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Agent-based modeling of the demand-side system reserve provision

Edin Lakić[a,*], Gašper Artač[b], Andrej F. Gubina[c]

[a] BSP d.o.o., Dunajska 156, 1000 Ljubljana, Slovenia
[b] GEN-I, d.o.o., Krško, Slovenia
[c] University of Ljubljana, Faculty of Electrical Engineering, Ljubljana, Slovenia

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ABSTRACT

Market simulators based on agent-based modeling techniques are frequently used for electricity market analyses. However, the majority of such analyses focus on the electricity markets bidding strategies on generation-side rather than on the demand-side. Meanwhile, the behavior of the demand-side in the system reserve provision has been less investigated. This paper presents a novel system reserve provision agent which is incorporated into a stochastic market optimization problem. The agent for the system reserve provision uses the SA-Q-learning algorithm to learn how much system reserve to offer at different times, while seeking to increase the ratio between their economic costs and benefits. The agent and its learning process are described in detail and are tested on the IEEE Reliability test system. It has been shown that incorporating the demand-side market strategies using the proposed agent improves the performance and the economic outcome for the consumers.

1. Introduction

Maintaining a high level of security of power system during operation continues to be a high priority in competitive electricity markets. The variable nature of renewable energy sources and demand combined with the possibility of a sudden loss of generating capacity require an adequate reserve in order to reduce the risk of load shedding. When these sources of variability compound they can lead to serious balancing problems, requiring an increase in the power reserve margin. The maintenance of power system security using only supply-side options will increasingly become technically more difficult and potentially more expensive [1].

A field of the demand response (DR) proposes a solution to this problem by introducing various demand response programs that could help enhance the demand-side participation at the electricity market [2,3]. In addition to a consumers' natural response to changes in electricity price, they may also be able to additionally modify their normal consumption in order to participate in the system reserve market [4]. Permitting and encouraging at least some retail consumers to face time-varying electricity prices provides economic, environmental, and reliability benefits. Action from DR technologies that are part of a portfolio of generators can be used to balance output and provide energy arbitrage opportunities, which could accrue as benefits to the portfolio owner or to intermittent generators using this resource [5]. Recent advances toward future intelligent grids (or smart grids, as they are known in Europe) enable the demand to respond quickly enough to provide some of the required system reserve. Day-ahead demand response program implemented as a source of spinning reserve can considerably reduce the total reserve cost and improve reliability indices [6]. The additional scheduling flexibility introduced by demand-side reserve offers brings significant gains in economic efficiency [7], and can lead to significant gains in social welfare in wholesale electricity market [8]. In recent literature regarding DR scheduling many different approaches were considered. Some of the authors adopted optimization techniques which usually minimize utility's cost to maximize social welfare [9–12]. Other authors adopted the ideas to random access protocols in data communications where the utility deals with customers' load demands which are sent to the utility and compete for the limited power generated over time [13,14]. Local demand response mechanisms can improve grid stability in island systems [15]. It can also be considered as possible business opportunity for the third party companies entering the domestic smart grid market which is affected by the changes due to advances in smart metering [16].

It is important to investigate whether a portion of the reserve requirements could be provided by demand, and to what extent. By providing reserve, consumers could maximize their benefits derived from electricity markets. To achieve this, consumers must determine their economic costs and benefits to decide if and when they should participate in the market. Their ability to provide reserve depends on their flexibility in modifying their

* Corresponding author. Tel.: +386 31 718 897; fax: +386 1 620 76 77.
E-mail address: lakicedo@gmail.com (E. Lakić).

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Nomenclature

Indices

b	index of season
D	demand
G	generation
j, k	index of loads and generating units
SRu	up-spinning reserve
SRd	down-spinning reserve
t	index of time (learning)
z	index of probability scenarios

Functions

$B_D(P_D)$	benefit function that loads derive from participating in the energy market
$c_R(r)$	cost function of employing reserve
$C_G(P_G)$	energy cost function
$C_R(R)$	reserve capacity cost function

Variables

a	action
EB^R	expected benefits that loads derive from participating in the reserve market
ESC	expected security cost participating in the reserve market
LC	involuntary load curtailment
P	scheduled real power
p_z	probability of scenario z
Q	Q-value
r	deployed reserve
R	scheduled reserve
$R^{\max}$	maximum reserve limit
S^{after}	net surplus after participating in the reserve market
S^{before}	net surplus before participating in the reserve market
$Temp$	the temperature in the Metropolis criterion
λ_R	market clearing price of security
σ	learning rate
ξ	random value
Γ	reward

Constants

n	number of states
ND, NG	number of consumers and number of generating units
NZ	number of probability scenarios
NT	number of scheduling hours
$P_{\max}, P_{\min}$	maximum and minimum forecasted consumption
$VOLL$	value of lost load
ζ	coefficient in Q-learning equations
φ	coefficient in the Metropolis criterion

consumption, the market prices of electricity and reserve services, and the frequency with which their reserve provision is called upon.

The demand-side strategies on the electricity market can be investigated using the agent-based modeling (ABM). This approach is able to capture a change in the behavior of different market participants and their adjustments to changes in the environment in which they operate. The application of the ABM combined with different reinforcement learning techniques has been rapidly developing in the area of power systems [17–19]. ABM is appropriate to apply to the systems where various entities i.e. agents, perform different actions but also take into consideration and modify their decisions based on previous experiences. This allows them to improve their performance to reach a certain goal.

The nature of the generation companies (GenCos) on one hand, and of the consumers (i.e. the demand-side) on the other, is appropriate for ABM approach because all players seek to adjust their behavior to market outcomes in order to improve their profits and benefits. However, most of the agent-based models were developed to investigate behavior of GenCos [20–24] although few also included analysis of the demand-side response [25–27].

To model and simulate the behavior of the GenCos Q-learning is typically used. In most cases it is used to evaluate how GenCos can raise their profits in the process of producing the electricity and offering it on the electricity market [21,24,28–31].

While various learning algorithms were applied to in different ABM electricity market simulators, a number of them argued for the application of the Q-learning [21,26,32]. In addition, several modifications of the Q-learning algorithm are being investigated, such as balancing between exploration and exploitation of an individual agent to reach the optimal policies for individual states, using the Metropolis criterion and the SA-Q-learning algorithm [29,30]. Also, almost all of electricity markets modeled diverse types of GenCos and used multi-agent system and learning approach [23]. They typically simulated either cooperative Q-learning [31], or take into consideration that each agent learned from its own individual learning experiences [28]. The results of ABM, together with reinforcement learning can be used for decision support systems in developing different strategies for submitting offers to the electricity market, as described in [33].

However, the majority of such analyses focus on the electricity markets bidding strategies, either on the generation-side or on the demand-side. To the knowledge of the authors of this paper, no attention has been paid to the ABM for the system reserve provision.

In the previous works we have presented new approaches to the stochastic modeling of the demand-side reserve provision in the co-optimised day-ahead electricity and reserve markets, where the consumer has the opportunity to participate as a reserve provider. Furthermore, the papers are focused on proposing a method to define the demand cost function for reserve provision. The method accounts for the costs and benefits that a consumer derives from its participation in the reserve market. The demand reserve offer function is determined by using optimization methods.

In contrast, in the proposed paper we present a novel agent for the demand-side system reserve provision. The intelligent agent is capable of learning how to improve its gain from its past actions. The agent learns how much system reserve to offer at different times, while seeking to increase the ratio between their economic costs and benefits.

The paper is divided in into the following sections: Section 2 describes the learning algorithm for the demand-side system reserve provision in detail, while in Section 3 the stochastic market model is explained. Section 4 presents the case study and the results are shown in Section 5. Finally, the conclusion is given in Section 6.

2. Learning algorithm for the demand-side system reserve provision

The objective of the demand agent is to maximize its reward, which in this case is defined as the difference between the expected benefit that consumer gains with the participation in system reserve provision and the expected security cost that consumers bear. The agent learns how to improve its gain by varying the amount of system reserve offered at different times, while seeking to increase the ratio between their economic costs and benefits. This is modeled using the SA-Q-learning approach, in which an