A Machine Learning Approach for Prosumer Management in Intraday Electricity Markets

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Abstract—Prosumer operators are dealing with extensive challenges to participate in short-term electricity markets while taking uncertainties into account. Challenges such as variation in demand, solar energy, wind power, and electricity prices as well as faster response time in intraday electricity markets. Machine learning approaches could resolve these challenges due to their ability to continuous learning of complex relations and providing a real-time response. Such approaches are applicable to their ability to continuous learning of complex relations and providing a real-time response. Such approaches are applicable with presence of the high performance computing and big data.

To tackle these challenges, a Markov decision process is proposed and solved with a reinforcement learning algorithm with proper observations and actions employing tabular Q-learning. Trained and solved with a reinforcement learning algorithm with proper observations and actions employing tabular Q-learning. Trained and solved with a reinforcement learning algorithm with proper observations and actions employing tabular Q-learning. Trained and solved with a reinforcement learning algorithm with proper observations and actions employing tabular Q-learning. Trained and solved with a reinforcement learning algorithm with proper observations and actions employing tabular Q-learning.

Index Terms—Battery energy storage system, intraday electricity market, machine learning, prosumer, reinforcement learning, solar energy, wind power.

NOMENCLATURE

| Constants | | | |
|---|---|---|---|
| NA | Number of action indices; | | |
| NB | Number of bus indices; | | |
| ND | Number of demand indices; | | |
| NE | Number of ESS indices; | | |
| NF | Number of feeder indices; | | |
| NO | Number of observation indices; | | |
| NS | Number of scenarios; | | |
| NT | Number of time indices; | | |
| NV | Number of PV units; | | |
| NW | Number of WT units; | | |

| Indices | | | |
|---|---|---|---|
| a ∈ A | Action index; | | |
| b ∈ B | Bus index; | | |
| d ∈ D | Demand index; | | |
| e ∈ E | ESS index; | | |

This work was financially supported by the Swedish Energy Agency (Energimyndigheten) under Grant 3233. The required computation is performed by computing resources from the Swedish National Infrastructure for Computing (SNIC) at PDC center for high performance computing at KTH Royal Institute of Technology which was supported by the Swedish Research Council under Grant 2018-05973. (Corresponding author: Saeed Mohammadi.)

Parameters (upper-case letters)

| Parameters | | | |
|---|---|---|---|
| α | Learning rate; | | |
| C_{f}^{(F)} | Price of electricity in feeder f (€/MWh); | | |
| \bar{E}_{e}^{(E)} | Maximum/Minimum stored energy in BSS e (MWh); | | |
| \eta_{e}^{(\pm)} | Charging/Discharging efficiency of BSS e; | | |
| \gamma | Discount factor; | | |
| P_{d}^{(D)} | Active power of demand d (MW); | | |
| \bar{T}_{s}^{(E)} | Maximum charging active power in BSS e (MW); | | |
| \tau_{s} | Probability of scenario s; | | |
| U_{est}^{(E)} | Availability of BSS b; | | |

Variables (lower-case letters)

| Variables | | | |
|---|---|---|---|
| e_{ext} | Stored energy BSS e (MWh); | | |
| p_{ext}^{(\pm)} | Charging/Discharging active power in BSS e (MW); | | |
| f_{est}^{(F)} | Active power of feeder f (MW); | | |
| P_{d}^{(V)} | Active power of solar unit v (MW); | | |
| P_{v}^{(W)} | Active power of wind unit v (MW); | | |
| q_{ao} | Score of action a in observation o; | | |
| r | Reward after taking one action in the proposed algorithm; | | |
| u_{est}^{(\pm)} | Charging/Discharging option binary variables u_{est}^{(\pm)} ∈ \{0, 1\}; | | |
I. INTRODUCTION

INTRADAY electricity markets could be categorized into continuous trading and discrete auctions. As the names imply, continuous trading is first-come-first-serve and bids and offers are matched continuously without applying any auction. This type of trades are used in Elbas market in 10 European countries (the Nordics, Baltics, Germany, Belgium and the Netherlands) as well as Germany [1]. On the other hand, discrete auctions apply the same price to all market participants by employing an auction in each time interval. For instance Germany introduced both discrete auctions and continuous trading. Therefore, it is critical to decrease response time in the continuous intraday markets. On the other hand, finding an optimal solution in deregulated electricity market is challenging due to stochastic nature of this problem. Structure of the modeled prosumer, unit who both produce and consume electricity, is shown in Fig. 1. Prosumers bring different uncertainties such as variation in solar energy and wind power which adds to the existing uncertainties such as deviation in the electricity price and demand.

In recent studies, machine learning approaches are employed in electricity markets mostly to predict the uncertain parameters as in [2], [3], and [4]. Specifically, reinforcement learning (RL) approaches are studied due to their generality as discussed in [2], [5], and [6]. Besides, RL is used for energy management as in [7]. These approaches are applicable and scalable in presence of high performance computing (HPC) and big data. This paper focuses on using machine learning approaches to manage prosumers with battery energy storage systems (BSSs) to trade in the continuous intraday markets with the proceeding uncertainties. Using the publicly available historical data, a responsive approach is developed for continuous bidding in the intraday markets to balance the prosumer’s active power in real-time without defining several scenarios which is a great advantage compared to the well-known stochastic optimization approach. A Markov decision process (MDP) is demonstrated and a RL algorithm (tabular Q-learning) is employed to train a RL-based network (agent) to bid/offer in the continuous intraday markets. Performance of the proposed approach is presented in the Elbas intraday market adopting the historical data for demands, solar energy, wind power, and cost of electricity in 2018-2019 period in Stockholm, Sweden.

A. contributions

The main contributions of this paper are the following: (i) applying tabular Q-learning for prosumer management in the intraday electricity markets, (ii) comparing the trained agent (trained with the historical data) with the optimal solutions from stochastic and deterministic optimization, and (iii) proposing an MDP approach to solve the prosumer management problem with RL. The rest of this paper is organized as follows. Section II formulates the prosumer management problem and explains the proposed MDP algorithm to train the agent. Section III presents operation of a trained agent for a two weeks period and compares the results with the benchmark approaches, i.e. deterministic and stochastic optimization. Section IV concludes the paper.

II. METHODOLOGY

As illustrated in Fig. 1, the prosumer management problem in the intraday continuous market is formulated employing the well-known stochastic optimization in (1) with set of decision variables $X = \{P_{f_{st}}^{(p)}, u_{est}, u_{ext}, u_{wst}, u_{wst}^{-}\}$ as deviation in the electricity price and demand.

In (1a), $C_{f_{st}}^{(p)}$ and $P_{f_{st}}^{(p)}$ are the cost of storage systems (BSSs) to trade in the continuous intraday market and offers are matched continuously without applying any auction. As the names imply, continuous trading is first-come-first-serve and bids and offers are matched continuously without applying any auction. This type of trades are used in Elbas market in 10 European countries (the Nordics, Baltics, Germany, Belgium and the Netherlands) as well as Germany [1]. On the other hand, discrete auctions apply the same price to all market participants by employing an auction in each time interval. For instance Germany introduced both discrete auctions and continuous trading. Therefore, it is critical to decrease response time in the continuous intraday markets. On the other hand, finding an optimal solution in deregulated electricity market is challenging due to stochastic nature of this problem. Structure of the modeled prosumer, unit who both produce and consume electricity, is shown in Fig. 1. Prosumers bring different uncertainties such as variation in solar energy and wind power which adds to the existing uncertainties such as deviation in the electricity price and demand.

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Efficient use of the generated power in the prosumer. These can be minimized in total by charging/discharging the BSS and costs/rewards are employed in training process by minimizing.

Proposed MDP in Algorithm 1 is implemented in Python to train agents with the best approximation of the qao table.

A. Sequential process
The prosumer management problem \( \text{[1]} \) is formulated as a sequential decision making process employing the MDP and the following elements.

1) Observations: Observations \( o \) of the studied prosumer are day \((0-365)\), hour \{(00-01),(01-02),...,(23-00)\}, stored energy \((0-100\%)\), solar energy, wind power, price of electricity, and demand. These observations build the state space which describes the current state of the prosumer and changes based on previous actions.

2) Action space: Action space \( A \) includes buy/sell from/to the intraday market and charge/discharge active power of the prosumer. Which are five actions in total \( A = \{-1,-0.5,0,0.5,1\} \). The actions \( a \) represent discrete values for \( (p_{est}^{(i)} - p_{est}^{(j)})/P_e^{(k)} \). It can be written as \( 0.5u_{est}^{(i)} + u_{est}^{(i)} - 0.5u_{est}^{(j)} - u_{est}^{(j)} \). For instance action \( a = 0.5 \) represents charging with \( p_{est}^{(i)} = 0.5P_e^{(k)} \) and similarly for other actions. One of these five actions \((N_A = 5)\) should be taken by the prosumer based on the current observation \( o \).

3) Cost/reward: Cost/reward is price of the exchanged power \( (C_{(i)}^{(j)}, p_{(j)}^{(k)}) \) with grid in the intraday market which should be minimized in total by charging/discharging the BSS and efficient use of the generated power in the prosumer. These costs/rewards are employed in training process by minimizing total cost at each time step. Stored energy is limited in \((1g)\) and actions that violate this constraint should be avoided. To illustrate this, another action is used to avoid this violation and if all actions cause violating this constraint the total cost is penalized by a relatively large number.

4) Tabular Q-learning: As explained before, the agent should take the best action based on the current observation \( o \). To do so, actions with highest score \( q_{ao} \) value are selected in MDP using a table of \( q_{ao} \) values. Therefore, the agent will take action \( a \) when \( q_{ao} = \max_{a'\in A} q_{a'\omega} \) for observation \( o \). Present MDP requires \( q_{ao} \) values in the current observation for all valid actions which is obtained by executing tabular Q-learning method. Proposed MDP in Algorithm 1 is implemented in Python to train agents with the best approximation of the \( q_{ao} \) table.

Hyper-parameters of Algorithm 1 have to be selected in the training process such as ITR_LIM, REW_EPS, AGT_NUM, \( \alpha \), and \( \gamma \) which are iteration limit, reward epsilon, maximum number of agents, learning rate, and discount factor respectively. In Bellman optimality equation (2), the learning rate \( 0 \leq \alpha \leq 1 \) is employed to define effect of new or historical \( q_{ao} \) values. Higher learning rate increases effect of historical data and vice versa. It is used to avoid instability in rapid changes. In addition, a discount factor \( 0 \leq \gamma \leq 1 \) is applied to escape from infinite loops in training. For instance, when a single action \( r \) is available in observation \( o \) which takes us to the observation \( o' \) and similarly there is a single action \( r' \) in observation \( o' \) which takes us back to observation \( o \) over and over. This is an example of infinite loops, which will not happen using the discount factor, we proposed above.

Algorithm 1: Proposed MDP approach

Data: Historical electricity market data from Nord Pool \([8]\)

Result: Trained agents saved for further use

Initialize \( q_{ao} \) table;

while number of saved agents less than AGT_NUM do

Discover observation \( o \);

while there are more actions available do

Select a random action \( a \) from remaining actions;

Find out corresponding reward \( r \) and next observation \( o' \);

if \( o' \) does not violate constraints then

\[ q_{ao} \leftarrow (1 - \alpha)q_{ao} + \alpha(r + \gamma \max_{a'\in A} q_{a'\omega}) \]  \( (2) \)

else

penalize the reward \( r \);

end

end

Update \( q_{ao} \) with Bellman optimality equation:

while the best reward is more than REW_EPS do

Initialize the best reward;

while iteration is less than ITR_LIM do

Let the trained agent to perform in the trained period;

if total reward is more than best reward then

best reward = total reward;

end

end

end

end

if the best reward is more than saved reward then

save the trained agent;

saved reward = the best reward;

end

end
Subsequently, an agent is trained employing this historical optimization approach. The algorithm hyper-parameters are ITR\_LIM = 20, REW\_EPS = 0.4, AGT\_NUM = 20, \( \alpha = 0.2 \), and \( \gamma = 0.9 \). Stored energy \( e_{ext} \) in percent as state of charge (SOC) of the trained agent for the same two days are shown in Fig. 3 and compared to the benchmarks solutions. Our first benchmark provides deterministic solution. It is optimal solution of (1) with only one scenario (\( NS = 1, \tau_s = 1 \)) where the prosumer knows the exact values for the uncertain parameters shown in Fig. 4. Our second benchmark is stochastic optimization solution. Where 30 scenarios with the same probabilities (\( NS = 30, \tau_s = 1/NS \)) are considered for the uncertain parameters as shown in Fig. 5. The trained agent charges the BSS unit when the price of electricity is relatively lower and sells the extra generation to the intraday electricity market when the price is relatively higher.

Optimal actions \((0.5u_{est}^{(+)}) + u_{est}^{(-)} - 0.5u_{est}^{(-)} - u_{est}^{(-)}\) for the deterministic solution, stochastic solution, and the trained agent are shown in Fig. 6. Also the agent’s reward \( r \) is shown in this figure. Total operation cost \((\sum_{f=1}^{30} r_C(f) p_{f}^{(p)})\) for these cases are \(-544 \, \text{€}, -234 \, \text{€}, \) and \(-265 \, \text{€}\) respectively. Which

III. RESULTS AND DISCUSSION

The proposed Algorithm in Fig. 1 is applied to one prosumer with volatile demands, solar energy, wind power, and electricity prices. The second Modern-Era Retrospective analysis for Research and Applications (MERRA-2) is used for solar irradiation data which are NASA atmospheric analysis publicly available in [9]. The irradiation data are used to calculate output of the solar units for 2019. The remaining data (i.e., demands, wind power, and market price) is from Nord Pool database available in [8] in Sweden for 2019 (2018 for wind power). The uncertain parameters of the prosumer sensitive to date, time, and place. For instance changes in demands are shown in Fig. 2 for four regions SE1-SE4. The problem (1) parameters are \( \eta_{(c)} = \eta_{(s)} = 0.9, E_{(c)} = 0\% \), \( E_{(s)} = 100\% \), and \( \tau_s = 1/NS, P_{(s)} = 10 \) MW. First, optimal solution is obtained by solving (1) with CPLEX 12.8 solver in the GAMS 25.1.3 software which is used as a benchmark in Section III. This problem is solved with different number of scenarios to study effect of the scenario set on operation cost. Total operation cost \((\sum_{f=1}^{30} \tau_s C(f) p_{f}^{(p)})\) is shown in Fig. 3 to visualize convergence rate of the stochastic optimization approach by changing number of scenarios. The costs are less volatile for problems with 30 or more number of scenarios. Therefore, 30 scenarios are sufficient for stochastic optimization approach.

Market data for the first two days of January are shown in Fig. 4. All values are in per unit. All active power values are divided by 1, 000 MW as base and market price is divided by its maximum value (567.15 SEK or 56.71 €).

Subsequently, an agent is trained employing this historical data with the proposed Algorithm 1 in Section II. The algorithm hyper-parameters are ITR\_LIM = 20, REW\_EPS = 0.4, AGT\_NUM = 20, \( \alpha = 0.2 \), and \( \gamma = 0.9 \). Stored energy \( e_{ext} \) in percent as state of charge (SOC) of the trained agent for the same two days are shown in Fig. 3 and compared to the benchmarks solutions. Our first benchmark provides deterministic solution. It is optimal solution of (1) with only one scenario (\( NS = 1, \tau_s = 1 \)) where the prosumer knows the exact values for the uncertain parameters shown in Fig. 4. Our second benchmark is stochastic optimization solution. Where 30 scenarios with the same probabilities (\( NS = 30, \tau_s = 1/NS \)) are considered for the uncertain parameters as shown in Fig. 5. The trained agent charges the BSS unit when the price of electricity is relatively lower and sells the extra generation to the intraday electricity market when the price is relatively higher.

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means that the prosumer is able to make a profit, hence the negative sign of the total operation cost, by selling the generated electricity from the wind and solar units. Profit of the prosumer using the trained agent is between its profit using the deterministic and stochastic solutions ($544 > 265 > 234$). The profit of the prosumer employing the trained agent is higher than the stochastic approach and lower than the deterministic approach. This is because the deterministic approach is the global optimal solution which requires a perfect knowledge about future which is not realistic in ID continuous markets. In the stochastic approach, the prosumer is more cautious and considers different scenarios for the uncertain parameters which is more realistic. But it leads to reducing the prosumer’s profit in the stochastic approach. Advantage of the trained agent is to adapt the prosumer’s actions based on the real-time changes in the market which increases the total profit by 13.39% compared to the stochastic solution. However, there is an opportunity to improve the trained agent as the total profit is still less than the global optimal solution (i.e. deterministic solution).

**IV. Conclusion**

Energy storage systems cannot be managed without considering the uncertainties in the current power system. This paper focused on using machine learning approaches to deal with these uncertainties and finding the best action in intraday electricity markets. A reinforcement learning network (agent) is trained based on historical changes in demands, solar irradiation, wind power, and electricity price in Stockholm, Sweden to solve the modeled Markov decision process efficiently. Preliminary results demonstrate the trained agent convergence to a policy with high scores in validation data. The trained agent managed to find a solution better than the stochastic solution (13.39%) while it is less than the deterministic solution with perfect information about the uncertain parameters in future. In our planned future works, the proposed algorithm will be used to train the agent with larger database, more elements (such as hydropower units), participation in both day-ahead and intraday markets, and different observation will be employed to improve performance of the trained agent.

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