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Scheduling deferrable appliances and energy resources of a smart home applying multi-time scale stochastic model predictive control



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ABSTRACT

In this paper, the problem of scheduling deferrable appliances and energy resources of a smart home (SH) is studied. The SH has a variety of sources that include photovoltaic (PV) panels, diesel generator (DG), and plug-in electric vehicle (PEV) as an energy storage, and also it can transact power with the local distribution company (DISCO). Herein, the appliances of the SH are categorized into non-deferrable and deferrable appliances, and also the deferrable appliances are divided into two groups with hour-scale and day-scale deferrable features. The challenges of the problem include modeling the economic and technical constraints of sources and appliances and addressing the variability and uncertainties concerned with the power of PV panels that make the problem a mixed-integer nonlinear programming (MINLP), time-varying (dynamic), and stochastic optimization problem. In this study, a multi-time scale stochastic model predictive control (MPC) and a combination of genetic algorithm (GA) and linear programming (GA-LP) are applied to address the above mentioned issues and solve the problem. The numerical study demonstrates the competence of multi-time scale approach in the stochastic MPC, and also the proficiency of proposed approach for hour-scale and day-scale deferrable appliances scheduling.

1. Introduction

Installing renewable energy resources, as the clean and free sources of energy, in the residential buildings have been proposed as the solution for the quickly using up the vast but finite amount of fossil fuels and its related environmental issues such as global warming and climate changes (Anonymous, 2017a; Pengwei & Ning, 2011). A smart home (SH) is defined as a well-designed structure with sufficient access to assets, communication, controls, data, and information technologies for enhancing the occupants' quality of life through comfort, convenience, reduced costs, and increased connectivity (Harper, 2003). SHs have a considerable potential for decreasing cost of energy use, increasing energy efficiency, decreasing the carbon footprint by including renewables, and transforming the role of the occupant (United States Congress, 2007). Based on the statistics presented in (Anonymous, 2017b; U.S. Energy Information Administration, 2012; OECD, 2013), the building sector contributes up to 30% of global annual greenhouse gas emissions and consumes up to 40% of all energy.

A SH can include distributed energy resources such as wind turbine, photovoltaic (PV) panels, and diesel generator (United States Congress, 2007). Also, a SH has several appliances that some of them are deferrable and can be scheduled concurrently with the energy resources of the SH. On the other hand, a SH, as a part of the smart grid on the demand side, can deliver its extra energy to the grid and sell it to the

local distribution company (DISCO), but at a lower price compared to the purchasing price from the local DISCO (Federal energy regulatory commission, 2017). However, there are several challenges in solving the above mentioned problem listed below.

- Power of a renewable energy resource such as PV panels is uncertain that makes the problem a stochastic optimization problem.
- Another issue for the power of a renewable energy resource is variability of its power that change the problem into a dynamic (time-varying) optimization problem.
- There are several economic and technical constraints for the appliances and energy sources of the SH. These constraints make the problem a mixed-integer nonlinear programming (MINLP) problem.
- Some of the deferrable appliances are utilized every day, while some
 of them are not needed every day and they might be used just once
 or twice a week. Therefore, the deferrable appliances scheduling
 problem must be investigated in an operation period longer than a
 day and at least about one week. This point indicates the necessity
 for having both hour-scale and day-scale deferring approaches.

There are several papers that have separately investigated the deferrable appliances scheduling problem (Adika and Wang, 2014; Chen, Wang, Heo, & Kishore, 2013; Paterakis, Erdinç,

Bakirtzis, & Catalao, 2015; Wu, Zhou, Li, & Zhang, 2014; Agnetis, Pascale, Detti, & Vicino, 2013) and the energy resources scheduling problem of a SH (Liu, Hu, Huang, Ranjan, & Zomaya, 2016; Pedrasa, Spooner, & MacGill, 2010; Gatsis and Giannakis, 2012; Chang, Alizadeh, & Scaglione, 2013). Moreover, these studies have not considered some of the aforementioned aspects of the deferrable appliances and energy resources scheduling problem of a SH. In (Chen et al., 2013; Liu et al., 2016; Gatsis & Giannakis, 2012; Chang et al., 2013), presence of renewable energy resources have been disregarded; in (Adika & Wang, 2014; Chen et al., 2013; Wu et al., 2014; Liu et al., 2016; Chang et al., 2013), energy storage has not been modeled; and in (Adika & Wang, 2014; Chen et al., 2013; Wu et al., 2014; Agnetis et al., 2013; Liu et al., 2016) presence of DG has not been taken into consideration.

In addition, the defined scheduling problem does not have any dynamic and adaptive characteristics in (Adika & Wang, 2014; Paterakis et al., 2015; Agnetis et al., 2013; Pedrasa et al., 2010; Gatsis & Giannakis, 2012). In other words, the problem has been optimized once for the whole operation period (one day), while the optimization of the problem must be updated at every time step of the operation period (e.g., at every hour or every five minutes) due to the time-varying feature of the power of renewables or load demand.

In (Adika & Wang, 2014; Chen et al., 2013; Paterakis et al., 2015; Wu et al., 2014; Agnetis et al., 2013), the list of the considered deferrable and non-deferrable appliances of a SH are not complete. Furthermore, the considered scheduling period for the deferrable appliances in is not long enough to take into account the weekly utilized deferrable appliances.

Also, multi-time scale optimization has not been applied in any of the above mentioned studies. In other words, this paper is the first study that applies the multi-time scale stochastic MPC in the deferrable appliances and energy resources scheduling problem of a SH.

In this study, the aforementioned challenges are addressed by applying the following proposed techniques.

- Addressing uncertainty of power of the PV panels: In order to deal with
 the uncertainty concerned with the power of the PV panels, a
 stochastic approach that includes predicting value of the solar
 irradiances over the optimization time horizon and defining the
 appropriate scenarios for the estimated solar irradiances is applied.
- Addressing time-varying power of the PV panels: In order to deal with
 the variability concerned with the power of the PV panels, multitime scale MPC technique with five-minute and one-hour time scales
 is applied in the problem. The applied multi-time scale MPC with
 short time step (five min) and long time step (one h) has characteristics of vast vision for the optimization time horizon (12 h) and
 precise resolution for the problem variables (five-minute time step).
- Modeling economic and technical constraints of the appliances and sources: Despite the studies presented in (Adika & Wang, 2014; Chen et al., 2013; Paterakis et al., 2015; Wu et al., 2014; Agnetis et al., 2013; Liu et al., 2016; Pedrasa et al., 2010; Gatsis & Giannakis, 2012; Chang et al., 2013), all the economic and technical constraints of the appliances and energy sources of the SH including the DG, the battery of the PEV, and the PV panels are modeled.
- Scheduling day-scale and hour-scale deferrable appliances: In this study, the appliances of the SH are classified into non-deferrable

and deferrable appliances. Also, the deferrable appliances are divided into two groups. The first group of the appliances are hour-scale deferrable appliances. In other words, these appliances can be shifted in the scale of some hours and within a day. The second group of the appliances are both hour-scale and day-scale appliances. In other words, these appliances can be shifted in the scale of some hours within a day and in the scale of some days within a week.

- Comprehensive list of appliances: In this study, a comprehensive list of
 deferrable and non-deferrable appliances of a SH are modeled in the
 problem. In addition, the deferrable appliances are scheduled
 simultaneously with the energy resources of the SH.
- The optimization tool: A combination of genetic algorithm (GA) and linear programming (GA-LP) is applied as an optimization tool to solve the energy scheduling problem of the SH. Herein, the GA, which deals with the discrete variables of the problem, addresses the nonlinearity of the problem and the LP, which handles the continuous variables of the problem quickly finds the globally optimal solution.

The paper is organized as follows. In Section 2, the proposed technique for solving the deferrable appliances and energy resources scheduling problem of the SH is presented. In Section 3, the problem is formulated. The numerical study is done in Section 4, and finally Section 5 concludes the paper.

2. Proposed technique

In the following, different parts of the proposed technique are presented and described.

2.1. Multi-time scale stochastic MPC

A stochastic optimization is applied in a multi-time scale MPC technique with one-hour and five-minute scales.

2.1.1. Stochastic approach

In this study, in order to address the variability and uncertainties concerned with the power of the PV panels a stochastic approach is applied in the multi-time scale MPC. The stochastic approach includes forecasting the solar irradiances and addressing the predictions uncertainties.

2.1.1.1. Forecasting the value of the uncertain states. The uncertain states of the problem include the values of solar irradiances (ρ) over the optimization time horizon that are predicted using the Levenberg-Marquardt back-propagation technique available in neural network toolbox of MATLAB. As can be seen in Fig. 1, the historical data related to the previous 20 time steps are entered to the first layer (hidden layer) of neural network (available in MATLAB) that includes 40 neurons. The output layer that includes 12 neurons represents the predicted values for the uncertain states (solar irradiances) for the next 12 time steps. Thus, the duration of optimization time horizon for any time scale (five-minute scale or one-hour scale) in stochastic MPC is 12 time steps (n_τ) is equal to 12). In other words, the values of solar irradiances are predicted for every time step of the optimization time horizon for

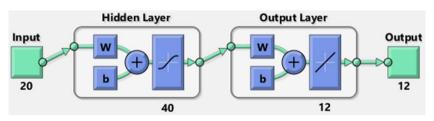


Fig. 1. The structure of neural network used for prediction of an uncertain state.

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