Integration of Parking Lot Capacity in Retail Energy and Reserve Market Mechanism

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***Abstract*— The fast-paced proliferation of Distributed Energy Resources (DERs), including the aggregated capacity of electric vehicles and renewable generation sources on the day-ahead market clearance mechanism, has deteriorated the complexity of grid operation, especially at the distribution level. This study delves into a novel framework to perceive the insight into the interactions between the Distribution System Operator (DSO) and the Parking Lots (PLs), aiming to determine the power flow effectively and to estimate the charging and discharging profiles. Hence, a bi-level optimization model associated with the operational condition of DSO and parking lots aiming to minimize the costs subject to the prevailing technical and economic constraints is proposed. The suggested bi-level model seeks the equilibrium point regarding the mathematical constraints and optimality conditions by employing the Salp meta-heuristic algorithm. The results imply that the correlation between parking lots and DSO goals is the decisive factor in optimal scheduling and equilibrium point.**

Keywords*— *Parking Lots, Vehicle-to-Grid (V2G), Distribution System Operators, Salp Optimization Algorithm, Reserve Market, Distribution Network.

I. INTRODUCTION

Electric Vehicles (EVs) will be widely employed in future transportation systems due to their environmental benefits and great efficiency. EVs may operate in Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) modes. Parking lots (PLs) are an infrastructure that serves charging and power exchange services for plenty of EVs. Owing to the participation of parking lots as a new type of energy provider in the energy and reserve markets, it is crucial to look at their interactions with other market players [1,2].

For instance, in a study [3], the deployment of a bi-directional communication infrastructure for direct and real-time management and monitoring of a fleet of electric vehicles with the purpose of charging process control through a parking lot aggregator is evaluated. A load density framework is developed to determine the appropriate capacity of EV charging stations where EVs can act like both the load and the source [4,5]. An optimal charging paradigm to lower client charging costs is also proposed in [6]. Moreover, in recent years, various research studies associated with the ancillary service provision of EV aggregator capabilities have been conducted [7-9]. The controlling unit of the Distribution System Operator (DSO) should monitor and manage the charging stations of the EV fleet by deploying charging/discharging signals to estimate reserve. Such a method is suggested to redress the volatilities owing to the uncertain and intermittent generation by renewable resources [10]. In the mentioned study, both EV aggregators and DSO try to optimize the energy and reserve scheduling challenges regarding distribution network limitations. A multi-objective and multi-agent technique is suggested for optimal parking lot placement and size allocation in distribution systems [11].

In this study, a novel bi-level model for controlling the interactions between parking lots and DSO is proposed so that the PLs can act as a demand-side Distributed Energy Resource (DER) and participate in energy and reserve markets. The master problem in the upper level of the proposed bi-level model is to minimize the operation cost from the DSO perspective, subject to the prevailing restrictions of the distribution network. The sub-problem in the lower level, on the other hand, reflects the scheduling of energy and reserve from the parking lot perspective with the goal of reduction in the parking lot while satisfying operational constraints of parking lots [12,13].

The rest of the paper is organized as follows. In the next section, the mathematical modeling is presented. The relationships and associated explanation of the optimization tool are presented in Section 3. The simulation results and discussion about the obtained results are given in section 4. Finally, the conclusions are summarized in section 5.

II. MATHEMATICAL MODELLING

DSO aims to reduce operating costs, while the behavior of parking lots will have an unignorable impact on the decisions made by DSO in scheduling, and it changes the power exchange with the upstream grids and markets. On the other hand, the reduction of the charging cost of EVs is desired by the parking lot operator. When a parking lot operator has a precise estimation of EV energy integration for certain time intervals, it can sell this capacity to the local or upstream markets or retail markets through proper aggregators. This power can be offered in the market for the day-ahead energy market or reserve market or even can be negotiated directly and bi-laterally with uncertain renewable sources to mitigate possible imbalances. However, the decision made by the PLs must be made until a certain time. Hence, aggregators usually act differently concerning the level of risk-averseness and profitability. It is highly dependent on the market structure, the distribution network flexibility, penalty or supporting policies in case of unpledged commitment, the level of uncertainty in the operation model, and the size of V2G interaction compared to the scale of demand [14].

A bi-level model is designed to find the optimum point in the solution space of the operation problem, in which the conflict between DSO and PL goals creates a challenge for decision-making. Finally, the power exchange level for each feeder at different intervals can be specified subject to the condition of the distribution network, and the amount of power consumption or provision by aggregated PL capacities as well as the amount of reserve capability of PLs should be reported to the upstream layers for grid secure operation adjustments. The following equations express the proposed bi-level model [15]. The objective function of DSO consists of the cost of purchasing energy from the main grid and parking lots deducted from the profit of responsive demand, as well as the profit based on the declaration of up/down spinning reserve of participants in the ancillary service market, reserve market incomes, and considering the cost of wind curtailment and load shedding, respectively, as it is given in Eq. (1). In addition, Eq. (2) gives the maximum energy trade limitation with the upstream grid. The hourly power balance for each scenario is also presented in Eq. (3).

$$OF = \sum_{t=1}^{N_T} \left\{ \sum_{\omega=1}^{N_W} \pi_\omega \begin{bmatrix} P_{t,\omega}^{G} \times C_t^{E} + P_{t,\omega}^{PL} \times C_t^{PL} - P_{t,\omega}^{D} \times C_t^{D} \\ + \left(R_{t,\omega}^{Up,PL} + R_{t,\omega}^{Dn,PL} \right) \times C_t^{\mathrm{Re}} \\ + \left(R_{t,\omega}^{Up,PL} - R_{t,\omega}^{Dn,PL} \right) \times \rho_t^{Del} \times C_t^{PL} \\ - \left(R_{t,\omega}^{Up,PL} + R_{t,\omega}^{Dn,PL} \right) \times \rho_t^{Del} \times FOR^{PL} \times C_t^{PL} \\ + WS_{t,\omega} \times C_t^{Curtailment} + L_{t,\omega}^{Shed} \times VOLL \end{bmatrix} \times \Delta t \right\} \tag{1}$$

subject to

$$P_{t,\omega}^{G} \le \overline{P}_t^{G} \; ; \forall t, \forall \omega \tag{2}$$

$$P_{t,\omega}^{G} + P_{t,\omega}^{Wind} - WS_{t,\omega} + P_{t,\omega}^{PL} + R_{t,\omega}^{Up,PL} - R_{t,\omega}^{Dn,PL} - P_{t,\omega}^{D} + L_{t,\omega}^{Shed} = 0 \; ; \; \forall t, \forall \omega \tag{3}$$

$$\min \left\{ \sum_{t=1}^{N_T} \left\{ \sum_{\omega=1}^{N_W} \pi_\omega \begin{bmatrix} P_{t,\omega}^{Ch,PL} \times C_t^{PL} - P_{t,\omega}^{Dch,PL} \times C_t^{PL} \\ - \left(R_{t,\omega}^{Up,PL} + R_{t,\omega}^{Dn,PL} \right) \times C_t^{\mathrm{Re}} \\ + \left(R_{t,\omega}^{Dn,PL} - R_{t,\omega}^{Up,PL} \right) \times \rho_t^{Del} \times C_t^{PL} \\ + \left(R_{t,\omega}^{Up,PL} + R_{t,\omega}^{Dn,PL} \right) \times \rho_t^{Del} \times FOR^{PL} \times C_t^{PL} \end{bmatrix} \times \Delta t \right\} \right\} \tag{4}$$

$$0 \le P_{t,\omega}^{Ch,PL} + R_{t,\omega}^{Dn,PL} \le \overline{P}^{Ch,PL} \; ; \underline{\mu}_{t,\omega}^{Ch,PL}, \overline{\mu}_{t,\omega}^{Ch,PL}, \forall t, \forall \omega \tag{5}$$

$$0 \le P_{t,\omega}^{Dch,PL} + R_{t,\omega}^{Up,PL} \le \overline{P}^{Dch,PL} \; ; \underline{\mu}_{t,\omega}^{Dch,PL}, \overline{\mu}_{t,\omega}^{Dch,PL}, \forall t, \forall \omega \tag{6}$$

$$E_{t,\omega}^{S,PL} - E_{t-1,\omega}^{S,PL} - \eta^{Ch,PL} \times P_{t,\omega}^{Ch,PL} \times \Delta t + \frac{1}{\eta^{Dch,PL}} \times P_{t,\omega}^{Dch,PL} \times \Delta t = 0 \; ; \; \lambda_{t,\omega}^{S,PL}, \forall t, \forall \omega \tag{7}$$

$$\psi^{PL} \times E^{Cap,PL} \le E_{t,\omega}^{S,PL} \le \overline{\psi}^{PL} \times E^{Cap,PL} \; ; \underline{\mu}_{t,\omega}^{S,PL}, \overline{\mu}_{t,\omega}^{S,PL}, \forall t, \forall \omega \tag{8}$$

$$0 \le \eta^{Ch,PL} \times \left(P_{t,\omega}^{Ch,PL} + R_{t,\omega}^{Dn,PL} \right) \times \Delta t \le \left(\overline{\psi}^{PL} \times E^{Cap,PL} \right) - E_{t-1,\omega}^{S,PL} \; ; \; \underline{\gamma}_{t,\omega}^{Ch,PL}, \overline{\gamma}_{t,\omega}^{Ch,PL}, \forall t, \forall \omega \tag{9}$$

$$0 \le \frac{1}{\eta^{Dch,PL}} \times \left(P_{t,\omega}^{Dch,PL} + R_{t,\omega}^{Up,PL} \right) \times \Delta t \le E_{t-1,\omega}^{S,PL} \; ; \; \underline{\gamma}_{t,\omega}^{Dch,PL}, \overline{\gamma}_{t,\omega}^{Dch,PL}, \forall t, \forall \omega \tag{10}$$

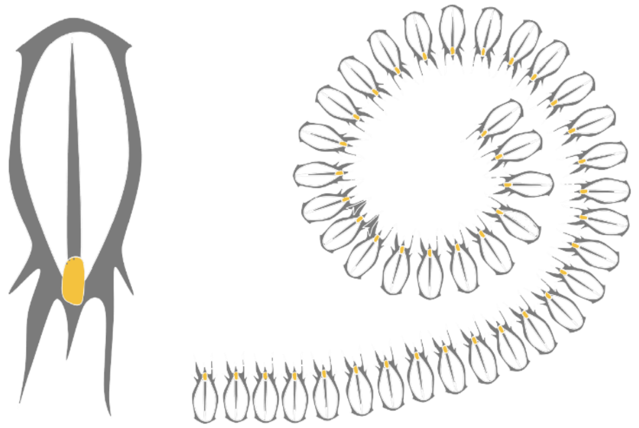
$$P_{t,\omega}^{PL} - P_{t,\omega}^{Dch,PL} + P_{t,\omega}^{Ch,PL} = 0 \; ; \lambda_{t,\omega}^{PL}, \forall t, \forall \omega \tag{11}$$

$$-\overline{P}_{t,\omega}^{Ch,PL} \le P_{t,\omega}^{PL} \le \overline{P}_{t,\omega}^{Dch,PL} \; ; \underline{\mu}_{t,\omega}^{PL}, \overline{\mu}_{t,\omega}^{PL}, \forall t, \forall \omega \tag{12}$$

Parking lots aim to minimize the overall cost by optimizing the charging and discharging schedule as given in Eq. (4). The charge and discharge power limits are stated in Eqs. (5) and (6). The state of charge (*SoC*) corresponded with an assumed parking lot at the time interval of t+1 highly relates to the *SoC* at hour t along with the amount of exchanged electrical power with the upstream network. Equation (8) reveals that the parking lot charge level is bounded within a specific range and cannot exceed this limitation. In Eq. (8), $E^{Cap,PL}$ implies the parking lot capacity. $\overline{\Psi}^{PL}$ and $\underline{\Psi}^{PL}$ denote the maximum and minimum estimated state of charge for the parking lot, based on the estimated arrival of EVs, the average EV battery capacity, the charge/discharge rates, and the lifetime of batteries, respectively. In addition, Eqs. (9) and (10) show the boundaries of parking lot charge and discharge capacity, including the state and of charge at the previous interval. The subtraction of charged power from discharged power, known as parling lot hourly capacity or parking lot power, is presented in Eq. (11). This parameter is restricted by the charge/discharge rates of the parking lot, which are highly dependent on the charging equipment and EV battery technologies as given in Eq. (12). Following the relevant constraints of each lower-level issue is a colon, followed by the dual variables of that lower-level problem. These dual variables will be utilized to change the lower-level problem into its dual problem [16-18].

III. SALP COMMUNITY ALGORITHM

Metaheuristic algorithms have gained extensive popularity in many real-world engineering problems and applied disciplines due to lower computation burden requirements and higher performance to tackle non-smooth, non-convex, non-differentiable non-linear problems. Compared to conventional mathematical deterministic solutions, metaheuristics have more power to reach an approximate answer in the close vicinity of global optima due to taking advantage of stochastic operators and randomized exploration and exploitation phases [19-21].



(a) (b)

Fig. 1. (a) Single Salp (b) 2-dimensional view of a group of Salpas (chain salp)

The Salp Swarm Optimization Algorithm (SSA) was propounded by Mirjalili et al. In 2017 concerning the social behavior of Salpas [22]. Salp belongs to the family Salpidae, which have a clear, tubular body. Their body tissue is very similar to jellyfish, and their movement is similar to jellyfish. This animal pumps water through their body to provide forward thrust. The shape of a Salp individually and in groups can be seen in Fig. 1.

In mathematical modeling of the Salp community algorithm, their social and chain behavior has been used for better movement and movement using rapid coordinated changes in pursuing food sources. To mathematically model Salp chains, the population is first divided into two groups: leader and follower. The leader group is the same Salp, which is located in front of the chain, and the other Salpas are considered followers of the leader. Like other collective methods, the position of the Salpas is defined in an *n*-dimensional search space, where *n* is the number of variables of a given problem. Therefore, the position of all the Salpas is stored in a two-dimensional matrix called *x*. A food source called *F* is in the search space as the common target of the entire group. Equation (13) is employed to update the position of the leader at each iteration.

$$X_j^1 = \begin{cases} F_j + c_1 \times ((ub_j - lb_j) \times c_2 + lb_j) & c_3 \geq 0 \\ F_j - c_1 \times ((ub_j - lb_j) \times c_2 + lb_j) & c_3 < 0 \end{cases} \tag{13}$$

Where X_j^1 represents the position of the first Salp (leader) in the *j* dimension, F_j represents the position of the food source in the *j* dimension, ub_j denotes the upper bound of the *j* dimension, lb_j stands for the lower bound of the *j* dimension, c_1, c_2, and c_3 are also randomly extracted numbers from a uniform distribution. Equation (13) implies that the leader only updates his position relative to the food source. In addition, the c_1 factor is the most important parameter in the Salp optimization algorithm because it adjusts and balances the exploitation and exploration metrics of this swarm algorithm.

$$c_1 = 2e^{-(\frac{4l}{L})^2} \tag{14}$$

In the above, *l* stands for the current iteration, and *L* represents the maximum number of iterations. Parameters c_2 and c_3 are random numbers that are evenly generated at intervals [0,1]. In fact, they indicate whether the next position in the *j* dimension should be infinitely positive or infinitely negative and specify the size of the step. Newton's law of motion rules are applied to update the position of the followers:

$$X_j^i = \frac{1}{2} a \times t + v_0 \times t \tag{15}$$

In the above equation, $i \geq 2$, then the parameter X_j^i indicates the position of the i^{th} follower Salp in the dimension *j*, at time *t*, and v_0 indicates the initial velocity so that $\alpha = \frac{v_{final}}{v_0}$ and $v = \frac{x - x_0}{t}$.

Since the time in optimization is considered the iteration number, the difference between the iterations (step time) is 1, and considering v_0 =0, Eq. (15) can be reformulated as follows:

$$X_j^i = \frac{1}{2}(X_j^i + X_j^{i-1}) \tag{16}$$

In which $i \geq 2$, and X_j^i indicates the i^{th} salp position following *i* in the *j* dimension. Equations (13) to (16) convey how the salp chains can be simulated. The pseudo-code of the SSA algorithm is shown in Fig. 2.

Initialize the salp population x_i (i = 1, 2, ..., n) considering ub and lb
***while** (end condition is not satisfied)*
Calculate the fitness of each search agent (salp)
F=the best search agent
Update c_1 by Eq. (14)
  ***for** each salp (x_i)*
    ***if** (i==1)*
      Update the position of the leading salp by Eq. (13)
    else
      Update the position of the follower salp by Eq.(16)
    end
  end
  Amend the salps based on the upper and lower bounds of variables
end
return F

Fig. 2. SSA algorithm pseudo-code

IV. Numerical Results

The suggested paradigm is implemented on a test distribution grid where the targeted parking lot and DSO interact, and the operation schedule is controlled in the same region. According to [23], the open market power price is determined on an hourly basis. All integrated electric vehicles are expected to have a battery capacity of 15-kWh. Table I demonstrates all details and data pertaining to the targeted parking lot. The proposed paradigm to incorporate parking lots in a retail market is shown in Fig. 3.

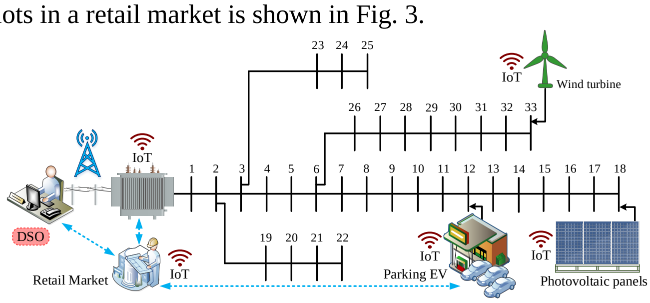


Fig. 3. The schematic of the proposed market considering the presence of a parking lot and renewable sources under DSO monitoring

The topology of the selected grid is shown above. The hourly wind power data in Fig. 4 are obtained from [24]. Figure 5 also depicts the predicted load profile for the next 24 hours. Since demand estimates and wind power generation forecasts are inaccurate due to uncertainties and intermittencies, the suggested model incorporates the prediction error into feasible scenarios. The normal distribution function can precisely model forecast errors. The standard deviations associated with the forecast errors of demand and wind power are considered to be 2% and 10% of the anticipated hourly amount, respectively. The DSO acquires routine statistical data about the state of parking lot generation. The spinning reserve price for the parking lot is 12% of the target energy price. Furthermore, the energy not supplied value is estimated to reach about $800 per kWh. The amount of power absorption is shown in Fig. 6. In addition, Fig. 7 also depicts the charge/discharge profile of the parking lot. Owing to the goal of the problem, which is cost reduction, it is evident that most charging takes place when power prices are lower. It conveys that the EV owners are inclined to adjust their transportation to pay less for energy. In addition, the discharge is done when energy costs are greater to lower the amount of power imported from the upstream network. It implies that the EV owners are encouraged to sell their surplus energy during peak hours to earn profit. Such tendencies by EV owners are not the same for all owners, but it is tried to persuade them to follow this pattern. The parking lot owner, on the other hand, is eager to sell the majority of its available energy as much as possible technically in the reserve market since it can have more finical profitability and more money-saving by calling reserve capacity or incorporating the reserve declarations instead of selling energy in the retail energy market.

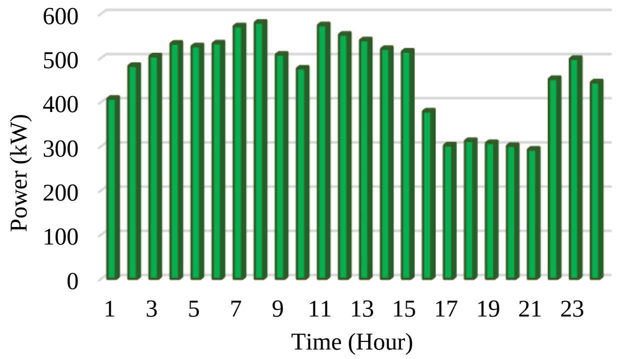


Fig. 4. The forecast of hourly wind power generation

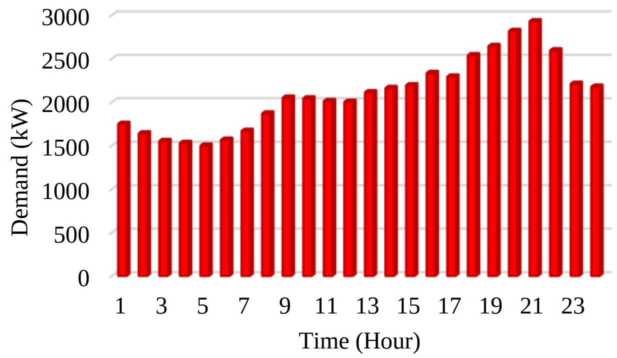


Fig. 5. Hourly load profile forecast

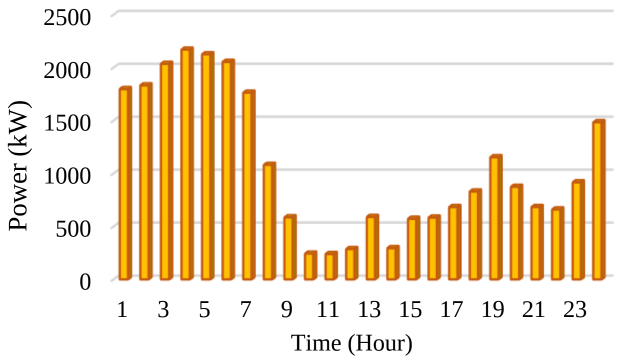


Fig. 6. Scheduled power generation of the main grid

Figure 9 shows the operational schedule of the parking lot for up and down reserves. As shown in Fig. 9, the parking lot can contribute as an energy storage system in the energy market. As a result, such a participant is regarded as a powerful, flexible, and influential player in the market that may also be called to redress surplus wind power generation when loads demand a low level of electric power, and there is considerable wind power generation. In addition, they can adjust and redress real-time wind power generation imbalances as well as the volatilities caused by the load consumption uncertainties. This scheme underlines the capability of a parking lot facility to balance generation and consumption for each scheduling time interval while also providing DSO reserve service. The parking lot owner prefers to participate in the reserve market more than the energy market when the power price rises, as Fig. 9 conveys. With decremental electricity prices, a parking lot owner or PL aggregator would still rather buy more electricity from the upstream network in the retail marketplace. However, the parking lot may decide to contribute to downward reserve procurement in the reserve market.

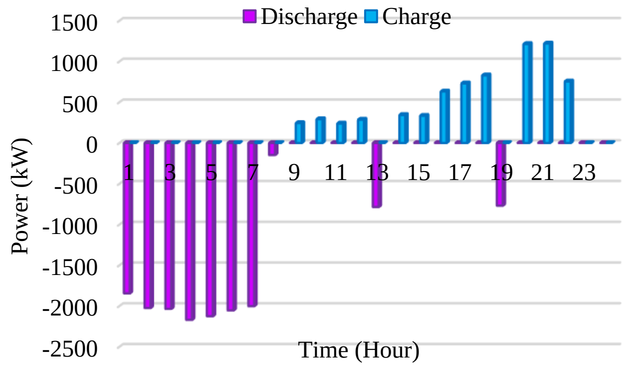


Fig. 7. Charge and discharge Schedule of the parking lot

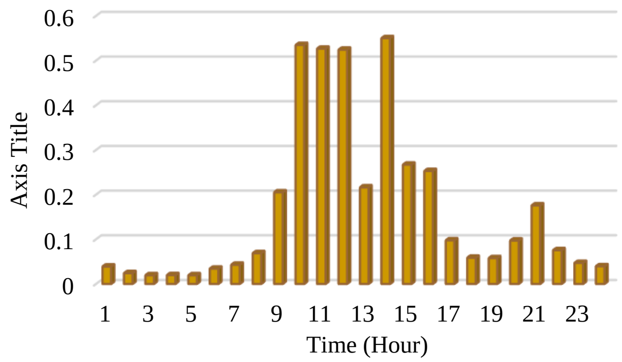


Fig. 8. The hourly price of electricity ($/kWh)

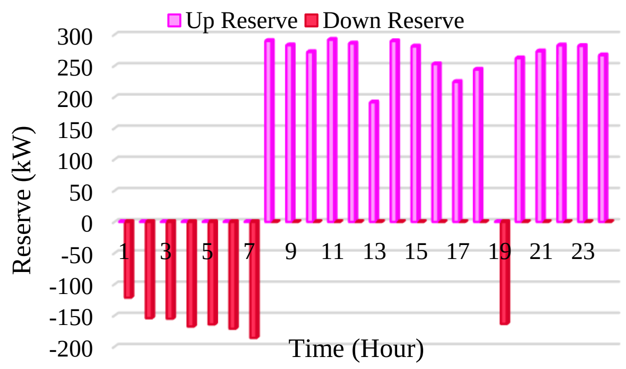


Fig. 9. Spinning reserve procurement by the parking lot

V. Conclusion

This paper has introduced a novel approach to describe how the DSO and a parking lot (or even a set of parking lots via an aggregator) interact with each other in a restructured environment. The problem of day-ahead scheduling has been arranged as a bi-level problem. In the proposed model, the upper-level (master) problem aims to satisfy the targeted objective function, which is the minimization of the costs from the DSO perspective, while the lower-level problem (sub-problem) intends to optimize the scheduling arrangement of a parking lot for energy and reserve market participation. In other words, the sub-problem is designed from the point of view of the parking lot owner, with the goal of cost minimization of the parking lot. The Salp Swarm Optimization Algorithm (SSA) is employed to find the optimality condition in this non-smooth and non-convex problem subject to satisfying the operational and economic constraints. The results imply that the proposed bi-level model for the mechanism of interaction between parking lots or associated aggregators and DSO can improve the economy and reliability of the power system, and it makes it possible to have more integration of uncertain renewable sources.

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