GENETIC ALGORITHM FOR DEMAND RESPONSE: A STACKELBERG GAME APPROACH

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ABSTRACT

Demand response (DR) has gained a significant recent interest due to its potential for mitigating many power system problems. Game theory is a very effective tool to be utilized in DR management. In this paper, the DR between a distribution system operator (DSO) and load aggregators (LAs) is designed as a Stackelberg game, where the DSO acts as the leader and LAs are regarded as the followers. Due to the limitations of the centralized solution approaches, a genetic algorithm-based decentralized approach is proposed. To demonstrate the proposed approach, a case study concerning a day-ahead optimization for a real-time pricing market with a single DSO and three LAs is designed and optimized. The proposed approach is able to shift the demand peaks and prove that it has a great potential to be used for the Stackelberg game between a DSO and multiple LAs to fully exploit the potential of DR.

Keywords: Stackelberg game, demand response, genetic algorithms, smart grid.

1 INTRODUCTION

Demand response (DR) is defined as “changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” (FERC 2016). DR programs can help mitigate many power system problems, including high generation cost, high demand’s peak to average ratio, high emissions, and reliability and congestion issues in generation, transmission and distribution systems by altering electricity consumption patterns of the consumers in a way that is more suitable in terms of system reliability and cost of supply (Jordehi 2019).

DR programs can be classified as incentive-based and price-based programs. In incentive-based programs, the consumers are given incentives for modifying their consumption based on the preferences of the supply side. Direct load control (DLC), load curtailment, demand bidding, and emergency demand reduction programs are examples of incentive-based programs. In price-based programs, the consumers are charged with different rates at different consumption times. Real-time pricing (RTP), time of use (TOU) pricing, critical peak pricing (CPP), and inclining block rate (IBR) are examples of price-based programs (Jordehi 2019). Among these, RTP has a great potential to provide significant benefits to both supply side and consumers because it can better exploit the demand-supply elastics. However, the application of RTP is challenging because it is difficult for consumers to follow the price updates and respond to it. Building automation systems will help utilize DR programs with RTP (Yan et al. 2018).

DR programs can be implemented for industrial, commercial, and residential consumers. Among different types of consumers, the industrial consumers are the most responsive group because electricity is a significant part of their manufacturing expenses and, by nature, they always aim to reduce their expenses to maximize their profits. The commercial consumers might be considered as similar to the industrial consumers, however, in most of the cases they operate within a fixed hours with low flexibility and therefore they cannot modify their energy consumption patterns much (Bode et al. 2013). The residential consumers, on the other hand, are not as responsive as the industrial consumers due to two reasons. First, residential consumers prefer not to participate in the DR programs at the expense of their comfort. Thus, researches that focus on implementing DR programs while maintaining occupant comfort is essential for increasing the participation of residential consumers in DR programs. Second, and most importantly, the magnitude of the demand modification that a single residential consumer can provide is very limited as compared to an industrial consumer. Thus, traditionally, the DR programs did not focus adequately on residential consumers (Elghitani and Zhuang 2018). However, this can be changed with the advancement of the modern smart grid systems. In this regard, integration of load aggregators (LAs) to the energy market is essential for the success of the DR programs in the residential sector. A LA (also known as DR provider) is a commercial entity that specializes in electricity demand side participation. In practice, an aggregator contracts with the individual demand sites (e.g., industrial, commercial, and residential consumers) and combine them together to operate as an individual DR participant against a distribution system operator (DSO) (Wang et al. 2019).

In any DR program, a particular attention should be given to implementation, infrastructure, and funding (Alasseri, Rao, and Sreekanth 2020). In order to fully exploit the potential of the DR programs for all the parties, DR programs must be implemented in an optimal way (Jordehi 2019). Game theory is an effective approach to deal with such optimization (Ye and Hu 2017). Game theoretical approaches, such as Stackelberg game, have been successfully implemented in many DR-related optimization studies (e.g., Yu and Hong 2016; Chen et al. 2019). However, the majority of these studies utilized a centralized approach, such as the backward induction (BI) method, to perform the optimizations. In centralized approaches, a central unit collects all the necessary information and makes a decision accordingly. For this reason, centralized approaches are computationally expensive and may arise privacy concerns among the participants. In response to this, decentralized approaches have gained popularity in recent years. In decentralized approaches, aggregators are responsible for making their own decisions based on the information provided by the DSO.

In this paper, the DR between a DSO and LAs is designed as a Stackelberg game where the DSO acts as the leader and LAs are regarded as the followers. In the proposed game, there is an electricity market in which there is a single DSO and multiple LAs. The DSO is the price maker, while LAs are the price takers. The DSO adjusts the prices based on the total load, while LAs adjust their consumption based on the market price. The game was optimized in a decentralized way using genetic algorithms (GAs). The expected contributions of this paper are threefold. First, the proposed approach is compatible to the RTP market and therefore will help utilize DR programs with RTP. Second, the proposed approach is targeting residential consumers through the use of LAs. Third, the proposed approach is decentralized and can help overcome the limitations associated with the centralized approaches.

The remainder of this paper is structured as follows. Section II presents a literature review focusing on game theoretical approaches for DR programs. Section III introduces the proposed game including the upper and lower levels and their optimization problems, the methodology to solve the game between a DSO and LAs, and the design of a case study targeting to demonstrate the effectiveness of the proposed method. Section IV provides the optimization results for the case study. Finally, Section V provides the summary and conclusion.

2 RELATED WORKS

Game theory is a very effective modeling and analysis tool to be utilized in DR management (Vardakas, Zorba, and Verikoukis 2015). In recent years, there has been a significant research interest in applying the Stackelberg game in power markets (Lu et al. 2019; Esther and Kumar 2016). For example, Nguyen, Song, and Han (2012) presented a game-theoretic framework to model independent decision-making of consumers' energy consumption. The presented framework included a new pricing model and offered a decentralized algorithm which aims to achieve the Nash equilibrium of a Non-cooperative Energy Consumption and Storage (NECS) game, where each user aims to minimize its individual energy cost. The results showed that the proposed framework can minimize both the Peak-to-Average Ratio (PAR) and the total energy cost.

Saghezchi et al. (2014) presented a smart grid scenario with a day-ahead pricing strategy and proposed a binary-linear-programming-based solution, which reduced the energy cost of users by 25%. Stephens, Smith, and Mahanti (2015) proposed a game theoretic model predictive control (MPC) approach for demand-side management (DSM). Unlike the traditional approaches that focus on day-ahead optimization, their approach aim to adapt to real-time data. The results showed that the proposed approach reduced both the PAR and the electricity cost of all consumers in a neighborhood area network.

Nekouei, Alpcan, and Chattopadhyay (2015) proposed game-theoretic frameworks for DR at both the electricity market and consumer levels. In the electricity market, the interaction between a LA and electricity generators is modeled as a Stackelberg game where the LA is the leader and makes demand reduction bids, while the electricity generators are the followers and compete for maximizing their profits through reducing the demand. At the consumer level, the interaction between the LA and consumers is modeled as a mechanism design problem in which the LA aims to minimize the aggregate inconvenience of consumers while achieving the targeted demand management. The proposed frameworks were tested and validated using a case study in the South Australian electricity market where the penetration of renewables is significant.

Yaagoubi and Mouftah (2015) proposed a new DR approach that focuses on managing residential loads while maintaining user preferences. The proposed approach utilizes a simple comfort model that considers waiting time, type of appliance, as well as a weight factor to prioritize comfort over savings. Numerical experiments showed that the proposed approach achieved very high cost savings and maintained user comfort.

Fadlullah et al. (2014) proposed a two-stage game in a smart grid setting, in which the objective is to reduce the system PAR by optimizing consumers' energy schedules. The optimization was conducted using a novel energy price model that includes a two-step centralized game interacting between the power company and its consumers. The game was evaluated using computer-based simulations and achieved a significant amount of PAR reduction.

Soliman and Leon-Garcia (2014) studied a case when consumers were equipped with energy storage devices and introduced two games: A non-cooperative game across the consumers and a Stackelberg game between the utility provider and the consumers. Simulation results showed that energy storage devices helped reduce the total cost and PAR.

Chen et al. (2014) formulated an aggregative game in which the consumers were selfish and competed to minimize their individual energy cost. Based on the formulated game, three distributed algorithms were developed to enable the selfish consumers to optimize their own energy payments through scheduling their future energy consumption. The results showed that the developed algorithms can quickly converge to the Nash equilibrium of the formulated game and efficiently convince the consumers to shift their on-peak consumption.

3 METHODOLOGY

In an electricity market, electricity retailers purchase electricity from the generation companies and distribute it among the consumers. The role of the LAs in the market is responding to demand variations and reducing peak electricity prices (Nekouei, Alpcan, and Chattopadhyay 2015). This paper proposes an approach to study the interaction between a DSO and multiple LAs in a RTP market. As such, the DSO determines hourly electricity prices, while LAs modify their consumption based on the given price. Then, the DSO determines a new price based on the aggregators' load. This negotiation process continues until a convergence criteria is met. Figure 1 shows the interaction between the DSO and LAs.

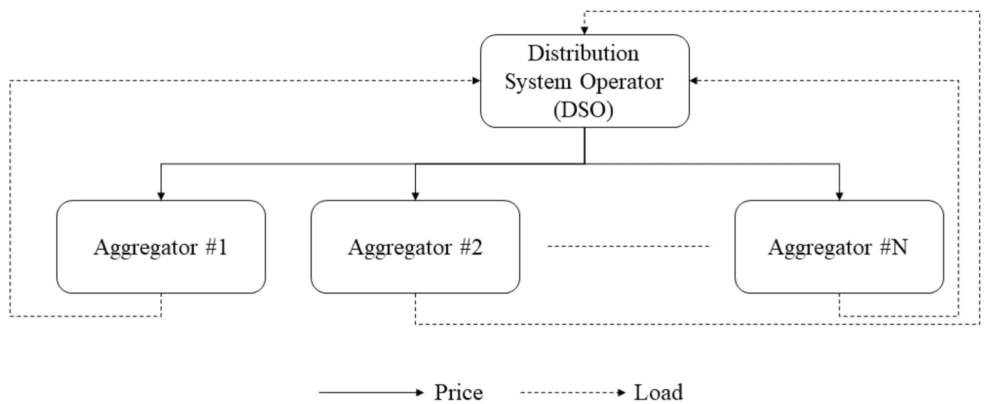

Figure 1: Interaction between the DSO and LAs.

3.1 Stackelberg Game

The interaction between the DSO and LAs is designed as a Stackelberg game, where the DSO acts as the leader and LAs are regarded as the followers. A Stackelberg game formally studies the multilevel decision making processes of a number of decision makers (followers) in response to the decision taken by the leading player (leader) of the game (Rui et al. 2019).

The game between the DSO and LAs can be formally defined by its strategic form as:

$$\Gamma = \{(N \cup \{DSO\}), \{E_n\}_{n \in N}, \{P_t\}, \{U_n\}_{n \in N}, U_{DSO}\}, \tag{1}$$

which consists of the following components.

1. The LAs in set *N* act as followers and choose their strategies in response to the price set by the DSO, which is the leader of the game.
2. E_n is the set of the strategies of each LA in set *N*.
3. P_t is the set of strategies set by the DSO, which is a vector of the price p_t.
4. U_n is the objective function of LA *n* (lower level), as in (5) and (6)
5. U_{DSO} is the objective function of the DSO (upper level), as in (2) – (4).

$$\max U_{DS0} = \sum\nolimits_{n,t} p_t \times l_{n,t} - \sum\nolimits_{n,t} C_t \times l_{n,t} + \omega \times \sum\nolimits_{n,t} \bar{L}_{n,t} \times \bar{P} \times S(l_{n,t}, D_{n,t}) - \sum\nolimits_{n,t} \theta \times \bar{P} \times \max(l_{n,t}). \tag{2}$$

$$s.t. C_t \leq p_t \leq \bar{P}, \forall t. \tag{3}$$

$$S(l_{n,t}, D_{n,t}) = 1 - e^{\frac{-4l_{n,t}}{D_{n,t}}}, \tag{4}$$

where p_t is the electricity price at time t, $l_{n,t}$ is the load consumption of LA n at time t, C_t is the unit cost of the electricity generation at time t, $\bar{L}_{n,t}$ is the maximum power that LA n can consume at time t , ω and θ are weighting coefficients to prioritize or deprioritize different objectives, $\bar{P}$ is the maximum electricity price that the DSO can set, $D_{n,t}$ is the nominal demand of LA n at time t, and $S(l_{n,t}, D_{n,t})$ is a function to represent consumer satisfaction for a given $l_{n,t}$. The relationship between $l_{n,t}$ and $D_{n,t}$ is illustrated in Figure 2. When the consumed power to nominal power ratio is one or greater than one, the consumers get the highest satisfaction. For ratios lower than one, the satisfaction of the consumers decreases exponentially. The function $S(l_{n,t}, D_{n,t})$ is defined in (4).

Equation (2) consists of four terms. The first term is the total revenue generated by the DSO from the sale of electricity. The second term is the cost of electricity to the DSO. The third term is the overall satisfaction of all LAs. Finally the fourth term is a penalty, which aims to eliminate demand peaks. Equation (3) makes sure that the electricity price at time t is always greater than its unit cost and less than the maximum price that the DSO can set.

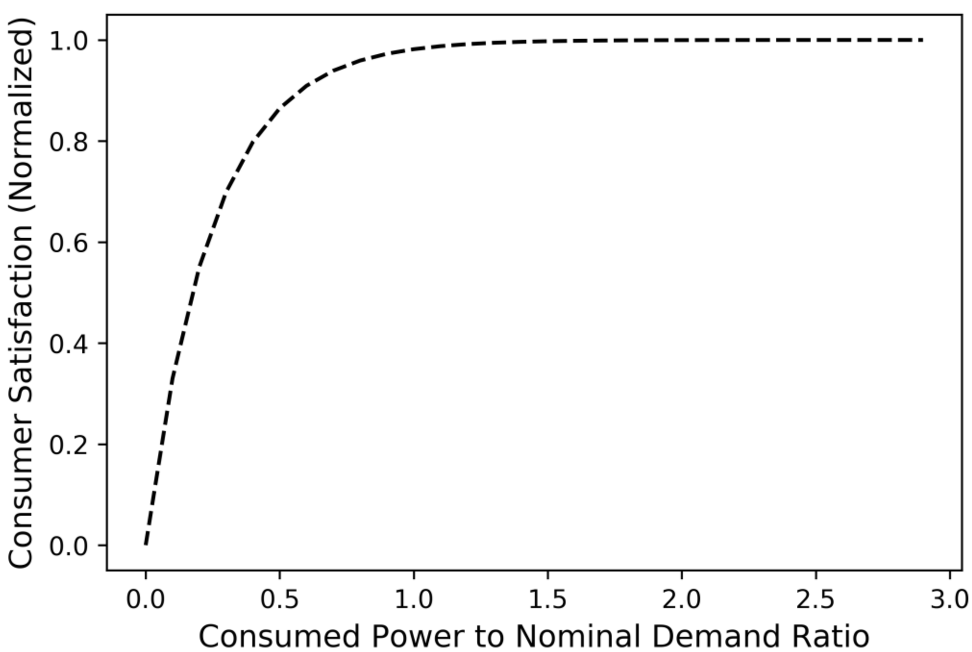

Figure 2: Satisfaction of an aggregated supplier.

$$\max U_n = \sum\nolimits_{t} \bar{L}_{n,t} \times \bar{P} \times S(l_{n,t}, D_{n,t}) - \sum\nolimits_{t} p_t \times l_{n,t}. \tag{5}$$

$$s.t. \underline{L}_{n,t} \leq l_{n,t} \leq \bar{L}_{n,t}, \forall n, \tag{6}$$

where $\underline{L}_{n,t}$ and $\overline{L}_{n,t}$ are the minimum and maximum powers that LA *n* can consume at time *t.*

3.2 Solution Approach

The proposed approach utilizes a GA-based decentralized solution for determining the optimal price and load values. The GA is an adaptive heuristic search algorithm inspired by the evolutionary idea of natural selection and genetics (Fernandez et. al. 2018). A simple GA works as follows:

1. Start with a random initial population.
2. Calculate the fitness function for each individual in the population. Stop if the stop criteria is satisfied.
3. Select the members with the best fitness function values (elites) from the current population.
4. Select random members from the current population for crossover operation.
5. Select random members from the current population for mutation operation.
6. Perform crossover and mutation operations to form children.
7. Replace the current population with the elites and crossover and mutation children and go back to Step 2.

The GA can be applied in many ways to any problem. In this paper, the GA was utilized to solve the upper level optimization in (2). The lower level optimization in (5), on the other hand, has an increasing concave function, and therefore can easily be optimized by obtaining the first-order derivative of (5), as described in (7). The load $l^*_{n,t}$ that makes the derivative equal to zero is the optimal load for LA *n.*

$$l^*_{n,t} = \frac{\partial U_n}{\partial l_{n,t}} = \frac{D_{n,t}}{4} \times \ln\left(\frac{4 \times \bar{P} \times \bar{L}_{n,t}}{p_t \times D_{n,t}}\right). \tag{7}$$

The overall optimization process consists of the following steps:

1. The DSO initializes a price vector p_t that satisfies (3).
2. LA *n* calculates its $l^*_{n,t}$ using (7) for the given price vector.
3. LAs send their $l^*_{n,t}$ to the DSO, and the DSO determines a new price vector that maximizes (2) using the GA method.
4. Compare the new and previous price signals and terminate the process if the similarity criteria is satisfied; otherwise go back to Step 2.

Unlike the centralized optimization approaches, the proposed optimization approach does not have a central decision unit that collects all the necessary information. Instead, in this approach, the DSO and LAs make their own decisions in a decentralized manner, as described above in Step 2 and Step 3. Because the information exchange is less, this approach is more computationally efficient and more respectful to privacy.

3.3 Case Study

To demonstrate the effectiveness of the proposed method, a case study was designed and optimized. The case study considers a day-ahead optimization for an RTP market with three LAs. Figure 3 shows the nominal demands for the three LAs along with the maximum and minimum powers that they can consume. Figure 4 shows the unit cost of electricity to the DSO. In this case study, the ω and θ coefficients are taken as 30 and 10, respectively. The maximum price $\overline{P}$ that the DSO can set is 30¢/kWh. For the GA-based optimization, a population size of 10 individuals, crossover probability of 70%, mutation probability of 20%, and termination criteria of 1,000 generations are selected as the parameters of the algorithm.

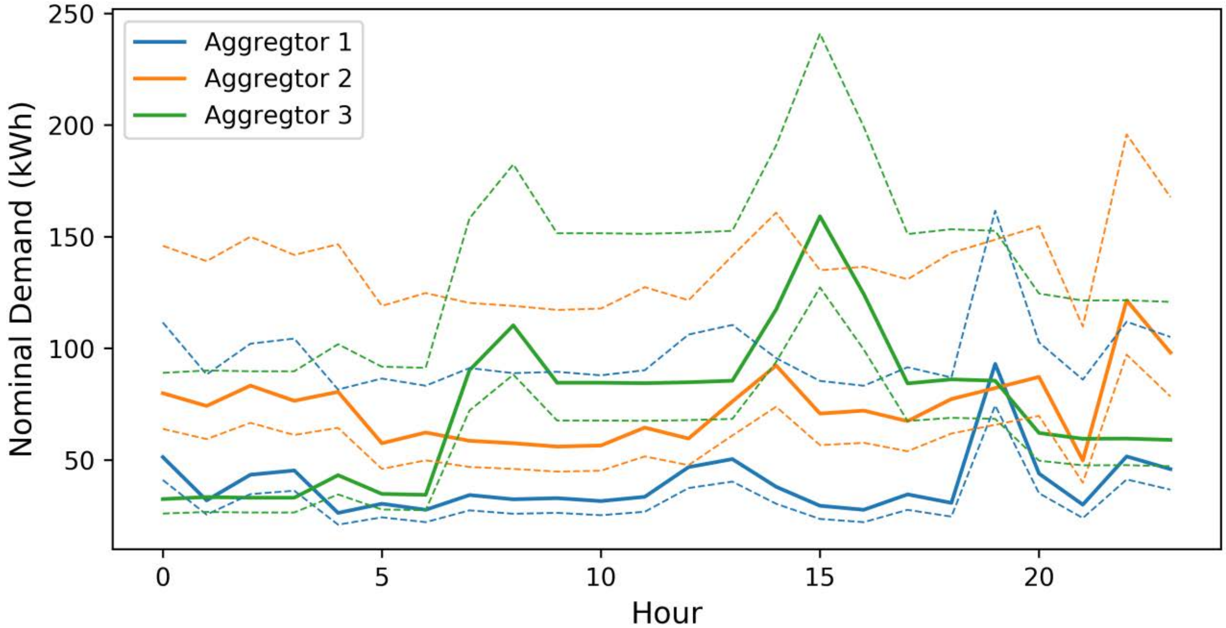

Figure 3: Nominal demands and maximum and minimum power consumption limits for the three LAs. (The solid lines represent the nominal demands; the dashed lines represent the maximum and minimum limits).

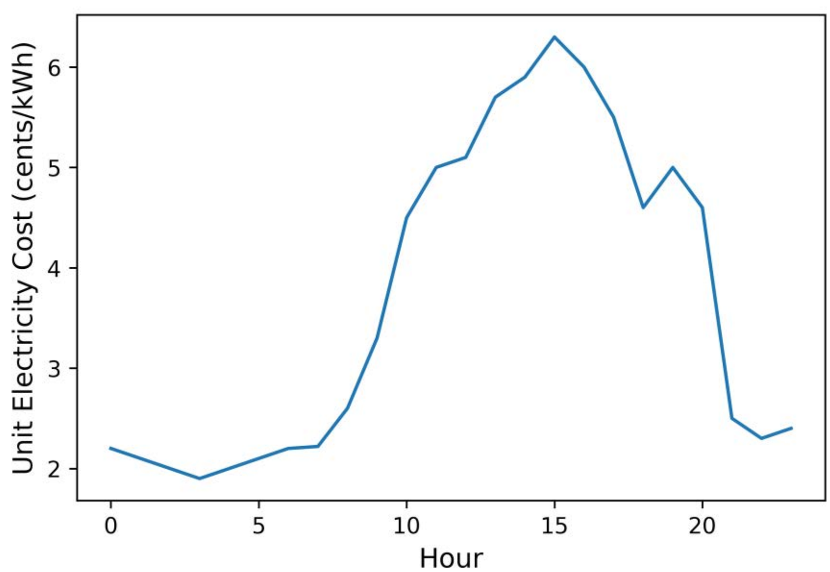

Figure 4: Unit cost of electricity to the DSO.

4 RESULTS

The optimization, as described in Section 3, was conducted on a personal computer with a 3.7 GHz Intel Xeon CPU and 16 GB memory and took only 9 seconds. Figure 5 shows the convergence of the objective functions of the DSO (U_{DSO}) and LAs (U_n). Both the DSO and LAs achieved 99% of the final optimal values at the 50th iteration. However, the optimization was not terminated to guarantee no further improvement is available. Overall, the values of U_1, U_2, and U_3 increased by 8%, 13% and 10%, respectively.

Figure 6 shows the optimal solution, including the individual loads of the LAs, total load, and the resulting price signal. The resulted solution has successfully shifted the two peaks around 15:00 and 19:00 using higher prices at those times. For example, the peak load was reduced from 260kW to 208kW at 19:00 by increasing the price to 30¢, the maximum electricity price that the DSO can set . Also, the resulted solution did not deviate much from the nominal demand of the LAs. This indicates that both the DSO and the LAs will benefit from this solution without sacrificing the comfort of the consumers. Overall, the results showed that the proposed method can be used for the Stackelberg game between a DSO and multiple LAs to fully exploit the potential of DR.

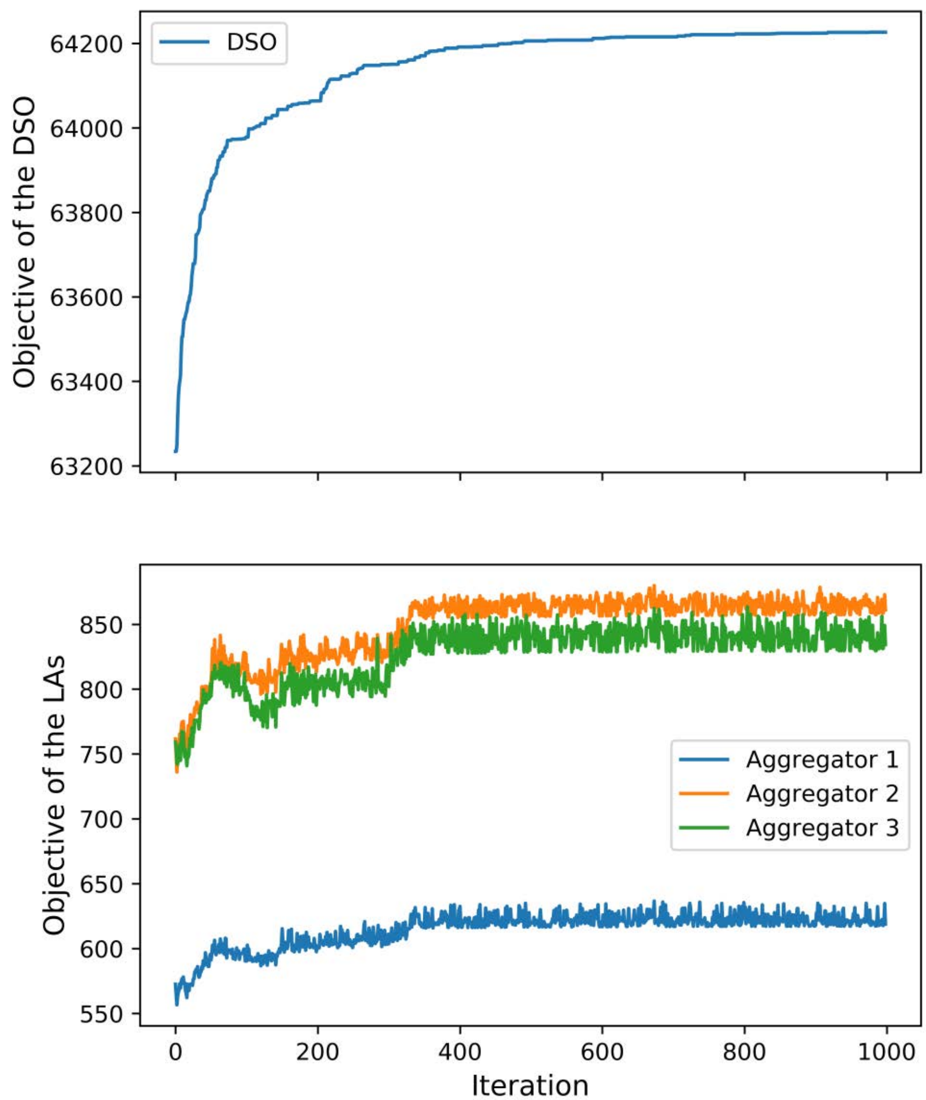

Figure 5: Convergence of the proposed GA-based optimization.

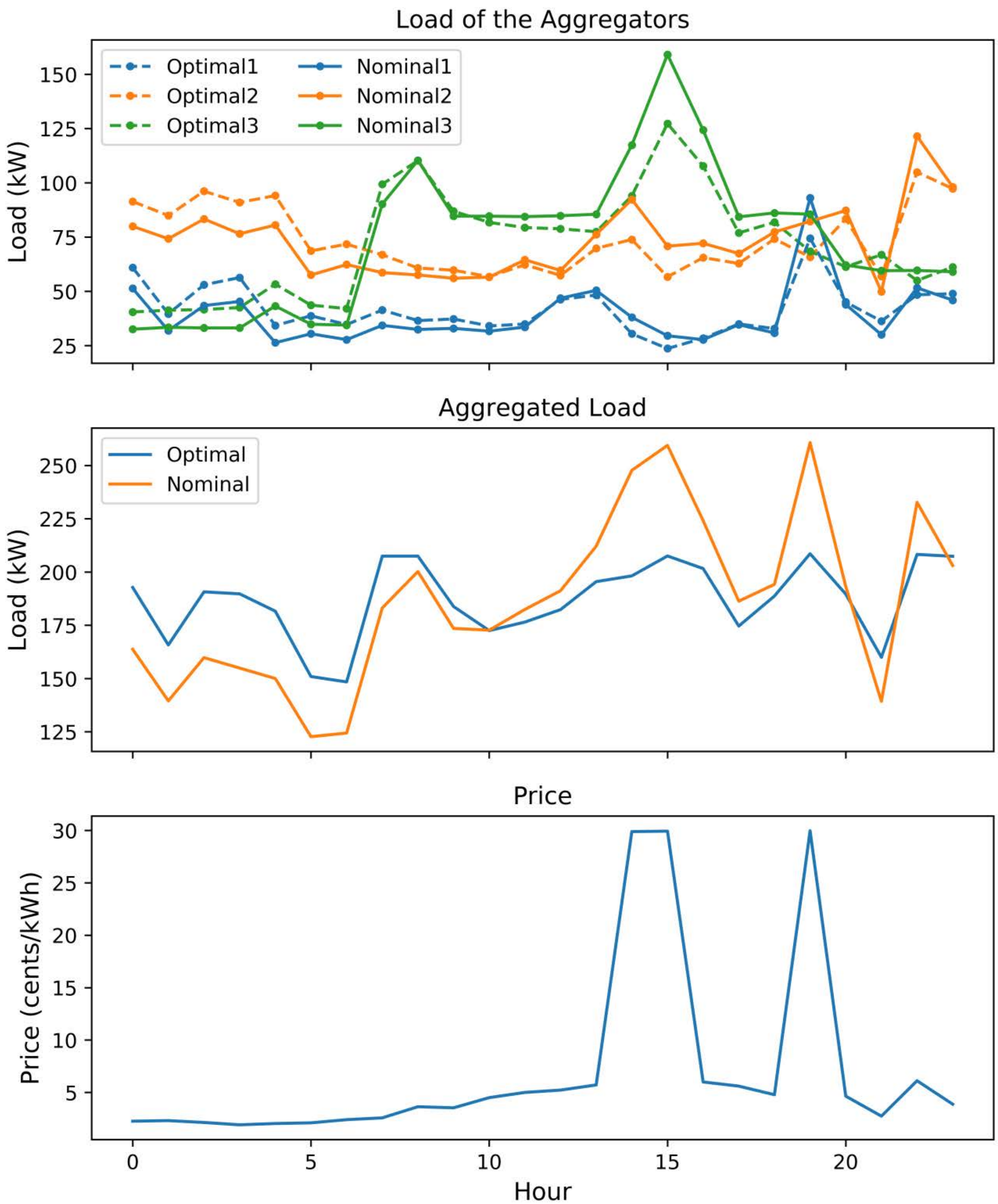

Figure 6: The solutions resulted from the optimization.

5 CONCLUSION

This paper proposed a new approach for the Stackelberg game between a DSO and multiple LAs, where the DSO acts as the leader and LAs act as the followers. The game was optimized in a decentralized way using GAs. In the proposed approach, the upper level (DSO) is optimized using GAs and the lower level is optimized using first-order derivative. To demonstrate the proposed approach, a case study concerning a day-ahead optimization for an RTP market with a single DSO and three LAs were designed and optimized.

The results of the case study showed that the proposed approach can help shift the demand peaks using higher prices at those times without sacrificing the comfort of the consumers. Overall, the results showed that the proposed approach has a great potential to be used for a Stackelberg game between a DSO and multiple LAs to fully exploit the potential of DR.

In this paper the authors aimed at the game between the DSO and the LAs. In their future work, the authors plan to extend this work to include the interaction between LAs and the individual consumers to ensure that the comfort of the consumers will not be compromised due to the modifications in the consumption of the LAs resulted from the optimization proposed in this paper.

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REFERENCES

Alasseri, R., T. J. Rao, and K. J. Sreekanth. 2020. "Institution of Incentive-Based Demand Response Programs and Prospective Policy Assessments for a Subsidized Electricity Market." *Renewable and Sustainable Energy Reviews* 117 (January): 109490. https://doi.org/10.1016/j.rser.2019.109490.

Bode, J. L., C. A. Churchwell, S. S. George, and F. Sullivan. 2013. "2012 California Statewide Non-Residential Critical Peak Pricing Evaluation." San Francisco, CA. http://www.calmac.org/publications/2012_non-res_cpp_statewide_evaluation_-_final.pdf.

Chen, H., Y. Li, R. H. Y. Louie, and B. Vucetic. 2014. "Autonomous Demand Side Management Based on Energy Consumption Scheduling and Instantaneous Load Billing: An Aggregative Game Approach." *IEEE Transactions on Smart Grid* 5 (4): 1744–54. https://doi.org/10.1109/TSG.2014.2311122.

Chen, Y., M. Olama, T. Rajpurohit, J. Dong, and Y. Xue. 2019. "Game-Theoretic Approach for Electricity Pricing between Distribution System Operator and Load Aggregators." In *2019 3rd International Conference on Smart Grid and Smart Cities (ICSGSC)*, 176–81. IEEE. https://doi.org/10.1109/ICSGSC.2019.00005.

Elghitani, F., and W. Zhuang. 2018. "Aggregating a Large Number of Residential Appliances for Demand Response Applications." *IEEE Transactions on Smart Grid* 9 (5): 5092–5100. https://doi.org/10.1109/TSG.2017.2679702.

Esther, B. P., and K. S. Kumar. 2016. "A Survey on Residential Demand Side Management Architecture, Approaches, Optimization Models and Methods." *Renewable and Sustainable Energy Reviews* 59 (June): 342–51. https://doi.org/10.1016/j.rser.2015.12.282.

Fadlullah, Z. M., D. M. Quan, N. Kato, and I. Stojmenovic. 2014. "GTES: An Optimized Game-Theoretic Demand-Side Management Scheme for Smart Grid." *IEEE Systems Journal* 8 (2): 588–97. https://doi.org/10.1109/JSYST.2013.2260934.

Federal Energy Regulatory Commission. 2016. "National Assessment & Action Plan on Demand Response." 2016. https://www.ferc.gov/industries/electric/indus-act/demand-response/dr-potential.asp.

Fernandez, R. A., S. C. Caraballo, F. B. Cilleruelo, and J. A. Lozano. 2018. "Fuel Optimization Strategy for Hydrogen Fuel Cell Range Extender Vehicles Applying Genetic Algorithms." *Renewable and Sustainable Energy Reviews* 81 (January): 655–68. https://doi.org/10.1016/j.rser.2017.08.047.

Jordehi, A. R. 2019. "Optimisation of Demand Response in Electric Power Systems, a Review." *Renewable and Sustainable Energy Reviews* 103 (April): 308–19. https://doi.org/10.1016/j.rser.2018.12.054.

Lu, T., Z. Wang, J. Wang, Q. Ai, and C. Wang. 2019. "A Data-Driven Stackelberg Market Strategy for Demand Response-Enabled Distribution Systems." *IEEE Transactions on Smart Grid* 10 (3): 2345–57. https://doi.org/10.1109/TSG.2018.2795007.

Nekouei, E., T. Alpcan, and D. Chattopadhyay. 2014. "A Game-Theoretic Analysis of Demand Response in Electricity Markets." In *2014 IEEE PES General Meeting | Conference & Exposition*, 1–5. IEEE. https://doi.org/10.1109/PESGM.2014.6939412.

Nguyen, H. K., J. B. Song, and Z. Han. 2012. "Demand Side Management to Reduce Peak-to-Average Ratio Using Game Theory in Smart Grid." In *2012 Proceedings IEEE INFOCOM Workshops*, 91–96. IEEE. https://doi.org/10.1109/INFCOMW.2012.6193526.

Rui, T., C. Hu, G. Li, J. Tao, and W. Shen. 2019. "A Distributed Charging Strategy Based on Day Ahead Price Model for PV-Powered Electric Vehicle Charging Station." *Applied Soft Computing* 76 (March): 638–48. https://doi.org/10.1016/j.asoc.2018.09.041.

Saghezchi, F. B., F. B. Saghezchi, A. Nascimento, and J. Rodriguez. 2014. "Game Theory and Pricing Strategies for Demand-Side Management in the Smart Grid." In *2014 9th International Symposium on Communication Systems, Networks & Digital Sign (CSNDSP)*, 883–87. IEEE. https://doi.org/10.1109/CSNDSP.2014.6923953.

Soliman, H. M., and A. Leon-Garcia. 2014. "Game-Theoretic Demand-Side Management With Storage Devices for the Future Smart Grid." *IEEE Transactions on Smart Grid* 5 (3): 1475–85. https://doi.org/10.1109/TSG.2014.2302245.

Stephens, E. R., D. B. Smith, and A. Mahanti. 2015. "Game Theoretic Model Predictive Control for Distributed Energy Demand-Side Management." *IEEE Transactions on Smart Grid* 6 (3): 1394–1402. https://doi.org/10.1109/TSG.2014.2377292.

Vardakas, J. S., N. Zorba, and C. V. Verikoukis. 2015. "A Survey on Demand Response Programs in Smart Grids: Pricing Methods and Optimization Algorithms." *IEEE Communications Surveys & Tutorials* 17 (1): 152–78. https://doi.org/10.1109/COMST.2014.2341586.

Wang, X., Y. Wang, J. Wang, and D. Shi. 2019. "Residential Customer Baseline Load Estimation Using Stacked Autoencoder with Pseudo-Load Selection." *IEEE Journal on Selected Areas in Communications*, 1–1. https://doi.org/10.1109/JSAC.2019.2951932.

Yaagoubi, N., and H. T. Mouftah. 2015. "User-Aware Game Theoretic Approach for Demand Management." *IEEE Transactions on Smart Grid* 6 (2): 716–25. https://doi.org/10.1109/TSG.2014.2363098.

Yan, X., Y. Ozturk, Z. Hu, and Y. Song. 2018. "A Review on Price-Driven Residential Demand Response." *Renewable and Sustainable Energy Reviews* 96 (November): 411–19. https://doi.org/10.1016/j.rser.2018.08.003.

Ye, M., and G. Hu. 2017. "Game Design and Analysis for Price-Based Demand Response: An Aggregate Game Approach." *IEEE Transactions on Cybernetics* 47 (3): 720–30. https://doi.org/10.1109/TCYB.2016.2524452.

Yu, M., and S. H. Hong. 2016. "Supply–Demand Balancing for Power Management in Smart Grid: A Stackelberg Game Approach." *Applied Energy* 164 (February): 702–10. https://doi.org/10.1016/j.apenergy.2015.12.039.

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