The Holcombe Department of Electrical and Computer Engineering

Clemson University, Clemson, SC, USA

Energy Scheduling for a Smart Home Applying Stochastic Model Predictive Control

Mehdi Rahmani-andebili and Haiying Shen

❑Outline

- ❖ Introduction
- ❖ Smart Home
- ❖ Energy Scheduling
- ❖ The Challenges of the Problem
- ❖ The Proposed Approach
- ❖ Problem Formulation
- ❖ Numerical Study

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- **Fossil Fuels are the Main Sources of Energy**
- Energy security issue:
  - This energy source is limited and finite.

- Environmental issues:
  - Global warming,
  - Climate changes, and
  - Health issues.

- The proposed solution:
  - Installing renewables as the clean and free sources of energy.

Introduction

- Residential buildings have a considerable potential for:
  - Decreasing cost of energy use,
  - Increasing energy efficiency, and
  - Decreasing the carbon footprint by including renewables.

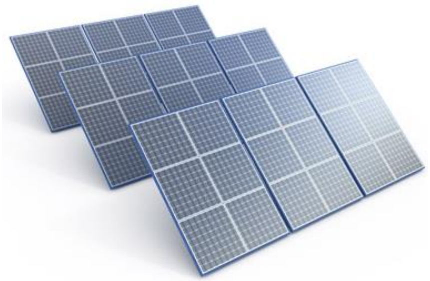
- The building sector is responsible for 30% of global greenhouse gas emissions.

- The building sector consumes about 40% of total energy.

Smart Home

❑ What is a Smart Home?

➢ A smart home (SH) is defined as a well-designed structure with sufficient access to assets, data, communication, and controls for improving the occupants' quality of life through convenience and reduced costs.



❑ Energy Resources of a SH

➢ A SH can include different energy resources such as:

- Photovoltaic (PV) panels, and
- Diesel generator.

➢ Also, a SH might have an energy storage like:

- A battery, or
- A plug-in electric vehicle (PEV), and
- Access to the local distribution company (DISCO)

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The Challenges of the Problem

- **Energy Scheduling:**
- The operation of energy resources to produce energy at the lowest cost to reliably serve the load considering the technical constraints of the energy resources.

- **The important question for energy scheduling of a SH is:**
- At every time step of the operation period,
- How much energy to use from the available energy sources such as diesel generator (DG), renewables (PV panels), and energy storage (battery),
- How much energy to purchase/sell from/to the DISCO to supply the demanded energy of the SH so that the daily energy consumption cost of the SH is minimized.

The Challenges of the Problem

- **The Uncertainty and Variability Issues of the Problem States:**
- Power of a renewable energy resource such as PV panels is uncertain that makes the problem a *stochastic optimization problem*.
- Power of the PV panels is variable that change the problem into a *dynamic (time-varying) optimization problem*.

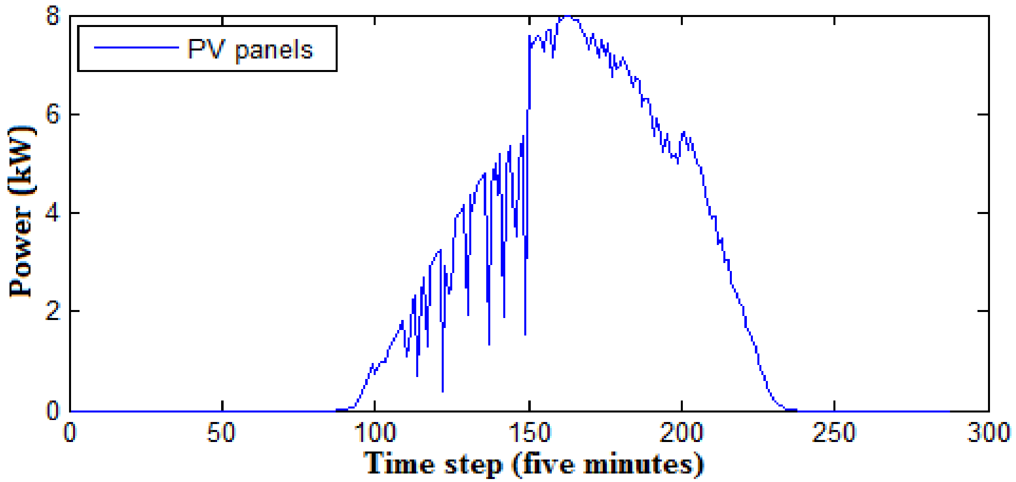

Fig. 1. The real solar irradiances for one day recorded in Clemson, SC 29634, USA in July 2014.

- **The Economic and Technical Constraints**
- The economic and technical constraints of energy sources of SH change the problem into a *mixed-integer nonlinear programming (MINLP) problem*.

The Proposed Approach

❑ Stochastic Optimization

➢ The *uncertainty issue* of the problem states is addressed by the *stochastic optimization*.

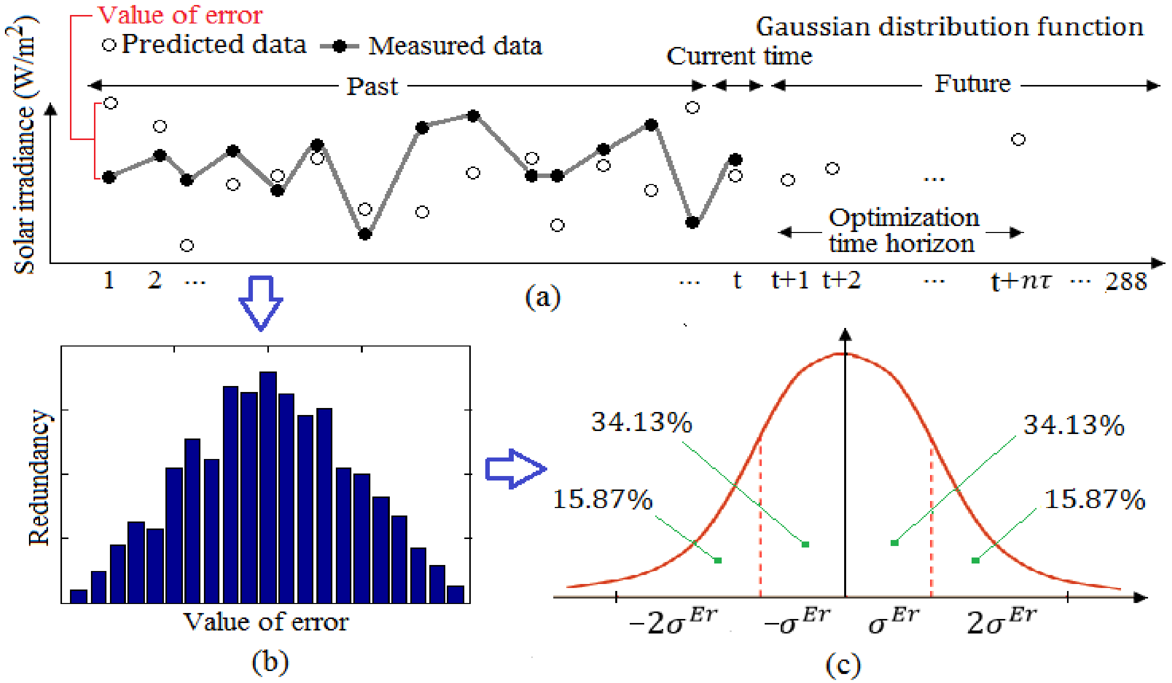

Fig. 2. (a): Predicted data, measured data, and value of prediction error (b): Redundancy of the prediction errors respect to the value of the prediction errors. (c): Gaussian probability density function related to the prediction errors.

- Forecasting value of uncertain states of the problem (solar irradiance) over the optimization time horizon.

$$\{\tilde{\rho}_{t+1}, \dots, \tilde{\rho}_{t+n_\tau}\}$$

- Modeling uncertainty of the predictions by defining appropriate scenarios for the estimated solar irradiance (ρ).

$$\rho_{h,t} \in \{\tilde{\rho}_{h,t} - 2\sigma^{Er}, \tilde{\rho}_{h,t} - \sigma^{Er}, \tilde{\rho}_{h,t} + \sigma^{Er}, \tilde{\rho}_{h,t} + 2\sigma^{Er}\}$$

The Proposed Approach

Power Model of PV Panels

- The output power of the PV panels is a nonlinear function of the estimated solar irradiance (ρ).

$$P^{PV} = \begin{cases} \overline{P^{PV}} \times \dfrac{(\rho\ )^2}{\rho^s \times \rho^c} & \rho\ \leq \rho^c \\ \overline{P^{PV}} \times \dfrac{\rho}{\rho^s} & \rho\ > \rho^c \end{cases}$$

- ρ^s is solar irradiance in the standard environment set as 1000 W/m2.
- ρ^c is certain solar irradiation point set as 150 W/m2.
- $\overline{P^{PV}}$ indicates the rated power of the PV panels.

The Proposed Approach

Model Predictive Control

- The variability issue of uncertain states of the problem (solar irradiance) is addressed by applying *model predictive control (MPC)* approach.
- MPC is capable of controlling a multi-variable constrained system by taking the control actions from the solution of an online optimization problem and predicting the system behavior repetitively.

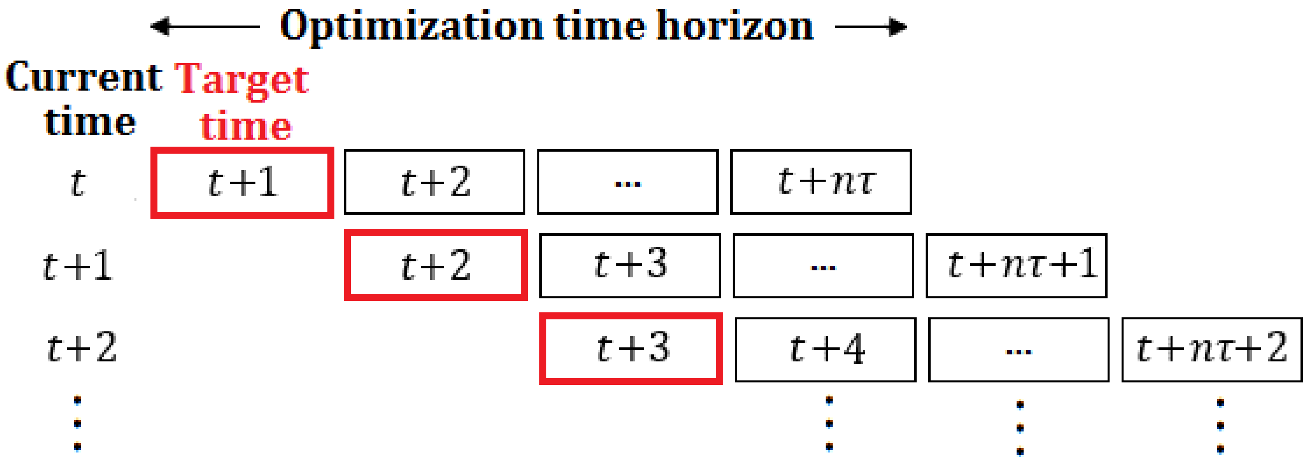

Fig. 6. The concept of the applied MPC with $n\tau$ as the number of time steps in the optimization time horizon and five minutes as the duration of each time step.

The Proposed Approach

Optimization Tool

- The discrete variables of the problem include:
  - Status of the DG (x^{DG}) in every time step of the optimization time horizon.
  - Status of the battery of the PEV (x^{PEV}) in every time step of the optimization time horizon.

$$\begin{Bmatrix} x_t^{DG} & \cdots & x_{t+n_\tau}^{DG} \\ x_t^{PEV} & \cdots & x_{t+n_\tau}^{PEV} \end{Bmatrix}, \forall t \in T, T = \{1, \cdots, n_t\}$$

- The continuous variables of the problem include:
  - Value of power of the DG (P^{DG}),
  - Value of generated or consumed power of the battery of the PEV (P^{PEV}),
  - Value of transacted power with the local DISCO (P^{Grid}) through the grid.

$$\begin{Bmatrix} P_t^{DG} & \cdots & P_{t+n_\tau}^{DG} \\ P_t^{PEV} & \cdots & P_{t+n_\tau}^{PEV} \\ P_t^{Grid} & \cdots & P_{t+n_\tau}^{Grid} \end{Bmatrix}, \forall t \in T$$

The Proposed Approach

Optimization Tool

- The problem is a mixed integer nonlinear (MINLP) problem.
- A combination of genetic algorithm (GA) and linear programming (LP), GA-LP, is applied to solve the energy scheduling problem of each SH.
- The GA deals with the discrete variables of the problem.
  - The GA addresses the nonlinearity of the problem (problem is changed to a linear problem).
- The LP deals with the continuous variables of the problem.
  - The LP quickly finds the globally optimal solution.

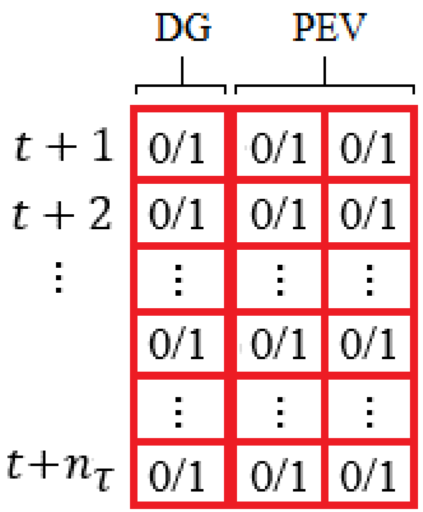

Fig. 3. The structure of a chromosome in the applied GA-LP.

The Proposed Approach

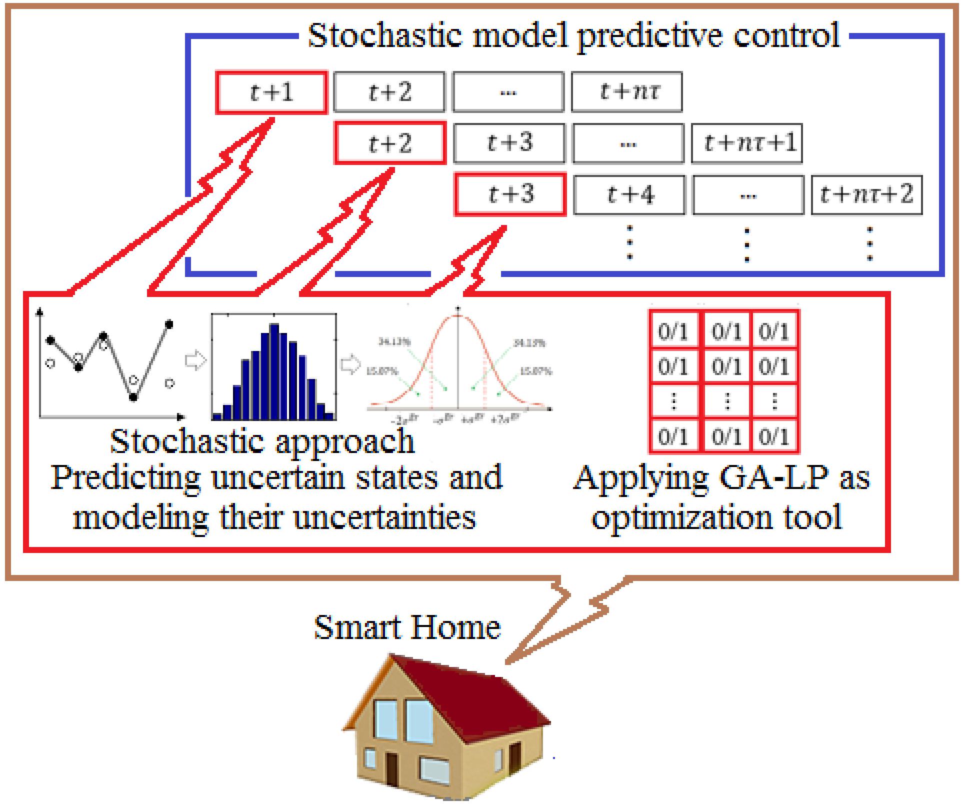

Fig. 4. The complete configuration of the proposed approach.

Problem Formulation

❑ Objective Function

- Minimizing value of the stochastic forward-looking objective function over the optimization time horizon is the aim of every SH.

$$min\, \mathbb{F}_t^{FL} = min \sum_{P_t^{PV}} F_t^{FL} \times \Omega_{h,t}^{PV}\, , t \in T$$

$$\Omega_t^{PV} \in \{0.1587,\ 0.3413,\ 0.3413,\ 0.1587\}$$

- Forward-Looking Objective Function:

$$F_t^{FL} = \sum_{\tau=1}^{n_\tau} F_{t+\tau}\, , t \in T$$

Problem Formulation

❑ Objective Function

$$F_t = \left\{ \begin{array}{c} \left[C_t^{F\_DG}\right] + \left[C_t^{E\_DG}\right] + \left[\left(1 - x_{t-1}^{DG}\right) \times x_t^{DG} \times C^{STU\_DG}\right] + \left[x_{t-1}^{DG} \times \left(1 - x_t^{DG}\right) \times C^{SHD\_DG}\right] \\ +\left[\acute{x}_t^{PEV} \times C^{SW\_PEV}\right] + \left[P_t^{Grid} \times \acute{\pi}_t^{DISCO}\right] \end{array} \right\}$$

- The time step objective function includes different cost and benefit terms such as:
  - Fuel cost of the generator,
  - Carbon emission cost of the generator,
  - Start up cost and shut down cost of the generator,
  - Switching cost of the battery,
  - Cost or benefit due to power transactions with the energy market.

Problem Formulation

❑ Objective Function

$$F_t = \begin{Bmatrix} [C_t^{F\_DG}] + [C_t^{E\_DG}] + [(1 - x_{t-1}^{DG}) \times x_t^{DG} \times C^{STU\_DG}] + [x_{t-1}^{DG} \times (1 - x_t^{DG}) \times C^{SHD\_DG}] \\ +[\acute{x}_t^{PEV} \times C^{SW\_PEV}] + [P_t^{Grid} \times \acute{\pi}_t^{DISCO}] \end{Bmatrix}$$

➢ The fuel cost function and carbon emissions function of the DG are quadratic polynomials.

$$C_t^{F\_DG} = x_t^{DG} \times (z_1^F \times (P_t^G)^2 + z_2^F \times (P_t^G) + z_3^F)$$

$$C_t^{E\_DG} = x_t^{DG} \times \beta^E \times (z_1^E \times (P_t^G)^2 + z_2^E \times (P_t^G) + z_3^E)$$

➢ Herein, β^E is the value of penalty for carbon emissions.

Problem Formulation

Objective Function

$$F_t = \begin{Bmatrix} [C_t^{F\_DG}] + [C_t^{E\_DG}] + \left[\left(1 - x_{t-1}^{DG}\right) \times x_t^{DG} \times C^{STU\_DG}\right] + \left[x_{t-1}^{DG} \times (1 - x_t^{DG}) \times C^{SHD\_DG}\right] \\ +[\acute{x}_t^{PEV} \times C^{SW\_PEV}] + \left[P_t^{Grid} \times \acute{\pi}_t^{DISCO}\right] \end{Bmatrix}$$

- If the status of the DG in the previous time step (x_{t-1}^{DG}) and current time step (x_t^{DG}) are 0 and 1, respectively, the DG has been stated up.

$$\left[\left(1 - x_{t-1}^{DG}\right) \times x_t^{DG} \times C^{STU\_DG}\right]$$

- If the status of the DG in the previous time step (x_{t-1}^{DG}) and current time step (x_t^{DG}) are 1 and 0, respectively, the DG has been shut down.

$$\left[x_{t-1}^{DG} \times (1 - x_t^{DG}) \times C^{SHD\_DG}\right]$$

Problem Formulation

Objective Function

$$F_t = \begin{Bmatrix} [C_t^{F\_DG}] + [C_t^{E\_DG}] + [(1 - x_{t-1}^{DG}) \times x_t^{DG} \times C^{STU\_DG}] + [x_{t-1}^{DG} \times (1 - x_t^{DG}) \times C^{SHD\_DG}] \\ +[\acute{x}_t^{PEV} \times C^{SW\_PEV}] + [P_t^{Grid} \times \acute{\pi}_t^{DISCO}] \end{Bmatrix}$$

- If the status of the battery of PEV in the current time step (x_t^{PEV}) is the same as the previous time step (x_{t-1}^{PEV}), the switching indicator is zero; otherwise, it is one.

$$\acute{x}_t^{PEV} = \begin{cases} 0 & x_{t-1}^{PEV} = x_t^{PEV} \\ 1 & x_{t-1}^{PEV} \neq x_t^{PEV} \end{cases}$$

- The value of switching cost of the battery of a PEV is determined based on the value of total cumulative ampere-hours throughput of the battery (ξ^{PEV}) in its life cycle and the value of the initial price of the battery (Pr^{PEV}).

$$C^{SW\_PEV} = \frac{Pr^{PEV}}{\xi^{PEV}}$$

Problem Formulation

- **Objective Function**

$$F_t = \left\{ \begin{array}{c} [C_t^{F\_DG}] + [C_t^{E\_DG}] + [(1 - x_{t-1}^{DG}) \times x_t^{DG} \times C^{STU\_DG}] + [x_{t-1}^{DG} \times (1 - x_t^{DG}) \times C^{SHD\_DG}] \\ + [\acute{x}_t^{PEV} \times C^{SW\_PEV}] + [P_t^{Grid} \times \acute{\pi}_t^{DISCO}] \end{array} \right\}$$

- The price coefficient φ (≈ 0.8) is applied by the local DISCO to determine the price of selling power to the DISCO by a SH based on the net energy metering (NEM) plan.
- In the NEM plan, the SH can deliver its extra power to the grid and sell it to the local DISCO at a lower price compared to the purchasing price from the local DISCO.

$$\acute{\pi}_t^{DISCO} = \begin{cases} \pi_t^{DISCO} & P_t^{Grid} > 0 \\ \varphi \times \pi_t^{DISCO} & P_t^{Grid} < 0 \end{cases}$$

- Herein, $P^{Grid} > 0$ means the SH purchases power from the local DISCO and $P^{Grid} < 0$ means the SH sells power to the local DISCO.

Problem Formulation

Technical Constraints of the Problem

- Supply-demand balance of the SH

$$P_t^{Grid} + P_t^{PV} + (x_t^{PEV} \times P_t^{PEV}) + (x_t^{DG} \times P_t^{DG}) = D_t^L$$

- Power limits of the DG

$$\underline{P^{DG}} \leq P_t^{DG} \leq \overline{P^{DG}}$$

- Minimum up/down time limits of the DG

$$\Delta t^{DG\_ON} \geq MUT^{DG}, \Delta t^{DG\_OFF} \geq MDT^{DG}$$

Problem Formulation

- **Technical Constraints of the Problem**

- Power limits of the battery of PEV

$$-\overline{P^{PEV}} \leq P_t^{PEV} \leq \overline{P^{PEV}}$$

- State of charge limits of the battery of PEV

$$DOD^{PEV} \leq SOC_t^{PEV} \leq 100$$

- Disconnection of the PEV from the SH

$$x_t^{PEV} = 0, t \in \{\Delta t_{Dep-Arr}\}$$

- Full charge constraint for the battery of the PEV before departure

$$SOC_{t_{Dep}}^{PEV} = 100$$

Numerical Studies

❑ Primary Data of the Problem

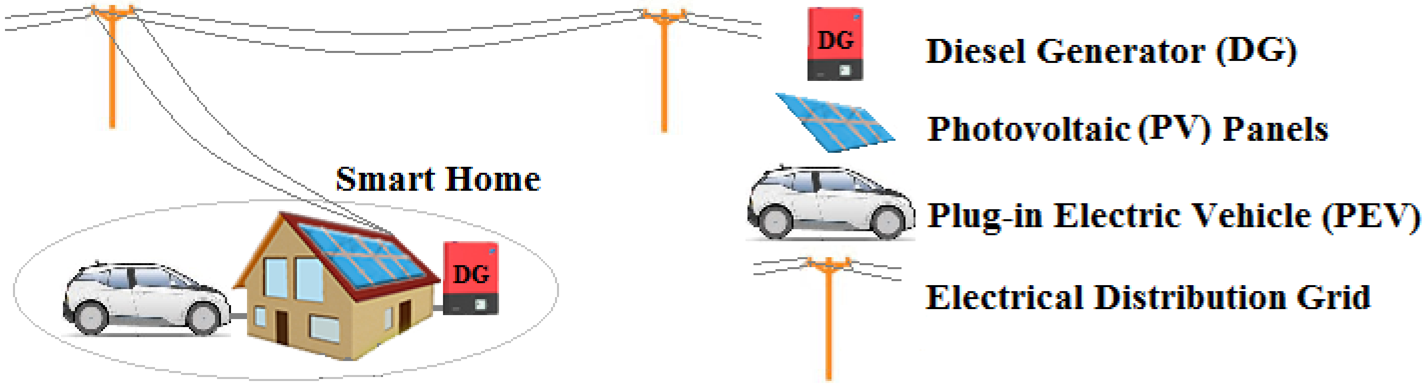

Fig. 5. The configuration of the case study in the second paper.

TABLE I

THE TECHNICAL DATA OF THE DIESEL GENERATOR.

Parameter	Value	Parameter	Value
z_1^F (¢/kWh²)	0.00491	$\underline{P}^{DG}$ (kW)	5
z_2^F (¢/kWh)	7.85	$\overline{P}^{DG}$ (kW)	20
z_3^F (¢)	0	MUT^{DG} (min)	10
z_1^E (kg/kWh²)	0.0008	MDT^{DG} (min)	10
z_2^E (kg/kWh)	0.61	C^{STU_DG} (¢)	100
z_3^E (kg)	0	C^{SHD_DG} (¢)	100

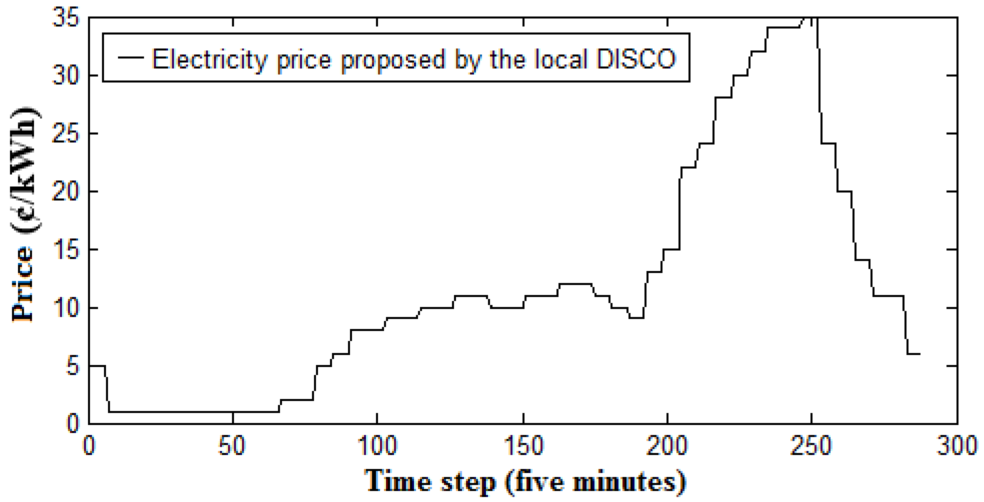

Fig. 6. The electricity price proposed by the local DISCO at every time step of the operation period.

TABLE II

THE VALUE OF PARAMETERS OF THE PROBLEM.

n_t	288	$\overline{P^{PEV}}$ (kWh)	10	Pr^{PEV} (¢)	200,000
t	5 min	Cap^{PEV} (kWh)	50	ξ^{PEV} (Ah)	10,000
n_τ	12	DOD^{PEV} (%)	20	θ^{Mut} (%)	5
φ	0.8	$SOC_{t_{Dep}}^{PEV}$ (%)	100	n_c	50
β^E (¢/kg)	1	$SOC_{t_{Arr}}^{PEV}$ (%)	80		
$\overline{P^{PV}}$ (kW)	10	$\Delta t_{Dep-Arr}$	9-10, 16-17		

Numerical Studies

- **Primary Data of the Problem**

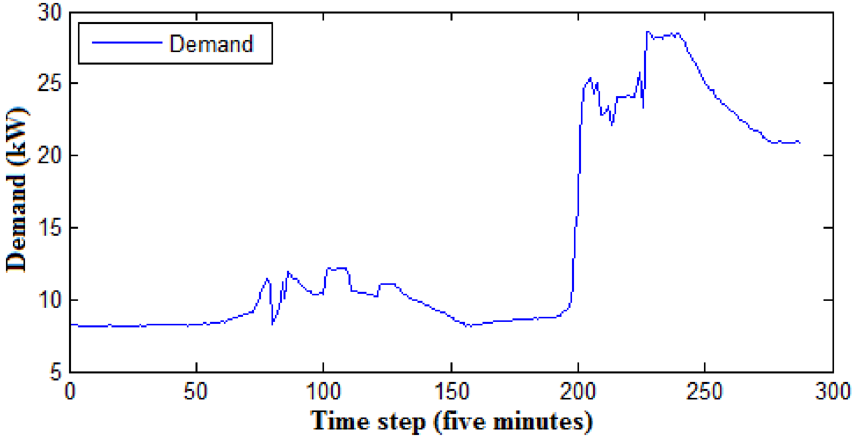

Fig. 7: The load demand of the SH at every time step of the operation period.

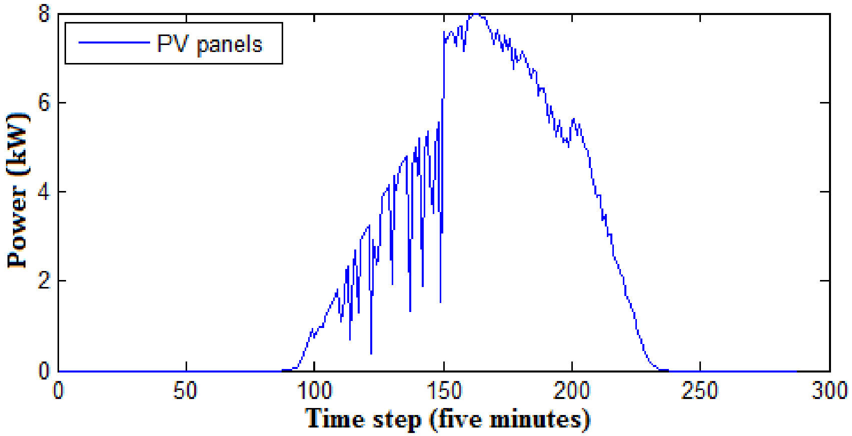

Fig. 8: The power pattern for the PV panels in a cloudy day (Clemson, SC, USA, in July 2014) at every time step of the operation period.

Numerical Studies

Problem Simulation

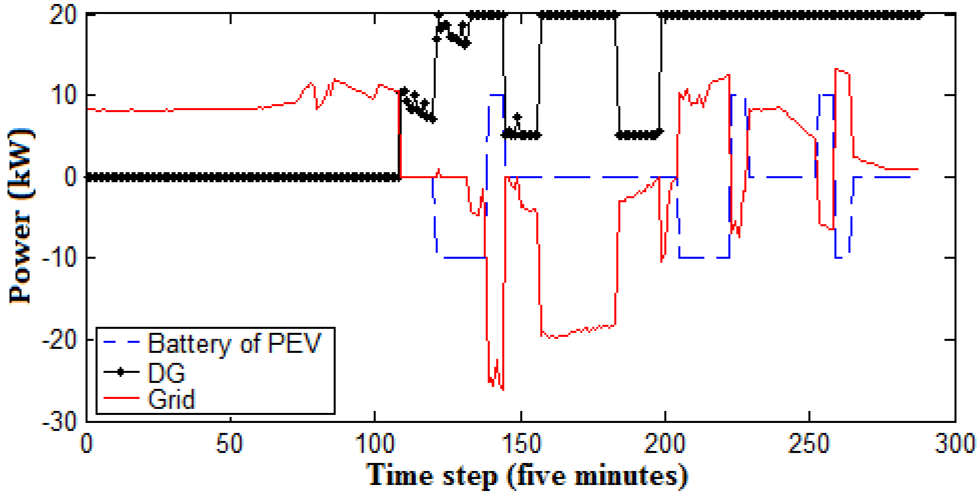

Fig. 9: The optimally scheduled power for the sources of the SH at every time step (five minutes) of the operation period (one day).

TABLE III
THE OPERATION COST OF THE SMART HOME ($/DAY) BEFORE AND AFTER ENERGY SCHEDULING.

-	Before scheduling	After scheduling
Operation cost ($/day)	51.1	29.8
Operation of the battery of the PEV (%)	0	12.5
Operation of the DG (%)	0	52.6

Conclusion

- It was proven that energy scheduling has a considerable potential for decreasing the daily operation cost of the SH.
- By application of MPC with five-minute time scale, the DG was able to adjust its output power within the small time step (five minutes).
- However, it was noticed that performance of the battery of the PEV as the energy storage was limited due to the short optimization time horizon (12 time steps, equal to one hour).
- Therefore, application of a multi-time scale MPC with short and long time scales are suggested as the extended work of the current study.
- Multi-time scale MPC is capable of simultaneously having vast vision for the optimization time horizon and precise resolution for the problem variables.


THANK YOU
ANY QUESTIONS?