The Holcombe Department of Electrical and Computer Engineering

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Cooperative Distributed Energy Scheduling for Smart Homes Applying Stochastic Model Predictive Control

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Outline

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

Introduction

❑ 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.

➢ A solution:

- Installing renewables as the clean and free sources of energy.

CLEMSON UNIVERSITY

Introduction

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

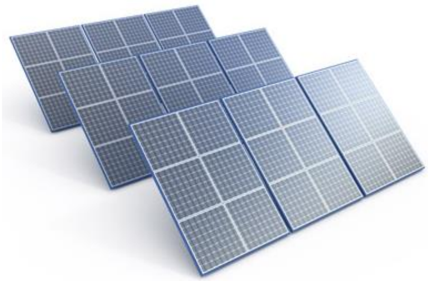
- ➢ The building sector is responsible for 30% of global greenhouse gas emissions.

- ➢ 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

- Photovoltaic (PV) panels
- Diesel generators
- Batteries
- Plug-in electric vehicles (PEVs)
- Access to the local distribution company (DISCO)

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 or other SHs to supply the demanded energy of the SH so that the daily energy consumption cost of the SH is minimized.

The Proposed Approach

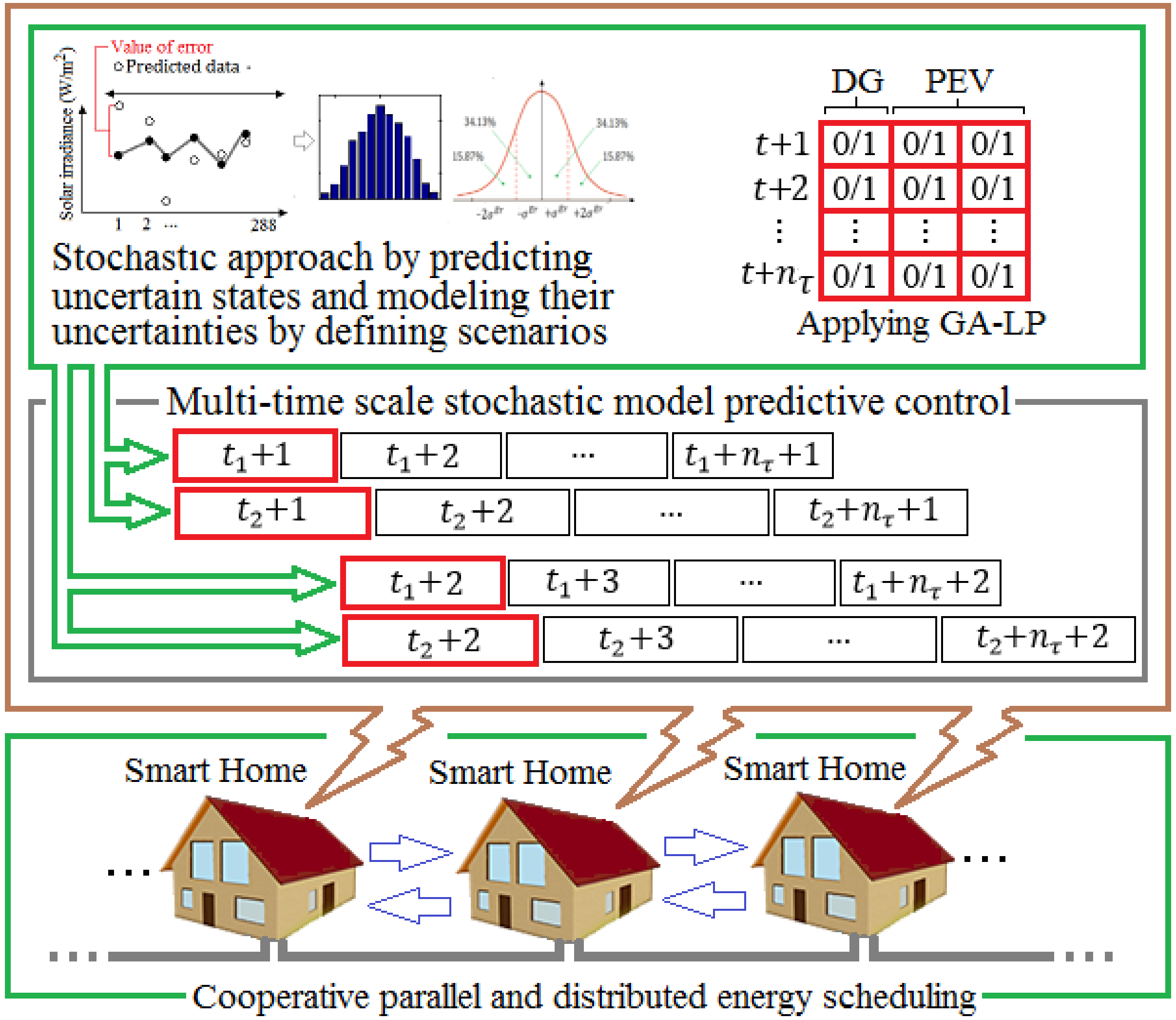


Fig. 4. The complete configuration of the proposed approach.

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*.

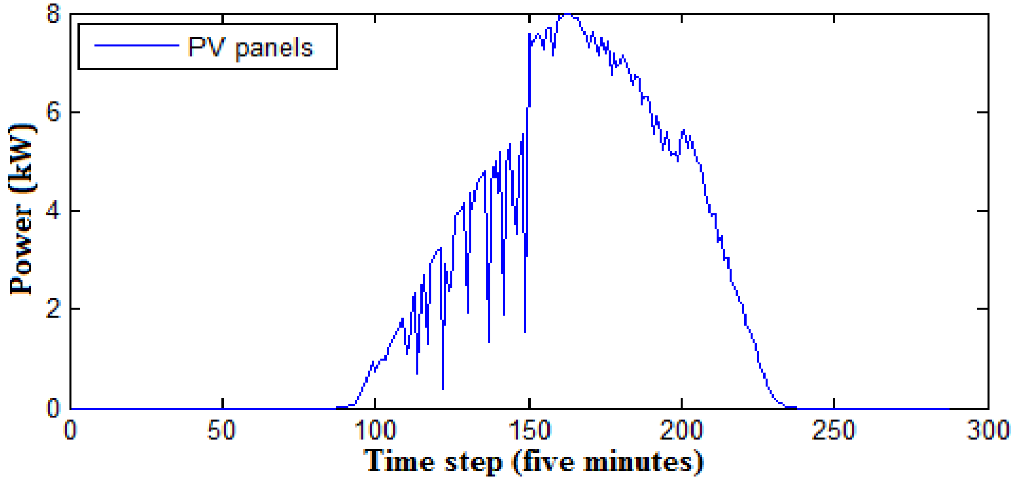


Fig. 1. The real solar irradiances for one day recorded in Clemson, SC 29634, USA in July 2014.

❑ 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*.

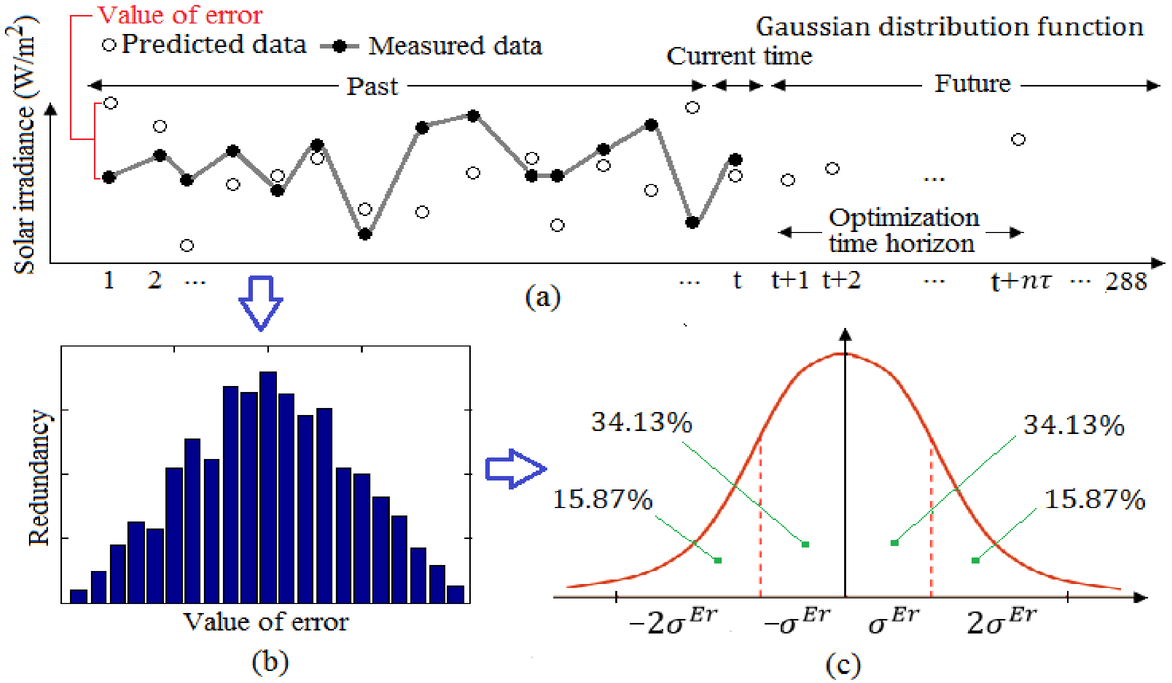


Fig. 2. (a): Predicted data, measured data, and value of prediction error (b): Redundancy of the prediction errors respect to the value of the prediction errors. (c): Gaussian probability density function related to the prediction errors.

- 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

❑ 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.

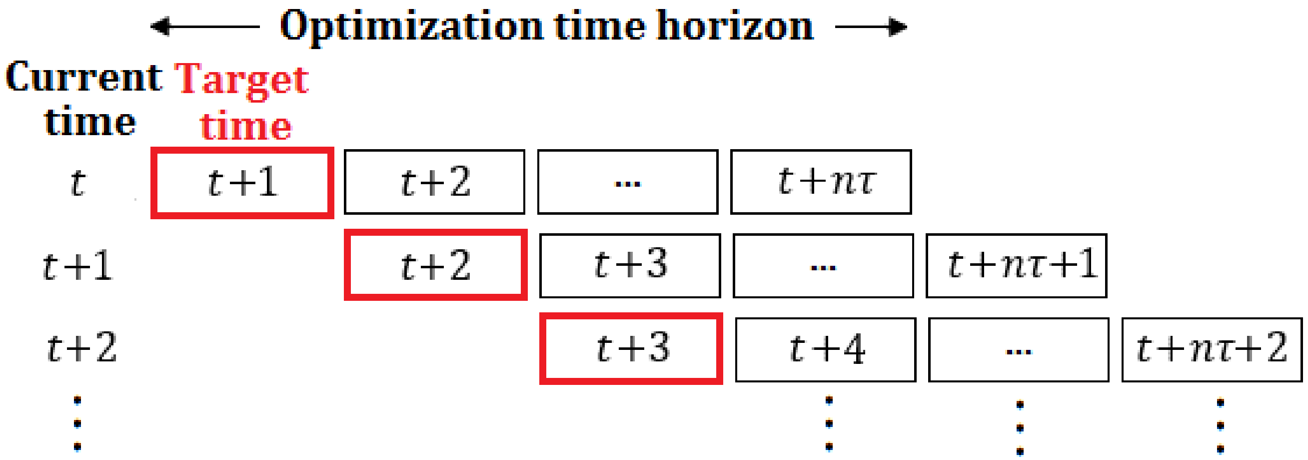
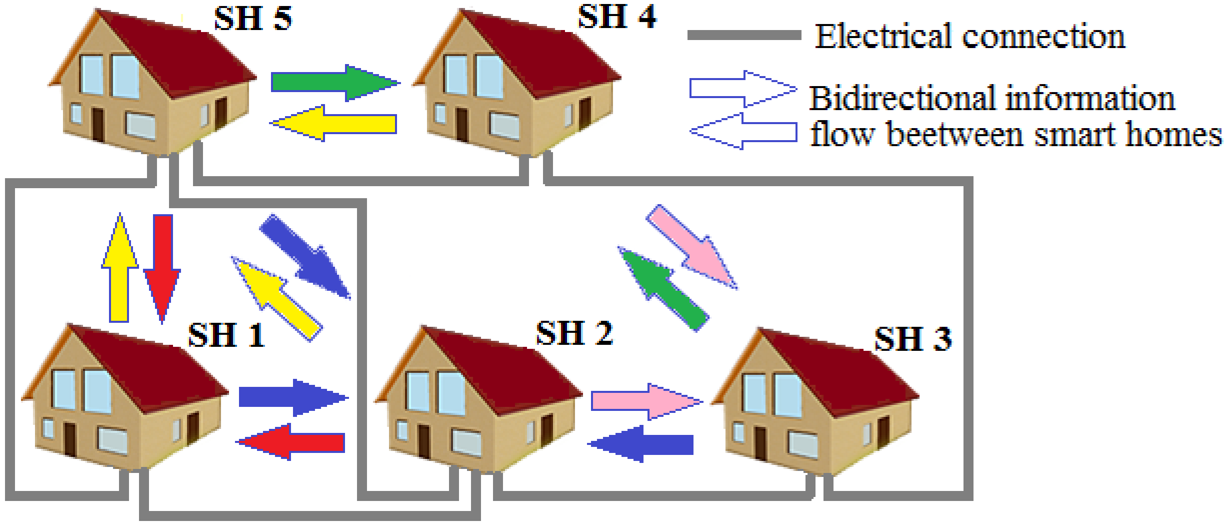


Fig. 6. The concept of the applied MPC with $n\tau$ as the number of time steps in the optimization time horizon and five minutes as the duration of each time step.

The Proposed Approach

❑ Cooperative Distributed Energy Scheduling

- Each SH electrically connects to a number of other SHs for energy transaction.
- Every SH can exchange the information just with its connected SHs.
- The information includes the value of available energy and price for transacting power between two SHs.
- At every time step, every SH solves its own energy scheduling problem considering the received information from the selected cooperator.
- This process is repeated several times until no significant improvement is observed in the value of the objective function of each SH.



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.
- Value of transacted power with the connected SHs ($P_{h,t,h'}^{N}, \forall h \in H'$) in every time step of the optimization time horizon.

$$\begin{Bmatrix} P_{h,t}^{DG} & \cdots & P_{h,t+n_\tau}^{DG} \\ P_{h,t}^{PEV} & \cdots & P_{h,t+n_\tau}^{PEV} \\ P_{h,t}^{Grid} & \cdots & P_{h,t+n_\tau}^{Grid} \\ P_{h,t,1}^{N} & \cdots & P_{h,t+n_\tau,1}^{N} \\ \vdots & \cdots & \vdots \\ P_{h,t,n_{h'}}^{N} & \cdots & P_{h,t+n_\tau,n_{h'}}^{N} \end{Bmatrix}, \forall h \in H, H' = \{1, \dots, n_{h'}\}, \forall t \in T$$

Problem Formulation

❑ Objective Function

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

$$min\, \mathbb{F}_{h,t}^{FL} = min \sum_{s \in S} F_{h,t,s}^{FL} \times \Omega_{s}^{PV}, \forall h \in H, \forall t \in T$$

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

- Forward-Looking Objective Function:

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

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.

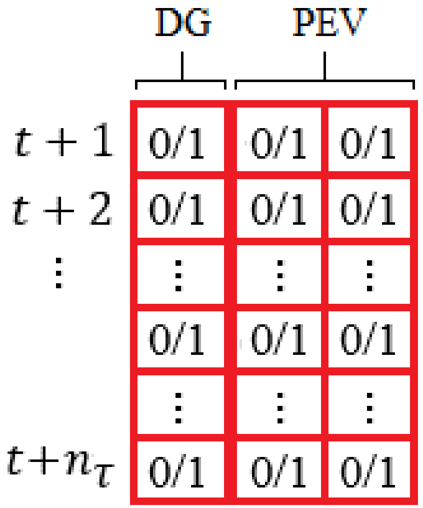
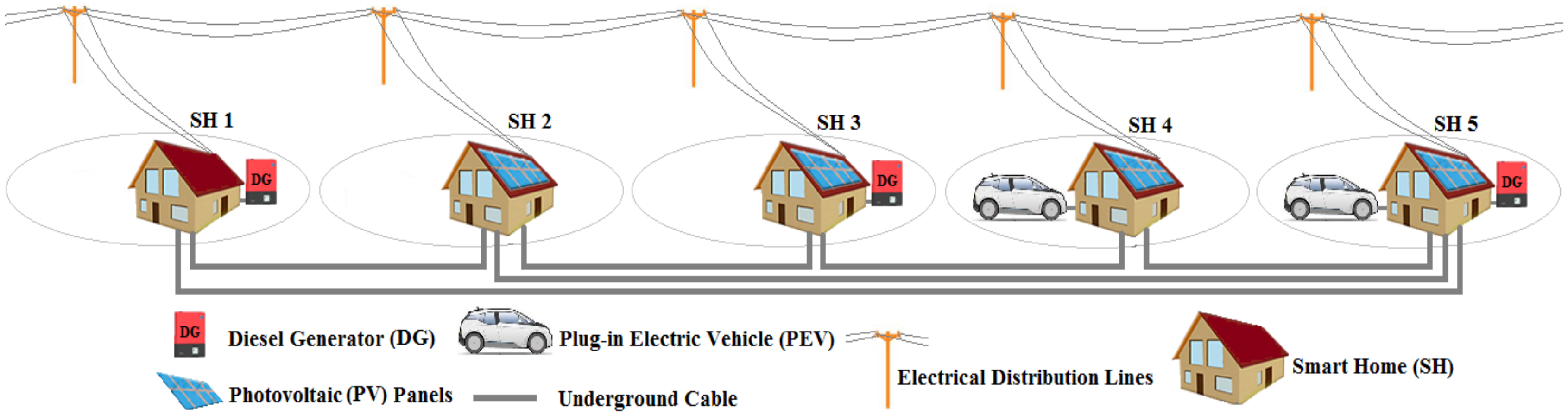


Fig. 3. The structure of a chromosome in the applied GA-LP.

Numerical Studies

❑ Primary Data of the Problem



The configuration of the case study in the second paper.

TABLE I

TECHNICAL DATA OF DIFFERENT TYPES OF THE DGS.

Parameter	Type 1	Type 2	Type 3
z_1^F (¢/kWh²)	0.00324	0.00243	0.00491
z_2^F (¢/kWh)	3.96	9.94	7.85
z_3^F (¢)	0	0	0
z_1^E (kg/kWh²)	0.0007	0.0008	0.0008
z_2^E (kg/kWh)	0.39	0.94	0.61
z_3^E (kg)	0	0	0
$\underline{P^{DG}}$ (kW)	5	5	5
$\overline{P^{DG}}$ (kW)	20	10	15
MUT^{DG} (min)	10	10	10
MDT^{DG} (min)	10	10	10
C^{STU_DG} (¢)	100	100	100
C^{SHD_DG} (¢)	100	100	100

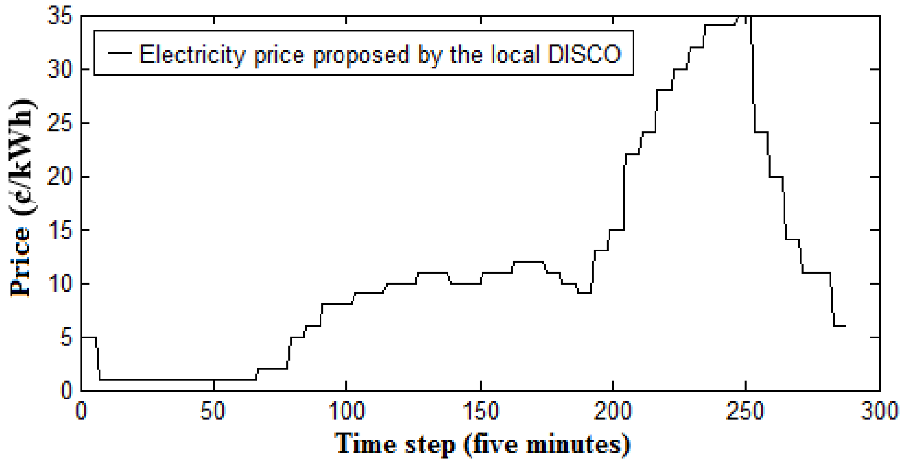


Fig. 6. The electricity price proposed by the local DISCO.

TABLE II

VALUE OF THE PARAMETERS OF THE SYSTEM AND PROBLEM.

n_t	288	$\overline{P_{Type\,1}^{PEV}}$ (kW)	10	$SOC_{t_{Arr}}^{PEV}$ (%)	50
n_τ	12	$\overline{P_{Type\,2}^{PEV}}$ (kW)	15	$\Delta t_{Dep-Arr}$	9-10, 16-17
φ	0.5	$Cap_{Type\,1}^{PEV}$ (kWh)	50	Pr^{PEV} (¢)	200,000
β^E (¢/kg)	1	$Cap_{Type\,2}^{PEV}$ (kWh)	75	ξ^{PEV} (Ah)	10,000
$\overline{P_2^{PV}}$ (kW)	10	DOD^{PEV} (%)	20		
$\overline{P_3^{PV}}$ (kW)	10	$SOC_{t_{Dep}}^{PEV}$ (%)	100		

Numerical Studies

- **Results**

TABLE III

THE OPERATION COST OF EVERY SH AND THE SYSTEM ($/DAY).

Energy scheduling	SH 1	SH 2	SH 3	SH 4	SH 5	Total
Without energy scheduling	10.21	11.47	14.54	13.38	16.38	66.01
Non-cooperative	-3.54	11.47	13.76	13.38	8.52	43.59
Cooperative distributed	-4.66	9.52	10.20	10.55	5.21	30.82

Numerical Studies

- **Problem Simulation**

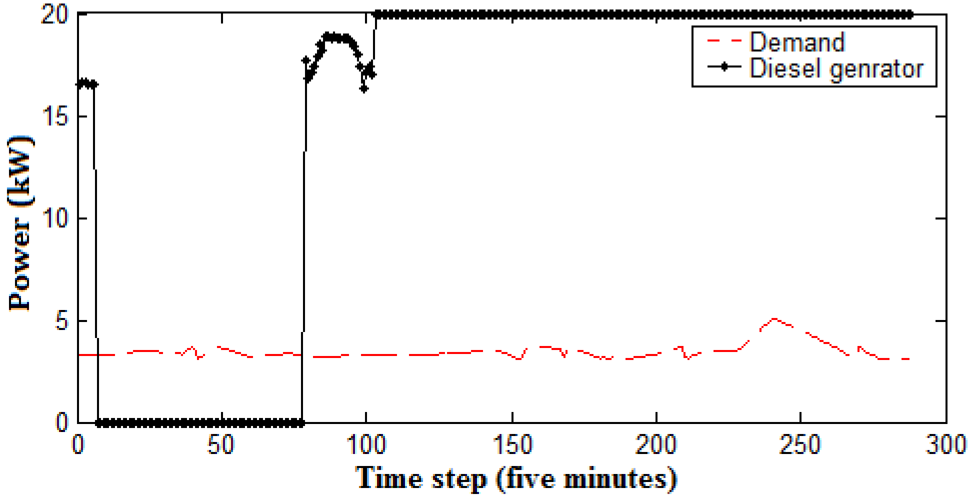


Fig. 7. The demand level and optimal power of energy sources in SH 1.

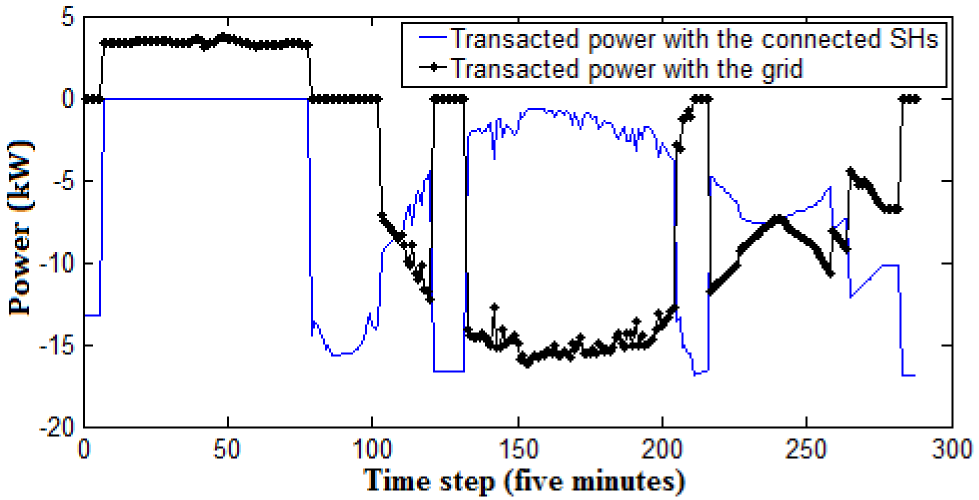


Fig. 8. The optimal transacted powers between SH 1 and the connected SHs and local DISCO.

Conclusion

- **Problem: Energy Scheduling for Smart Homes**
- **Solution:**
  - Stochastic approach by predicting uncertain states
  - Multi-time scale stochastic model predictive control
  - Cooperative parallel and distributed energy scheduling
  - Optimization problem formulation and solution

- **Future work:**
  - Apply a multi-time scale stochastic MPC with short and long time step durations to simultaneously have vast vision for the optimization time horizon and small scale resolution for the problem variables to improve the performance of each battery

Thank you!

Questions & Comments? Please contact:

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