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Dynamic load management for a residential customer; Reinforcement Learning approach

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ABSTRACT

United Nation aims to double the global rate of improvement in energy efficiency as one of the sustainable development goals. It means researchers should focus on energy systems to enhance their overall efficiency. One of the effective solution to move from suboptimal energy systems to optimal ones is analyzing energy system in Energy Hub (EH) framework. In EH framework, interactions between different energy carriers are considered in supplying the required loads. The couplings and selecting proper combinations of inputs energy carriers lead to more optimized and intelligent consumption. The appropriate combination is found by solving an optimization problem at each time step. Utilizing intelligent technologies such as *Advanced Metering Infrastructures* (AMIs) inevitably facilitate the decision making processes. This paper modifies the classic Energy Hub model to present an upgraded model in the smart environment entitling "Smart Energy Hub" and optimizes the operation of a residential customer equipped with combined heat and power (CHP), auxiliary boiler, electricity storage and heating storage in this framework. Supporting real time, two-way communication between utility companies and smart energy hubs, and allowing AMIs at both ends to manage power consumption necessitates large-scale real-time computing capabilities to handle the communication and the storage of huge transferable data. To address this concern and reduce the amount of calculations, *Reinforcement Learning* (RL) method is employed to find a near optimal solution, which does not need massive computations. Finally, communications to large numbers of endpoints in a secure, scalable, and highly-available environment, in this paper, we propose a cloud computing (CC) architecture. Simulation results show that by applying RL technique in smart energy hub framework for a residential customer, efficiency of the energy system is increased substantially and leads to decrease energy bills and electricity peak load.

1. Introduction

As an important sustainable development goal, UN has targeted to double the global rate of improvement in energy efficiency. To reach this high rate, researchers should try to find a global solution for energy system optimization instead of local answers. One of the potential category of energy customer, consuming more than 21% of whole energy over the world, are residential users; hence, improving their consumption patterns will increase energy efficiency substantially. By raising the use of micro combined heat and power (CHP) systems in a near future for household applications, synergy effects of coupling between electricity and natural gas networks draw researchers' attention to propose an integrated picture of these two physically separated networks (Ahcin and Sikic, 2010). Motivated by different reasons, a number of recent publications suggest an integrated view of energy systems including multiple energy carriers, instead of focusing on a single one (Geidl et al., 2007; Geidl and Andersson, 2007a; Ahcin and Sikic, 2010; Sheikhi, Bahrami, & Ranjbar, 2015; Sheikhi, Rayati, Bahrami, & Ranjbar, 2015; Sheikhi, Ranjbar, & Oraee, 2012; Ameri and Besharati, 2016; Sheikhi, Ranjbar, Safe, & Mahmoodi, 2011; Kienzle, Ahčin, & Andersson, 2011; Geidl and Andersson, 2007b; Parisio, Del Vecchio, & Velotto, 2011; Parisio, Del Vecchio, & Velotto, 2012). Coupling different energy carriers is recognized as Energy Hub (EH).

The EH modeling and concept was proposed for the first time by Geidl in his paper, which aims at a Greenfield approach for future energy systems (Geidl et al., 2007). Within the hub, energy is converted, stored, and conditioned using CHP technology, transformers, power-electronic devices, compressors, heat exchangers, storage systems, and other equipment.

A simple example of an EH modeling for supplying electrical and heating loads is discussed in Geidl and Andersson (2007a). Electric-

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ity and natural gas are provided at the input port of the hub and a gas tank, an electrical transformer, a gas turbine, a furnace, a battery, and heat storage are inside it. By using energy storages and converters, the energy consumer can manage their demand dynamically as it is described in Ahcin and Sikic (2010) and Sheikhi, Bahrami et al. (2015).

Based on hierarchical optimization structure that develops in Sheikhi, Rayati, Bahrami et al. (2015), there are two different optimization levels. First one focuses on finding the best layout and optimal sizing of energy hub converters and components (Sheikhi et al., 2012; Ameri and Besharati, 2016; Sheikhi et al., 2011; Kienzle et al., 2011) and the other one focuses on finding the best operational strategy in steady state condition (Sheikhi, Rayati, Bahrami et al., 2015).

Optimal hub operation and a generic steady state model for describing conversion and storage of multiple energy carriers, such as electricity, natural gas, hydrogen, or distinct heating, is developed in Geidl and Andersson (2007b). Based on this model, a number of publications suggest various optimization methods. For example, Parisio et al. (2011) and Parisio et al. (2012) present robust optimization (RO) techniques for solution of Energy Hub optimization to satisfy the energy request while minimizing the cost function.

From a number of recent publications (Geidl et al., 2007; Geidl and Andersson, 2007a; Ahcin and Sikic, 2010; Sheikhi, Bahrami et al., 2015; Sheikhi, Rayati, Bahrami et al., 2015; Sheikhi et al., 2012; Ameri and Besharati, 2016; Sheikhi et al., 2011; Kienzle et al., 2011; Geidl and Andersson, 2007b; Parisio et al., 2011; Parisio et al., 2012), it can be seen that the energy system was considered conventional and they are not implemented in the Smart Grid (SG) environment. Smart Grid is bidirectional flows of energy and two-way communications that will enable array of new functionalities and applications (National Institute of Standards and Technology, 2010). In the Smart Grid environment, there are "smart meters" which do not only show energy consumptions all the time, but also have two-way communication capabilities that enable users to communicate with utility companies directly (Fang, Misra, Xue, & Yang, 2012a; Fang, Misra, Xue, & Yang, 2012b; Fang, Xue, & Yang, 2013; Arnold, Negenborn, Andersson, & De Schutter, 2009). Rastegar in Rastegar and Fotuhi-Firuzabad (2015) modeled the residential energy hub and solved this model to optimally control all major of domestic loads in a deterministic environment.

So far, most of the proposed dynamic load management, i.e. demand response (DR) programs, are based on master-slave architecture (Parisio et al., 2012; National Institute of Standards and Technology, 2010; Fang et al., 2012a). Utility's energy management system (EMS) interacts with customers' EMS individually. Basically, master-slave architecture is host-address centric communication (the senders and the receivers need to know their addresses, e.g., IP addresses, for communication) and is good for a small-scale network due to its simplicity. However, from system protection perspective, master-slave architecture for demand response has several potential drawbacks (Rastegar and Fotuhi-Firuzabad, 2015; Adika and Wang, 2014; Sheikhi, Rayati, Bahrami, Ranjbar, & Sattari, 2015). It is possible that smart meters and EMS can be compromised by cyber attackers. From scalability perspective, the maximum numbers of clients are limited by the server capacity. Additionally, when demand response operates as an iterative process, the communication latency between a master and slaves can be high. Hence, if the utility wants to deploy a large-scale demand response program, the utility EMS server must be able to resolve the potential problems listed so far.

Based on above mentioned approaches, there are two main shortcomings when it comes to dynamic load management programming in the real world as follows:

1. Energy system parameter definition: almost all approaches, which are applied to optimize the energy consumption of residential customers, require defining some specific parameters, e.g., appliances efficiencies and energy prices, as constant (Fang et al., 2012a; Fang et al., 2012b; Fang et al., 2013; Arnold et al., 2009; Rastegar and Fotuhi-Firuzabad, 2015); however, such an assumption would not necessary hold accurate in practice. For instance, appliances efficiencies vary with time and energy prices are intrinsically stochastic.
2. In the conventional smart grid architecture, several problems are reported as follow: first, the master-slave architecture causes extensive exposure to cyber-attacks such as the distributed denial of service (DDoS), attacks from the compromised nodes in the demand response model. In a master-slave architecture, the utility provider acts as a master and the customers act as slaves. Second, one of the main concerns in the existing approaches is single failure in master-slave architecture. Third, in conventional smart grid system, demand response is performed in a utility energy management systems (EMS). Because of limited memory and storage capacity, increasing the number of customers will be a crucial issue for energy management. Finally, using sensor nodes and intelligent devices, an early warning system can be integrated with the grid. However, due to limited energy and bandwidth resources, real-time implementation is quite difficult.

Therefore, without tackling two mentioned deficiencies, EMS programing will arguably not lead to the accurate results in real life.

To tackle the latter concern, a model for utilizing the cloud computing technology is proposed, a next generation computing paradigm in the smart grid domain. Cloud computing refers to manipulate, configure, and access the applications online (Adika and Wang, 2014). It offers online data storage, infrastructure, and application. Computing, software, and data services can be used by end users without knowledge of the users' IP addresses or configurations of the systems. Cloud computing is probably the simplest and best fitted way for smart grids due to its scalable and flexible characteristics, and its capability to manage large amounts of data. The utility company and customers interact through the cloud, and the functions for realizing demand response are performed in a cloud rather than in the utility EMS (Sheikhi, Rayati et al., 2015). From utility perspective, cloud appears to be an information system that takes an input from utility (e.g., the amount of power deficit), processes the information, and gives an output to utility (e.g., how much loads per customers reduces at which incentive price) (Sheikhi, Rayati, & Ranjbar, 2015).

The current paper addresses former concerns by applying Reinforcement Learning (RL) algorithm, one of the machine intelligence techniques, to solve real-world problem with a dynamic environment, such as here that electricity, heating and cooling loads are stochastic. RL is the study of programs that improve their performance and adapt an agent to an unknown and dynamic environment by receiving rewards and punishments from the environment (Kaelbling, Littman, & Moore, 1996; O'Neill, Levorato, Goldsmith, & Mitra, 2010; Khan, Herrmann, Lewis, Pipe, & Melhuish, 2012; Quah, Quek, & Leedham, 2005; Agung and Lumban Gaol, 2012).

We also introduce new solution to model separate energy infrastructures in one framework which is entitled Smart Energy Hub (SEH). SEH models Smart Grid and Cloud Computing in multi-carrier energy systems. SEH solutions allow hubs to monitor and control energy usages in real time and therefore manage their energy consumption to reduce their energy bills. This paper is organized as follow: The Smart Energy Hub Modeling and Cloud Computing utilization are introduced briefly in Section 2 and 3,