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A Dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach

Renzhi Lu, Seung Ho Hong*, Xiongfeng Zhang

Department of Electronic Engineering, Hanyang University, Ansan 15588, Republic of Korea

HIGHLIGHTS

- Propose an artificial intelligence based dynamic pricing demand response algorithm.
- Reinforcement learning is used to illustrate the decision-making framework.
- Uncertainty of customer's demand and flexibility of wholesale prices are achieved.
- Effects of customers' private preferences in the electricity market are addressed.

ARTICLE INFO

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Demand response
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Artificial intelligence
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Markov decision process
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ABSTRACT

With the modern advanced information and communication technologies in smart grid systems, demand response (DR) has become an effective method for improving grid reliability and reducing energy costs due to the ability to react quickly to supply-demand mismatches by adjusting flexible loads on the demand side. This paper proposes a dynamic pricing DR algorithm for energy management in a hierarchical electricity market that considers both service provider's (SP) profit and customers' (CUs) costs. Reinforcement learning (RL) is used to illustrate the hierarchical decision-making framework, in which the dynamic pricing problem is formulated as a discrete finite Markov decision process (MDP), and Q-learning is adopted to solve this decision-making problem. Using RL, the SP can adaptively decide the retail electricity price during the on-line learning process where the uncertainty of CUs' load demand profiles and the flexibility of wholesale electricity prices are addressed. Simulation results show that this proposed DR algorithm, can promote SP profitability, reduce energy costs for CUs, balance energy supply and demand in the electricity market, and improve the reliability of electric power systems, which can be regarded as a win-win strategy for both SP and CUs.

1. Introduction

Owing to the modern advanced information and communication technologies in smart grid systems, demand response (DR) has become an effective method for improving grid reliability and reducing energy costs due to the ability to react quickly to supply-demand mismatches by adjusting flexible loads on the demand side [1,2]. According to the United States Department of Energy, DR refers to "a tariff or program established to motivate changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity usage at times of high market prices or when grid reliability is jeopardized" [3].

The existing literature generally discusses two categories of DR: price-based and incentive-based [4]. Price-based DR motivates customers (CUs) to change their energy usage patterns in response to time-varying electricity prices, while incentive-based DR provides fixed or time-varying incentives to CUs if they reduce their energy consumption during periods of power system stress [5]; both categories have their own benefits and take advantage of different aspects of the potential for flexible demand. This study focuses on price-based DR, whose efficiency has been evaluated in several studies [6–9].

A number of studies have investigated the price-based DR, focusing on directly controlling appliances to maximize the social welfare of the smart grid systems from the CUs' perspective. For example, in [10–12], energy consumption scheduling of residential appliances was studied considering time-of-use (TOU) pricing to reduce CUs' costs and enhance energy efficiency. Similarly, the work in [13] evaluated the impact of a large-scale field deployment of mandatory TOU pricing on the energy use of commercial and industrial CUs. In [14], the authors investigated the DR of commercial and industrial businesses to critical peak pricing plots where the time and duration of the price increase were

* Corresponding author.
E-mail address: shhong@hanyang.ac.kr (S.H. Hong).

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Nomenclature

Variables

$e_{t,n}$	energy consumption of customer n at time slot t
$E_{t,n}$	energy demand of customer n at time slot t
$e_{t,n}^{curt}$	energy consumption of customer n at time slot t for curtailable load
$E_{t,n}^{curt}$	energy demand of customer n at time slot t for curtailable load
$e_{t,n}^{critic}$	energy consumption of customer n at time slot t for critical load
$E_{t,n}^{critic}$	energy demand of customer n at time slot t for critical load
t	index for time slot
n	index for customer
$\lambda_{t,n}$	retail electricity price for customer n at time slot t
π_t	wholesale electricity price at time slot t
$\varphi_{t,n}$	dissatisfaction cost of customer n at time slot t
i	index for iteration in Q-learning

Parameters

ξ_t	elasticity at time slot t
α_n	customer preference parameter of dissatisfaction cost function
β_n	predetermined paremeter of dissatisfaction cost function
$D_{\min}$	lower bound of demand reduction at time slot t
$D_{\max}$	upper bound of demand reduction at time slot t
κ_1	coefficient of lower retail price bound
κ_2	coefficient of upper retail price bound
ρ	weighting factor between SP's profit and CUs' costs

Other symbols

DR	demand response
RL	reinforcement learning
SP	service provider
CU	customer
MDP	Markov decision process
GO	grid operator

predetermined. The works in [15–20] described a deterministic DR model with day-ahead prices for CUs, wherein the next-day electricity prices are known in advance and optimal energy consumption scheduling can be predefined though minimizing daily costs. In [21], the authors proposed a day-ahead price-based and real-time incentive-based strategy for large electricity CUs; however, the period and the value of the incentive rate were assumed to be decided ahead of schedule. In [22,23], two further price-based DR schemes were designed for industrial loads, considering both current and future load control in the schedule horizon; however, although the authors modeled the future price uncertainty, the mathematical formulations in these two papers were complex, and real-world implementation would be cumbersome. Thus far, the majority of previous works on energy consumption scheduling based on a given pricing policy, and cannot accommodate uncertainties in the dynamic electricity market environment. Given this, it is imperative to devise an innovative dynamic pricing DR mechanism for smart grid systems.

Dynamic pricing is a business strategy that adjusts the product price in a timely fashion, to allocate the right service to the right CU at the right time [24]. There have been several works on dynamic pricing DR algorithms for smart grids. The study in [25] investigated a dynamic pricing strategy with DR for a microgrid retailer in an integrated energy system, where the retail rates and microgrid dispatch were formulated as a mixed integer quadratic programming problem with the aim of maximizing the retailer's profit. In [26,27], Stackelberg games were used to model energy trading between a retailer and CUs, where the retailer determined the dynamic retail price based on the energy pricing scheme to maximize profit, and then the CUs minimized their payment bill by managing the energy usage of appliances according to the announced prices. More recently, another three works [28–30] proposed the dynamic price-based energy management scheme between the retailer and CUs. However, in these works, the dynamic pricing policies deployed by the retailer were predetermined by abstract models (e.g., linear model) without logical process of determination. To some degree, these studies are still deterministic and cannot react to the flexibility of CUs' demand profiles and wholesale electricity prices in the electric power market.

From the above existing literatures, we can conclude that the energy management system operation still relies on conventional ways such as deterministic rules and abstract models (e.g., mix integer linear programming), which mainly suffer two key criticisms: (a) applying deterministic rules for operating non-stationary system cannot guarantee optimality, any changes of a variable may result in a loss of money and (b) abstract models are usually approximations of the reality and therefore might be unrealistic compared with real energy systems, since the performance of the abstract model is strictly limited by the modeler's skill and experience. In recent years, with the rapid development of artificial intelligence, there has been growing interest in adopting reinforcement learning (RL) to solve the decision-making problem in smart grids. A number of breakthroughs in RL have been reported, in particular, like deep Q-network in Atari[31] and AlphaGo [32]. RL is an area of machine learning inspired by behaviorist psychology, concerned with how software agents ought to take actions in a stochastic environment to maximize some notion of cumulative reward, as shown in Fig. 1. An agent interacts with its environment in discrete time steps; at each time step, the agent chooses an action from the set of available actions, which is subsequently sent to the environment. Then the agent receives a reward and the environment moves to a new state. The goal of an agent is to collect as much reward as possible. In [33–38], RL algorithms were used to schedule energy storage systems and obtain an optimal charging/discharging policy, e.g., a battery or an electric vehicle. This scenario is relatively easy for its limited space of actions and states, and has thus been the focus of a number of papers. The studies in [39–42] used RL to obtain energy scheduling for specific devices in DR, e.g., electric water heaters, thermostatically controlled loads, or others. In [43], the authors considered microgrids as a whole, with each microgrid having the capacity to buy or sell energy to another microgrid; RL was used between the microgrids to choose a buying/selling strategy for energy trading, to maximize the average revenue. Motivated by the dominant and unique features of "no need of expert knowledge" and "model-free", RL is becoming one of the most promising tools to realize optimal operation of energy management system in face of ever-changing ambient factors, e.g., dynamic electricity prices and energy consumptions.

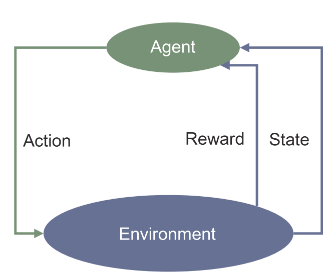

Fig. 1. Reinforcement learning (RL) setup.