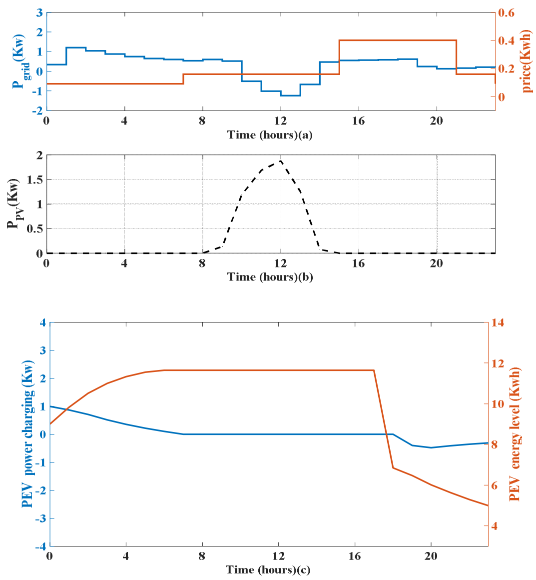


Fig. 6. Forecasted home load demand (from 15th to 21st, July 2017).

First the λ_1 and λ_2 are set to one in the cost function (11) to investigate the tradeoff behavior of the optimal operation and battery aging. The energy management result for one day is shown in Fig.7. As it is illustrated in (a), the grid power decrease when the electricity price increase. The grid power is negative from 10 Am to 2 PM because the amount of PV power output is bigger than the usage amount in the house. The PV power generation is plotted in Fig.7 (b) which follows a diurnal cycle. The PEV charging power and the PEV energy level are exhibited in Fig.7 (c). As you can see, in order to increase the battery life time the PEV discharged for a short period when the electricity price was very expensive around 7 PM and the rest of the day it is charged very smoothly when the electricity price was cheap. The household electric usage profile is illustrated in Fig.7 (d) and the PEV status is shown in Fig.7 (e) as well.



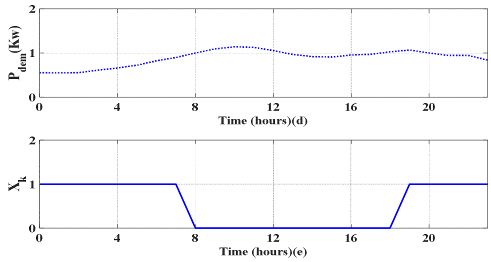


Fig. 7.energy management results: (a): optimal grid power and time varying electricity price ; (b): PV power production; (c): optimal PEV power charging and battery energy level profile under MPC control condition; (d): home load demand consumption profile; (e): the PEV status.

In order to do a comparison, the $\lambda_1 = 1$ and $\lambda_2 = 0$ are settled to analyses the energy management results without considering PEV battery aging. The results are shown in Fig.8. As it is evident, some unnecessary charging and discharging happened to minimize the cost of electricity as less as possible but it is harmful for battery life and increase the battery depredation in the long term use.

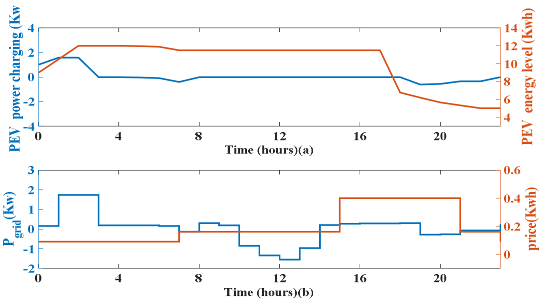


Fig. 8. Energy management result without tradeoff between economic performance and PEV battery aging: (a): grid power and electricity price; (b): PEV power charging trend.

V. Conclusion

In this paper, the uncertainties related to PV, PEV and home load demand models were introduced. The PEV trip time was model by Markov chain and the conditional probability distribution PEV energy at plug-in time was calculated by statistic data. The PVWatt model was utilized to forecast the PV power production pattern and ANFIS approach was used in order to model household demand. Smart energy management system was obtained by an online MPC to make trade-off between the cost and electricity while satisfying home and PEV charging requirement. The MPC was implemented and results demonstrated the ability of the proposed method.

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References

[1] M. Yousefi, A. Hajizadeh, and M. Soltani, "Energy management strategies for smart home regarding uncertainties: State of the art, trends, and challenges," in *2018 IEEE International Conference on Industrial Technology (ICIT)*, 2018, pp. 1219–1225.

[2] I. Lorzadeh, H. Askarian Abyaneh, and et al, "An enhanced instantaneous circulating Current control for reactive power and harmonic load sharing in islanded microgrids," Journal of Power Electronics, vol. 17, no. 6, pp. 1658-1671, Nov. 2017.

[3] N. Bayati, A. Hajizadeh, and M. Soltani, "Protection in DC microgrids: a comparative review," *IET Smart Grid*, vol. 1, no. 3, pp. 66–75, Oct. 2018.

[4] H. Kanchev, D. Lu, F. Colas, V. Lazarov, and B. Francois, "Energy Management and Operational Planning of a Microgrid With a PV-Based Active Generator for Smart Grid Applications," *IEEE Trans. Ind. Electron.*, vol. 58, no. 10, pp. 4583–4592, Oct. 2011.

[5] X. Guan, Z. Xu, and Q.-S. Jia, "Energy-Efficient Buildings Facilitated by Microgrid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 243–252, Dec. 2010.

[6] C. Sun, F. Sun, S.-J. Moura, "Nonlinear predictive energy management of residential buildings with photovoltaics & batteries," *J. Power Sources*, vol. 325, pp. 723-731, Sep. 2016.

[7] S. J. Moura and Y. A. Chang, "Lyapunov-based switched extremum seeking for photovoltaic power maximization," *Control Eng. Pract.*, vol. 21, no. 7, pp. 971–980, Jul. 2013.

[8] M. Yousefi, N. Kianpoor, A, Hajizadeh, and M. Soltani "ANFIS Based Approach for Stochastic Modeling of Smart Home," *in 2018 2nd European Conference on Electrical Engineering & Computer Science (EECS)*, 2018.

[9] X. Wu, X. Hu, S. Moura, X. Yin, and V. Pickert, "Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array," *J. Power Sources*, vol. 333, pp. 203–212, 2016.

[10] M. Yousefi, N. Kianpoor, A, Hajizadeh, and M. Soltani, "Stochastic Smart Charging of Electric Vehicles for Residential Homes with PV Integration," *in 2019 International Power Electronics, Drive Systems and Technologies Conference (PEDSTC)*, 2019.

[11] X. Wu, X. Hu, X. Yin, and S. Moura, "Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage," *IEEE Trans. Smart Grid*, vol. 3053, no. c, pp. 1–1, 2016.

[12] Y.-M. Wi, J.-U. Lee, and S.-K. Joo, "Electric vehicle charging method for smart homes/buildings with a photovoltaic system," *IEEE Trans. Consum. Electron.*, vol. 59, no. 2, pp. 323–328, May 2013.

[13] F. Luo, G. Ranzi, X. Wang, and Z. Y. Dong, "Service Recommendation in Smart Grid: Vision, Technologies, and Applications," in *2016 9th International Conference on Service Science (ICSS)*, 2016, pp. 31–38.

[14] F. Ge Luo, G. Ranzi, C. Wan, Z. Xu, and Z. Y. Ge Dong, "A Multi-Stage Home Energy Management System with Residential Photovoltaic Penetration," *IEEE Trans. Ind. Informatics*, pp. 1–1, 2018.

[15] M. Yousefi, A. Hajizadeh, and M. Soltani "A Comparison Study on Stochastic Modeling Methods for Home Energy Management System," *accepted in IEEE Trans. Ind. Informatics,* 2019.

[16] A. P. Dobos, "PVWatts Version 5 Manual,", Tech. Rep, National Renewable Energy Laboratory, 2014. www.nrel.gov/publications..

[17] Q. Yang, S. Sun, S. Deng, Q. Zhao, and M. Zhou, "Optimal sizing of PEV fast charging stations with Markovian demand characterization," *IEEE Trans. Smart Grid*, pp. 1–1, 2018.

[18] USDOT-FHWA, National Household Travel Survey, Tech. Rep, Department of Transportation, Federal Highway Administration U.S, 2009. http://nhts.ornlgov/index.shtml.

[19] H. K. Alfares and M. Nazeeruddin, "Electric load forecasting: Literature survey and classification of methods," *Int. J. Syst. Sci.*, vol. 33, no. 1, pp. 23–34, 2002.

[20] P. Liu, Y. Fu, and A. Kargarian Marvasti, "Multi-stage stochastic optimal operation of energy-efficient building with combined heat and power system," *Electr. Power Components Syst.*, vol. 42, no. 3–4, pp. 327–338, 2014.

[21] P. Gilman, A. Dobos, N. Diorio, J. Freeman, S. Janzou, and D. Ryberg, "SAM Photovoltaic Model Technical Reference Update," Tech Report, 93 pp. NREL/TP-6A20-67399, 2016.