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Revenue Analysis of a Lightweight V2G Electricity Trader Based on Real-Life Energy Demand Patterns

Junghoon Lee and Gyung-Leen Park*+

Dept. of Computer Science and Statistics, Jeju National University
Republic of Korea
{jhlee,glpark}@jejunu.ac.kr

Abstract

This paper analyzes the revenue of a microgrid employing the lightweight vehicle-to-grid energy trade coordinator, focusing on such parameters as seasonal rates, number of participating electric vehicles, stay time, and amount to sell. The heuristic method cuts down the vast search space for the complex optimization problem by by iteratively matching the time slot having the least available electricity. The analysis result, obtained from a real-life demand pattern, reveals that on the winter rate, 100 EVs can sell all of their energy, while for the 200-EV case, they can sell and double the revenue in 12 out of 20 days. Next, on the summer rate, in which the peak rate interval is extended, the revenue increases by 1.5 times. At the same time, the 200-EV case sometimes brings less benefit than the 100-EV case for the given parameter set. As the target brokering system responsively finds a near-optimal solution until a certian bound, it can be further scalable with a module-based distributed brokering mechanism.

Keywords: *electric vehicle, vehicle-to-grid, revenue analysis, demand response plan, trade broker*

1. Introduction

Along with the advent of smart grids, electric vehicles, or EVs in short, are penetrating into our daily lives, making even the transportation system a part of the power network [1]. EVs, equipped with batteries, have the potential to introduce a new energy service such as V2G (Vehicle-to-Grid), in which EV batteries provide electricity storage capacity to the grid. Here, EVs charge their batteries overnight through the cheap rate and sell back to the grid at a high price, earning economic profits [2]. Moreover, the electricity can come even from renewable energy. On the other side, namely, from the buyers' aspect, they can avoid expensive peak-rate electricity from the main grid and save energy costs [3]. It must be mentioned that the national grid cannot fully support this V2G flow due to safety threat and management complexity. Instead, a microgrid such as shopping malls and universities having their own power systems will be vigorous players in the V2G community.

Like other smart grid entities, intelligent information technologies can enrich the V2G application with sophisticated brokering, trade scheduling, and electricity flow control between EVs and the grid [4]. Such computational intelligence gets further improved along with the massive data processing capabilities [5]. However, according to the increase in the number of EVs participating in a V2G service, the complexity of those services will also increase. Hence, the information service must be scalable. Our previous

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work has designed a lightweight V2G brokering service which coordinates the electricity trade so as to reduce the insufficiency in the microgrid side [6]. It decides when each EV will be connected to the microgrid and when EV electricity will be supplied to the grid, desirably giving a guide when each EV will arrive at the microgrid.

For a microgrid to determine whether to employ a V2G service system, it is necessary to estimate how much the grid can enhance its economic profits by avoiding the expensive peak rate electricity based on its energy demand pattern and the potential EV participants [7]. The energy pricing plan is also an important factor which must be integrated in the estimation. In this regard, this paper presents an electricity trade brokering scheme between EVs and the microgrid and then analyzes the revenue from the EV side. As an extended version of our previous work [8], this paper gives more details on the brokering service scenario, trade coordination scheme, and subsequent on-off grid connection schedule. Then, the revenue analysis is conducted for a target microgrid, whose previous power consumption records are available. The experiment focuses on the expected revenue according to the number of EVs, the amount of energy to be sold, seasonal demand change, and stay time.

This paper is organized as follows: After issuing the problem in Section 1, Section 2 introduces related work on V2G services and resource schedules. Section 3 describes the system model and presents the lightweight energy trader broker. Section 4 conducts the revenue analysis applying a real-life energy demand according to various parameters, discussing the results. Finally, Section 5 summarizes and concludes this paper with a brief introduction of future work.

2. Related Work

[9] highlights the role of aggregators for EVs to participate in electricity markets. Aggregators coordinate the provision of ancillary services such as regulation and spinning reserves based on the formulation of a fuzzy linear program. Here, a microgrid gets revenues from the ancillary markets and the difference between the fixed energy charge and the mark energy price. In addition, to forecast electricity prices for the next day overcoming the inherent uncertainty, an ARIMA (Auto Regressive Integrated Moving Average) model is built on top of the history of hourly price changes. Next, fuzzy objective and constraints are defined considering the membership functions of income, ancillary service prices, and expected deployments. The fuzzy set-based model embraces the uncertainty in ancillary service prices and deployment signals for regulation up, regulation down, and response reserve.

[10] presents a day-ahead energy resource scheduling scheme for smart grids, taking into account the distributed energy generation and V2G. The authors put the main focus on the effect of uncontrolled charging, smart charging, and demand response (DR) programs within the context of V2G applications. Specifically, trip reduce and trip shift DR programs are designed, while the proposed models are activated every time the energy price reaches a predefined value. The trip reduces program encourages users to get profits by voluntarily reducing their travel needs and minimum battery level requirements. On the contrary, the trip shift program allows the grid to shift the EV charging load by adjusting the traveling period of their expected trips. To solve the large mixed integer nonlinear combinational problem in complex resource scheduling, a PSO (Particle Swarm Optimization) approach is employed with integrated AC power flow.

[11] investigates the optimal operation of distribution feeder reconfiguration (DFR) strategy, employing the idea of V2G to allow bi-directional power flow involving EVs. The authors suggest a stochastic framework based on unscented transformation to model EVs' behavior, which can be considered as a mobile demand and storage in the power network. Here, the DFR is the process of automatically changing the network topology by means of relevant switch types without violating the given constraints. The objective

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function measures operation and reliability costs, including the cost of power received from the upstream grid, expected customer interruption costs, power loss costs, and battery degradation costs brought by extra battery cycling. Moreover, the uncertainty of EV behavior and wind energy is modeled by means of an approximation method to complement the non-linear correlated transformations.

Our research team has been designing and developing a V2G energy trade service at the microgrid level. The data exchange mechanism allows both parties, namely, EVs and a microgrid, to fix a trade set and generate a connection control schedule. Here, individual EVs either accept the current schedule or keep waiting for another schedule until the complete schedule is built [6]. An EV can defer its acceptance decision during the coordination process, possibly contacting with other microgrids until it meets a satisfactory schedule and profit guarantee. In addition, for the allocation of EVs to time slots according to the power demand, two scheduling schemes are designed. The first one is an exhaustive scheme which traverses the whole search space to find an optimal schedule when the number of EVs is not so large. The other one is a heuristic-based scheme capable of coping with a large number of EVs and this paper is built on top of this scheme.

The unit scheduler runs on a microgrid and the interaction between the EV party and the microgrid party is shown in Figure 1. Here, multiple EVs simultaneously negotiate with multiple microgrid and select the best one in which an EV can receive best reward. As shown in the figure, each EV is charged overnight with cheaper electricity. Then, it wants to decide a microgrid it will sell its electricity. The EV can visit multiple microgrid during the daytime of the next day. If an EV fixes the microgrid to which it sells its electricity, it will be removed from the set of other microgrid. Hence, each EV must make its decision until the final deadline of each microgrid, while the unit scheduler is invoked each time a new request arrives, namely, a change in the EV set takes place.

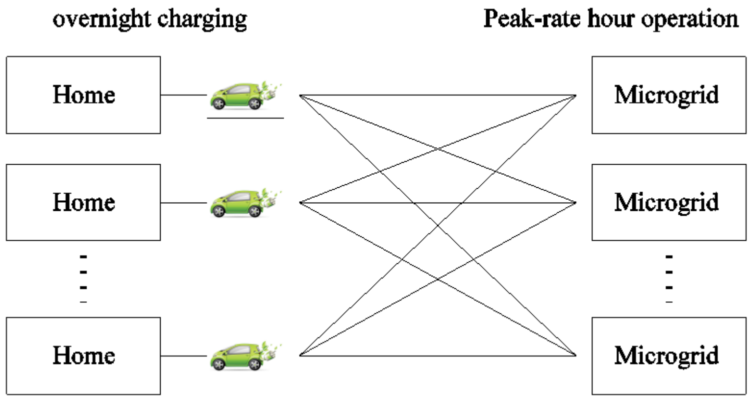

Figure 1. Interaction between 2 Parties

3. Service Scenario

Figure 2 illustrates the V2G energy trade scenario. The trade contract is made one-day advance under the control of the V2G trader broker running in the aggregator [12]. It first estimates the hour-by-hour electricity demand of the microgrid according to its own demand forecast model, which is usually built using the previous records [13]. Considering the electricity price, the amount of electricity it wants to buy during each slot is decided. Here, the price it can affordably pay is also generated. Then, the aggregator initiates the brokering process by announcing the request-to-bid. Each addition of an EV invokes the on-off control scheduler to calculate the reward each EV can receive. After the brokering phase, the contract is finalized [14]. On the next day, EVs will obey the contract by arriving at and being plugged-in to the microgrid on the reserved slot [15].

During the system operation, the controller connect or disconnect the EV battery to or from the microgrid to allow electricity flow. If a sufficient amount of energy can be purchased during a slot, the microgrid cannot but use the expensive energy supplied by the main grid.

In the brokering phase, each EV sends a request-to-sell record, R_i. R_i is specified by (E_i, L_i, D_i, A_i), where each element denotes earliest arrival time, latest arrival time, plug-in duration, and amount to sell, one by one [6]. This model conforms to the situation that an EV driver will go shopping while he or she can flexibly arrive during the interval from E_i to L_i and wants to select the arrival time according to the guide of the broker. The amount to sell is decided by the electricity not used for driving [7]. It must be mentioned that the time scale is aligned with the length of a time slot, for example, 0.5 hours. The amount-to-sell can be represented also by the number of slots for uniformity. In this case, 1 slot corresponds to the amount of electricity which can flow from an EV to the microgrid during a single slot or vice versa. Essentially, the demand is the amount of energy the microgrid wants to buy from EVs, and it can be denoted by the number of slots after ceiling to the slot boundary. Then, an EV can be aware of its time to be plugged-in and makes its own tour schedule [16].

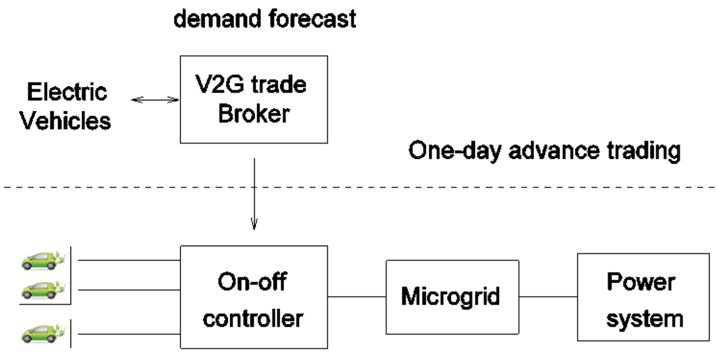

Figure 2. V2G Energy Trade Service Architecture

To avoid the search space expansion accompanied by the conventional exhaustive search, the lightweight scheduler iteratively finds and matches both the time slot having the smallest number of available EVs and the EV which has the least flexibility in staying at the microgrid. For each match, an EV is assigned to a time slot, its amount-to-sell decreases by one unit and also its availability interval will be modified. The availability interval, initially set to all feasible ranges from earliest to latest arrival time instants, will shrink as more slots are assigned to an EV. It is because if the EV is to be plugged-in during a slot, its latest arrival time and earliest depart time will be changed. This step iterates until all EVs are assigned, namely, every electricity is sold out, or no EV is available on the slots in which the microgrid wants to buy electricity. This approach can achieve the computation time linearly dependent on the number of EVs for the fixed number of slots, as the heuristic iterates at most for the number of EVs.

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	0	1	2	3	4	5	6	7	8	9	10	11	12	13
EV_0												1	1	
EV_1			1	1		1								
EV_2												1		
EV_3								1	1					
EV_4						1		1						

Figure 3. Operation Table

After the completion of a trade coordination, the next-day schedule is created as a form of time Tables as shown in Figure 3. In this figure, 5 EVs from EV_0 to EV_4 are participating in the V2G trade. According to the schedule, EV_1 must arrive at and be plugged-in to the microgrid before the beginning of slot 2. Then, the connection switch between EV_1 and the microgrid will be turned on slots 2, 3, and 5, while turned off during slot 4. EV_1 sells electricity of 3 slots and can leave the microgrid after slot 5. Here, the stay time of EV_1 must have been longer than 4 slots. Slot 7 takes electricity from 2 EVs, namely, EV_3 and EV_4. If the demand during a slot is not met, insufficiency takes place. On the contrary, the electricity cannot be sold when the microgrid doesn't need electricity during the slots included in the availability interval of an EV. The amount of unsold electricity is surplus energy. The heuristic-based method works well even when many EVs submit their request-to-sell messages to a single microgrid, just with a small accuracy loss. For more detail, refer to [6].

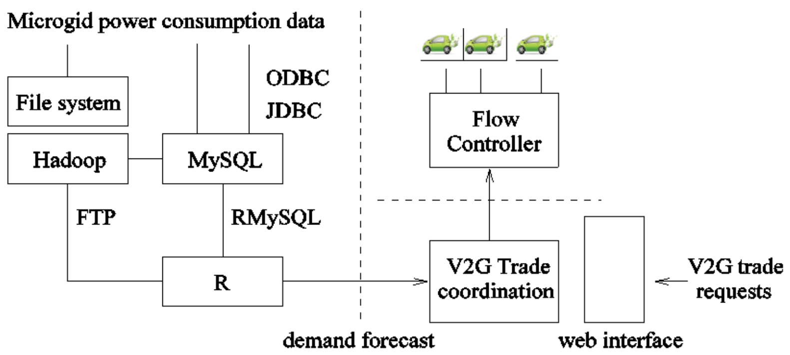

Figure 4. Data Flow

Figure 4 illustrates the data flow of a microgrid. The left part builds a power consumption model to provide the next day demand forecast to the V2G energy purchase plan. Here, the model is necessarily built based on the past consumption data. The consumption history for a microgrid has been accumulated since the microgrid requested the data profiling service to the energy company, specifically, KEPCO (Korean Electric Power Corporation) in the Republic of Korea. Each record contains the amount of energy consumption for every 30 minutes. It is downloaded from the KEPCO web site after a series of authorization steps and stored in the Linux file system. If the amount of target data is too much, Hadoop conducts a preliminary analysis and hands over the result to MySQL database. Here, other data which can be usefully combined for power consumption modeling such as weather records and geographic information can be uploaded via ODBC or JDBC (Object or Java DataBase Connection). Then, the R statistical package retrieves the digested stream from the MySQL database and builds a consumption forecast model, taking advantage of a bunch of modeling methods provided by various library extensions.

4. Revenue Analysis

This section analyzes the performance of the fast heuristic by applying to a real-life power demand scenario acquired from Jeju National University, Republic of Korea. The university microgrid consumes more energy when more students and faculty members stay, and the consumption sharply drops over the weekend. In our assumption, EVs participating in the V2G trade are plugged-in to the grid in the parking area. This microgrid wants to buy electricity from EVs especially when the overall consumption exceeds the flat-rate boundary contracted with the power provider company. Based on the consumption profile, our experiment calculates the V2G demand for every 30-minute interval from 10 AM to 5 PM for a given day. This duration corresponds to the period of price signal change, and the time slot length is also set to 30 minutes. We assume that the university takes the demand response rate plan offered by Korean Electric Power Corporation, and the per-time slot electricity rate is shown in Table 1. [17]. The revenue is denoted in Korean Won (KRW), and 1,100 KRW roughly corresponds to 1 USD.

Hours	10.0	10.5	11.0	11.5	12.0	12.5	01.0	01.5	02.0	02.5	03.0	03.5	04.0	04.5
Winter	108	108	164	164	164	164	108	108	108	108	108	108	164	164
Summer	108	108	164	164	164	164	164	164	164	164	164	164	164	164

There are several parameters we are interested in. First of all, the brokering scheme is designed for a large number of EVs, the experiment sets the number of EVs to 100, 200, and 300, even though in most scenarios, tens of EVs will be enough. Next, an EV will stay at the microgrid 3 to 8 time units and the amount to sell ranges from 2 to 7 time units. The arrival time distributes randomly during the operation time of the microgrid. Actually, the arrival time tends to concentrate on a specific interval, namely, around the beginning of office hours for faculty members. However, the experiment takes the random distribution to take into account different types of microgrids.

Figure 5 plots the revenue according to the number of EVs participating in the V2G service on a specific day according to the price plan during the winter months. Here, the revenue depends not only on how much electricity is purchased from EVs but also when it is purchased. The monetary gain differs from slot to slot as shown in Table 1. The amount of purchased energy does not always increase according to the increase in the number of EVs, especially beyond 200 EVs. The performance of the lightweight brokering scheme may get poorer with 300 EVs. The revenue-focused lightweight scheme also shows the similar pattern as in the case of insufficiency-based scheduling. As shown in Figure 2, the microgrid buys almost every electricity in the case of 100 EVs, hence the revenue during the weekdays is largely constant. In the 200-EV case, the revenue is doubled in 12 days and almost the same in 5 days, compared with the 100-EV case.

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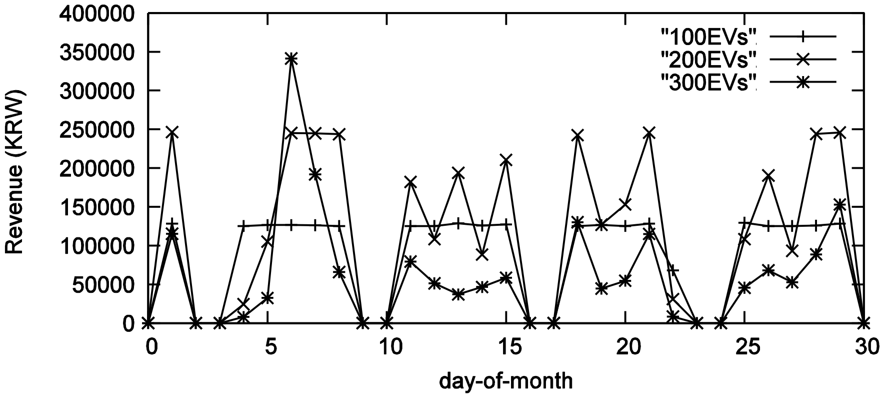

Figure 5. Winter Rate

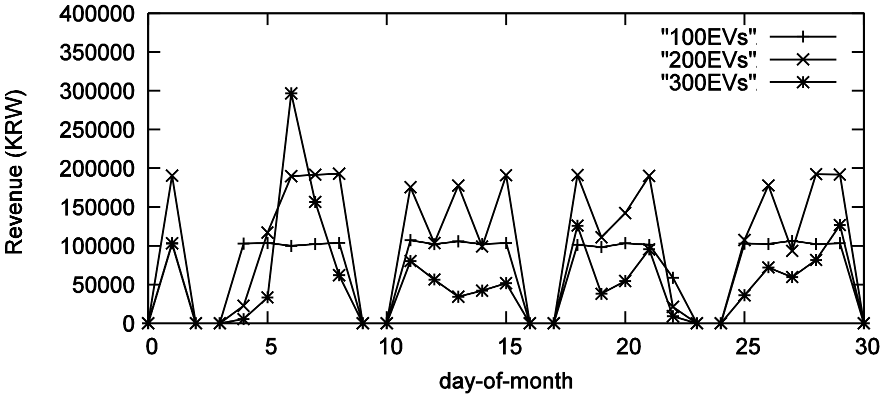

Figure 6. Summer Rate

Next, Figure 6 plots the revenue for the same month according to the power rate during the summer months. As the energy consumption of the same month is investigated, the overall curve patterns are similar to Figure 2. However, the revenue gap between the 100-EV case and the 200-EV case gets larger by about 1.5 times, compared with the winter rate. It's mainly because the peak rate interval is extended during the summer season, and there are more high-price time slots as shown in Table 1. Moreover, on 5 days, the 200-EV case saves less money than the 100-EV case by up to 29.6 %. In addition, the 300-EV case outperforms the other two just on a single day. This anomaly indicates that it's not enough to reduce the search space based on the availability of EVs on high-load slots. Anyway, the microgrid can expect a profit gain by energy cost reduction employing the V2G trade broker.

Next, Figure 7 plots the revenue according to the average amount of electricity an EV wants to sell. Here, the amount is aligned to the time slot. As the connection cable between EVs and the microgrid is standardized, the amount of electricity flowing across them is linear to the time length. Specifically, 3 *kwh* can flow during an hour in AC chargers. In the experiment, we changed the average amount to sell from 1 to 5 slots, while making the microgrid take the winter price plan. Day-by-day profits are added up to yield the monthly revenue. As shown in the figure, this parameter hardly affects the revenue. This is because only a small fraction of electricity can be sold from an EV. Especially, the revenue tightly sticks to 2,000,000 KRW. The deviation from the value is less than 46,000 KRW and this amount is just 2.3 %.

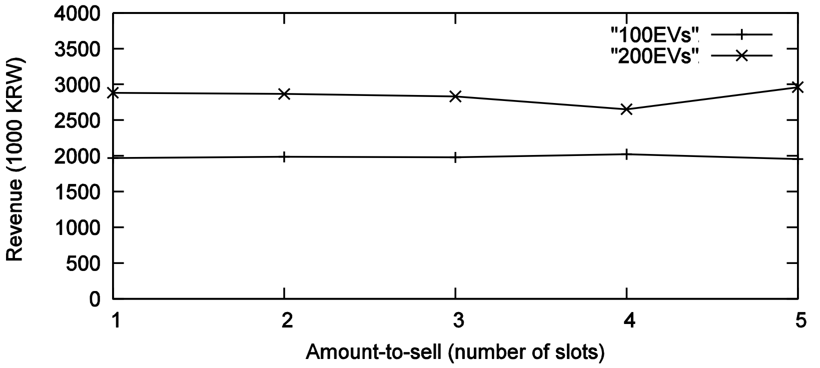

Figure 7. Effect of the Amount-to-Sell

Figure 8 shows the monthly revenue according to the number of EVs on both winter and summer rates. In both curves, the revenue increases almost linearly according to the number of EVs until 150 EVs. This result implies that the heuristic scheme finds a near-optimal solution until this point. However, beyond 150, the revenue does not increase according to the number of EVs, and thus the available electricity. During the allocation process, a wrong EV-slot match makes subsequent placement fall to a wrong direction. As the linear complexity does not permit backtracking, the effect of a mismatch cannot be overcome. Then, the revenue even decreases in spite of better availability of electricity to sell. However, the responsiveness and efficiency until 150 EVs must not be overlooked.

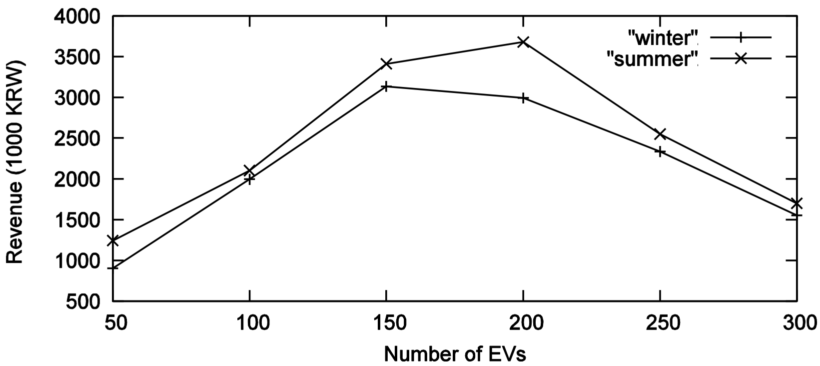

Figure 8. Effect of the Number of EVs

Finally, Figure 9 traces the revenue according to the stay time for two cases of 100 and 200 EVs, respectively, on the winter rate. The experiment fixes the stay time with the given value ranging from 3 to 8. A longer stay time means more options for an EV to be placed in a time slot. Here, the amount-to-sell distributes from 1 to (*slot* -1), hence the available amount also increases according to the increase in the stay time. In the 100-EV case, the revenue gets better in proportion to the stay time for the whole parameter range. On the contrary, the revenue is twice as much as in the 100-EV case only when the stay time is 3 and 4 slots. Beyond this point, more options and more electricity yet do harm to the performance of the trade brokering scheme.

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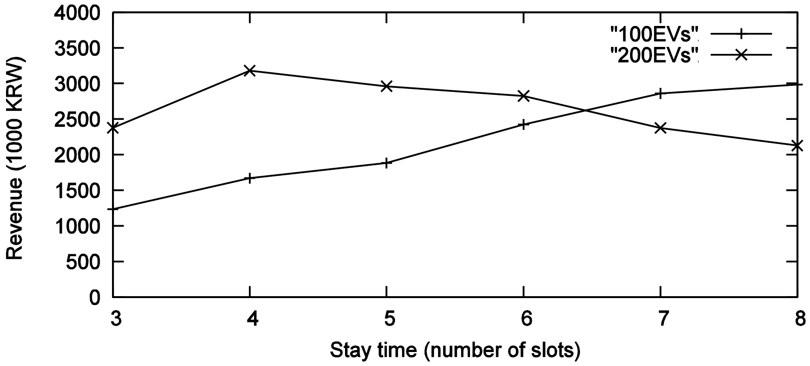

Figure 9. Effect of the Stay Time

5. Conclusions

EVs allow a V2G service capable of shaping the energy consumption over the power system and avoiding a new power plant construction. Brokering the electricity trade between EVs and a microgrid is a very important service and requires intelligent computer algorithms. In this paper, we have analyzed the revenue obtained by a heuristic-based lightweight broker based on a real-life power consumption profile. The experiment result indicates that the trade broker, while providing an accepTable response time, finds a schedule having the maximum profit largely until 150 EVs for the given parameter set. Even if this scheme is quite scalable for a large number of EVs, the space search without backtracking imposes a limitation when there are explosively large number of EVs. Moreover, a better availability of electricity to sell and a more options cannot contribute to the improvement of revenue in V2G. However, if the brokering scheme can work in modular mode, that is, EVs are grouped such that total number of EVs in a group is 150 at maximum, our broker can create a near-optimal purchase plan for a microgrid and connection schedule responsively. Here, a distributed cooperative mechanism is necessary [18].

As future work, we are planning to develop a big data analysis framework for the power consumption profile, the real-time charger status monitor, and the EV battery dynamics [19]. Such data streams are being accumulated in our system and expected to create many value-added information services. To this end, our research team has built a data processing framework employing Hadoop and the R statistics package. The integration of multiple streams from diverse smart grid entities will give us systematic decision-making mechanisms in newly appearing smart grid cities.

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