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GENETIC ALGORITHM-BASED ADMISSION TEST FORVEHICLE-TO-GRID ELECTRICITY TRADE SERVICES

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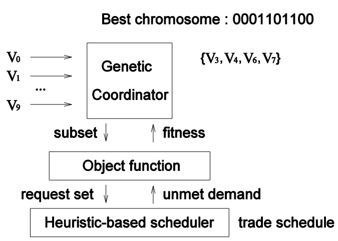
Graphical abstract



Abstract

This paper designs and evaluates a vehicle-to-grid (V2G) electricity trader capable of selecting an appropriate subset out of a large number of electric vehicles (EVs) which want to sell their energy to a microgrid. A genetic algorithm, tailored for this trade coordination, reduces the amount of unmet demand forecasted one day advance in the microgrid. Each subset is encoded to an integer r vector whose element has either 1 or 0 according to whether the associated EV is included in the subset or not. The evaluation function estimates the fitness of a feasible solution, employing a fast heuristic-based unit scheduler. Its lightweight-ness allows the genetic algorithm to calculate the fitness of the massive number of feasible subsets, each of which has a fixed number of EVs. This admission test gives a chance for EVs to contact with other microgrids when they are not accepted to the final trade schedule. The performance measurement result obtained from a prototype implementation reveals that the proposed scheme achieves up to 20.8 % performance improvement over the random selection scheme in terms of unmet demand. Moreover, the proposed scheme can efficiently cope with overload condition, that is, many EVs are concentrated in a single microgrid, judging from its stable performance curve.

Keywords: Electric vehicle, vehicle-to-grid, trade coordination, genetic algorithm, unmet demand reduction

1.0 INTRODUCTION

The modern power network called the smart grid pursues energy efficiency by orchestrating many heterogeneous grid entities and also taking advantage of leading-edge information technologies [1]. In the meantime, EVs (Electric Vehicles) electrify even the transportation system and make it as a part of the power network. Here, EVs are one of the most unique components in the smart grid as they do not only consume energy but also store electricity. In addition to their basic role, namely, driving, they can send the electricity stored in their batteries back to the grid [2]. This V2G (Vehicle-to-Grid) capability can shift peak load as EVs can be charged during the night time when the energy demand is very low. The peak shift can potentially avoid constructing a new power plant. Moreover, EV owners can earn money by charging at a low price and selling at an expensive peak time rate [3]. Promisingly, EV batteries can store electricity generated from renewable energy sources such as wind which inherently suffers from severe intermittency. Hence, V2G-enabled EV sare considered a new energy source in smart power systems.

However, the national grid hardly permits the backward electricity flow to the grid due to security risks, management problems, and others. Instead, a micro grid having autonomous control and its own power subsystem can vigorously purchase energy from EVs, which are plugged-in to it. The micro grid such as a shopping mall can implement its own V2G strategy and enhance economic benefits by avoiding expensive peak-rate electricity. During the peak time, many shoppers will highly likely stay inside the mall and more energy will be needed, increasing the energy cost. This time is also a chance for the micro grid to buy more energy from EVs. On the other hand, EV owners can be diversely rewarded by discount coupons, cash, and many other useful methods in shopping mall-style microgrids. Within a micro grid, EVs will charge, rest, and discharge under the regulation signals given by grid-specific control logic [4]. This control system must be built upon an efficient and real-time two-way interaction mechanism [5].

In most V2G scenarios, energy trading is carried out in day-ahead markets [6]. Here, an EV informs the microgrid of its sales request specifying current SoC (State-of-Charge), arrival time, plug-in time, and the like. In our previous work [7], we have designed an interaction mechanism between both parties, namely, EVs and a microgrid. The V2G coordinator, after running a unit scheduler, or V2G trade broker, for a given set of sales requests from EVs, tells them respectively when to arrive at the microgrid and how much electricity they can sell. It creates an electricity flow schedule in a time-table style, intelligently alleviating the imbalance between supply and demand. However, it is easily expected that the control logic will be very complex according to the increase in the number of EVs participating in the V2G trade. If a great number of EVs want to visit simultaneously and sell at a single grid during a specific time interval, not all electricity can be bought [8]. The coordinator is desirably required to notify each participant whether it is admitted in the next day trade. Then, unaccepted or unsatisfied EVs can begin a new negotiation with other microgrids.

For the given set of sales requests from EVs, the coordinator tries to meet the microgrid-side energy demand, which is estimated by a prediction model built upon energy consumption history [9]. If not all electricity can be purchased by the microgrid, the coordinator decides the subset of EVs, which best meets the given scheduling goal. However, the number of feasible subsets will exponentially increase according to the increase in the number of EVs, while the fitness of a single subset will be estimated only after the generation of its trade schedule, which is already an NP problem. On the contrary, if trade scheduling is carried out by a heuristic scheme having linear time complexity [8], we can just focus on finding a better subset. As its time complexity is estimated to be $O(2^n)$,where n is the number of set elements, it is necessary to employ a suboptimal technique even if it may sacrifice the accuracy. The genetic algorithm is one of the most widely used suboptimal techniques and can even manage the execution time, necessarily meeting the tolerance bound in response time [10].

In this regard, we are to design a genetic algorithm-based subset finding scheme for efficient V2G energy trading. It tries to find a subset of EVs admitted in the energy trade and creates an electricity flow schedule for a microgrid within a practical time bound. Here, as a basic building block, a lightweightV2G trade scheduler, or unit scheduler, for a fixed set of EV sis essentially exploited. Then, it is necessary to integrate this scheduler module to the genetic algorithm mainly in evaluating the fitness of a feasible subset, even if its original role is to create an on-off connection schedule between EVs and the microgrid. In the evolutionary process, each subset is encoded to an integer-valued vector to apply genetic operators such as selection, reproduction, and mutation. Each vector, or chromosome, is mapped to a sales request set and the unit scheduler is invoked to evaluate the fitness of the set. The object function calculates the unmatched demand, or insufficiency, and the chromosome having the least insufficiency will survive after the given number of iterations. This mechanism can cope with a large number of EVs participating in the trade.

2.0 RELATED WORK

It is well known that in most cases, over 90 % of a day, personal vehicles are not used. Hence, when they are parked and plugged-in to the grid, possibly via chargers, an EV can act as a battery device. [4] addresses a distributed V2G control scheme capable of efficiently suppressing system frequency fluctuation. Detecting a system-level frequency drop, the control mechanism reshapes the load by shifting EV charging or even making EVs instantly inject power back to the grid. Here, efficient action control mechanisms are essential forV2G and it can be carried out by centralized or decentralized manners. In addition, the real-time V2G capacity estimation is important to leverage the effectiveness of V2G services.[11] estimates the amount of energy that can be sold to the grid, considering the chargeability and drivability upon their EV charge scheduling algorithm. For each time slot, the estimation process calculates the minimum requirement of SoC and checks how much electricity can be charged before the next departure time.

As for energy trading, the trade coordination is carried out in day-ahead markets, combined with V2G services to mitigate trading risks stemmed from uncertainties in future energy prices and availability. [3] considers day-ahead resource scheduling. Its V2G-integrated demand response programs schedule the charging operation based on both *trip reduce* and *shift reduce* strategies. After the mathematical formulation, the coordinator customizes a particle swarm optimizer to achieve a practically acceptable execution time. In [12], to participate in the regulation service, EVs submit bids, specifying the amount of its regulation power and price. Accepted EVs follow an on-line regulation signal from the grid. Here, an EV acts as a single battery pack and how to decide control actions such as charge, discharge, and rest ,is essential for intelligent system-wide V2G services. Additionally,[13] exploits emerging reconfigurable battery packs to cope with cell imbalance mainly considering SOH (State-of-Health) levels. It reconfigures the battery pack connection according to whether packs are discharging or being charged.

3.0 SYSTEM MODEL

A. Interaction Between Evs And The Microgrid

We assume that an aggregator of the target microgrid interacts with each EV which wants to sell its electricity via an appropriate communication channel, highly likely through the Internet [14]. The reservation process is usually carried out one-day advance. The microgrid forecasts the electricity demand and decides how much it wants to buy from EVs for each time slot, mainly considering the necessary amount and energy prices [15]. EVs submit requests-to-sell messages to the aggregator, specifying their earliest and latest arrival times as well as the amount to sell. The request follows the same model used in our previous work [16]. In addition, the plug-induration, which corresponds to the stay time in the microgrid, is also given. Here, EV drivers can adjust their travel plans and the arrival times at the grid according to the schedule generated by the aggregator. While physically plugged-into the microgrid, an EV will be electrically connected or disconnected to the grid by the switch operation. During the connection time, the electricity flows to the microgrid.

B. Unit Scheduler

A request-to-sell record, R_i, consists of (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, respectively [8]. It accounts for 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 on which he or she can be best rewarded. The amount to sell is decided by the electricity not used for driving [11]. The time scale is aligned with the length of a time slot, for example, 0.5 hours. The slotted time brings the manageable time complexity to trade coordination. Here, the per-slot electricity flow from an EV to the grid is constant and thus linear to the number of time slots during which the EV is connected to the grid, as the charging or discharging power levels are standardized [17]. After all, the amount to sell can be also represented by the number of time slots. Essentially, the demand is the amount of energy the microgrid wants to buy from EVs. When the EV-side supply is not sufficiently available, the microgrid cannot but consume the expensive peak-rate electricity for the unmet demand. On the contrary, when there are more EVs than needed, the surplus electricity cannot be bought by the microgrid.

To avoid the search space expansion brought by the conventional exhaustive search, our unit scheduler iteratively identifies 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. While the exhaustive search should traverse the vast search space, this heuristic iterates at most for the number of time slots. Each time an EV is assigned to a time slot, its amount-to-sell decreases by one and also its availability interval will be modified. The availability interval will shrink as more slots are assigned to the EV, for the stay time is fixed. Here, an EV can be assigned to a single slot at most once, while a time slot can take as many EVs as it needs. This approach leads to the computation time linearly dependent on the number of EVs for the fixed number of slots. The procedure iterates until all slots are processed or no EV remains. According to the created trade schedule, which specifies when to connect or disconnect each EV, the amount of unmet demand can be estimated by scanning all time slots. For more detail, refer to [8].

4.0 GENETIC COORDINATOR

Figure 1 illustrates our V2G coordinator design combined with an example. In the figure, 10 EVs from V_0 to V_9 want to sell their electricity and each of them sends its request-to-sell message to the coordinator by the predefined time instant. The coordinator decides which one will be admitted to the final V2G trade schedule. The number of feasible subsets is2^{10}, and one of them will be selected. The investigation of all of them brings an intolerable response time even when the number of participating EVs increases just a little bit. Hence, It is practical to employ a genetic algorithm to complete within an acceptable execution time. The scheduling goal is to reduce the unmet demand and the object function calculates it. The smaller the unmet demand, the higher will be the fitness.

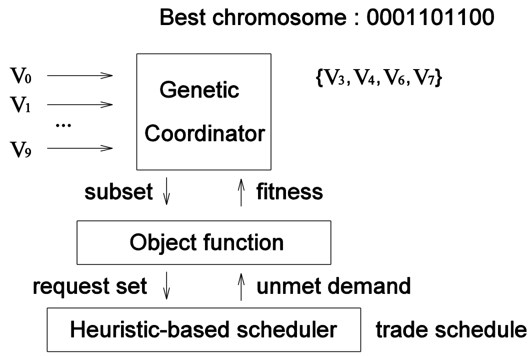


Figure 1 Overall architecture of the proposed V2G trader coordinator

To run a genetic algorithm, a subset of EVs is represented by an integer-valued vector. Here, the vector element at location *i* is bound to V_i and has either 0 or 1 according to whether the associated EV is included in the subset. The length of the vector is equal to the number of EVs participating in the trade procedure, namely, 10. As an example, a subset {V_0, V_1, V_3}is represented by 1101000000. In genetic iterations, each chromosome is evaluated. According to the vector, the subset of requests-to-sell is built and handed to the unit scheduler described in the previous subsection. It creates a trade schedule of the subset and calculates unsatisfied demand as well as the surplus electricity by inspecting the schedule table. Its linear execution time allows the genetic coordinator to call it each time a new chromosome is created, specifically, at the initialization of population or the reproduction of chromosomes .In this example, the chromosome of 0001101100,which represents the subset {V_3, V_4, V_6, V_7} is chosen as the final solution. Its trade schedule is already calculated and saved for the next day V2G operation.

In our implementation, the initial population consists of chromosomes created according to the random number generation. Each vector element has 0 or 1. For each chromosome, a new variable is added to store the cost or fitness derived from the insufficiency and to avoid redundant calculation. The iteration of regular genetic algorithms includes selection and reproduction. The selection operation picks parents according to the fitness value. The roulette wheel selection gives more chances to chromosomes having better fitness values for mating. Reproduction, or crossover, is the process of taking two parents and producing a child with the hope that the child will be a better solution [10]. Our implementation randomly selects a pair of two crossover points and swaps the substrings from each parent. Reproduction may generate the same chromosome as the already existing ones in the population. It meaninglessly reduces diversity to have multiple instances of a single chromosome. So, they will be replaced by new random ones. Additionally, mutation exchanges two elements within a single chromosome. As such, our genetic iteration largely takes the conventional parameter selection.

5.0 PERFORMANCE MEASUREMENT

This section evaluates the performance of the proposed scheme by means of a prototype implementation, mainly comparing with a random selection scheme, which generates the sufficiently large number of arbitrary subsets and picks the best one. Even though this scheme takes no intelligent control mechanism, its performance is not so poor and it gives us a good reference for performance comparison. Each version runs on the average-performance PC equipped with 2.5 GHz Intel(R) Core(TM) i5-3210 CPU and 8.0 GB memory. The main performance metric is the amount of unmet demand, which is denoted by insufficiency. The experiment measures insufficiency according to the change in the number of EVs, demand density, and population size. Here, the amount of electricity the microgrid needs exponentially distributes with the average value specified by demand density. In each experiment, one parameter is changed while the others are fixed to their respective default values. By default, the number of EVs, demand density, and population size have 30, 3.0, and60, respectively.

In each parameter setting, 10 experiment sets are generated and the results are averaged. Besides basic performance parameter setting, the number of genetic iterations is set to 500.In our observation, the fitness hardly gets improved beyond this point. In the experiment, the number of slots is fixed to14, hence, the scheduling window will be 7 hours if a single time slot is 0.5 hours long. We think that 7 hours is enough to cover the usual peak-time duration. Actually, if the number of slots in the scheduling window increases with a finer time slot, the search space size may get too much expanded, especially when the number of EVs increases. For R_i, the values of E_i, L_i, A_i, and D_i are selected randomly within 14 slots, with straightforward restrictions that L_i is larger than E_i and that D_i is larger than A_i. The unit amount coincides with the amount that can flow from an EV to the microgrid obeying the standard connection specification in a single time slot. In the case of regular AC chargers, the actual value will be approximated to 1.5 *kwh*.

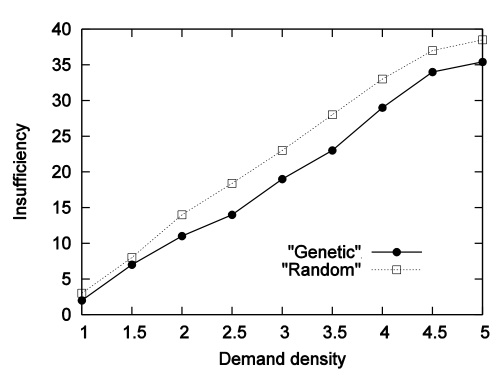


Figure 2 Insufficiency according to the number of tasks

Figure 2 plots the insufficiency observed changing the number of EVs from 5 to 50. As more EVs participate in trade scheduling, the amount of energy available to the microgrid increases. Both schemes reduce the insufficiency by 16 % and28.4 % with 50 EVs, respectively, compared with their own 5-EV cases. The performance gap between the two reaches 20.8% in the case of 25 EVs. With a large number of EVs, not all electricity can be bought and the large amount of unsold electricity, is yielded. However, there are more candidates to sell their electricity and the insufficiency can be reduced, benefiting from an intelligent computer algorithm. In addition, the search space also expands along with the increase in the number of EVs. So, it is difficult to find an efficient schedule out of vast solution space. Hence, the random scheme shows rather an instable behavior, its performance seeming more affected by the task set characteristics. This result indicates that the genetic scheme consistently finds a reasonable quality solution even in the case of an overload condition, in which many sales requests are concentrated on a single microgrid.

Next, Figure 3 shows the effect of demand density to the insufficiency. The experiment changes demand density from1.0 to 5.0, namely, from 1.5 *kwh* to 7.5 *kwh*. Here, the amount of energy a slot needs from EVs is converted to the number of EVs. Basically, the more the microgrid wants, the more the insufficiency will be, as the available supply from EV sis fixed. In both schemes, the insufficiency increases almost linearly to demand density. The maximum performance gap between them is 5 slots when demand density is 3.5. The linear behavior indicates that each scheme can hardly increase the amount of energy trade as most additional energy remains unsold beyond a certain point, actually, 2.0. However, the genetic scheme enhances the trade performance especially during the interval from 2.5 to 4.0, finding more EVs that can be admitted to the final schedule.

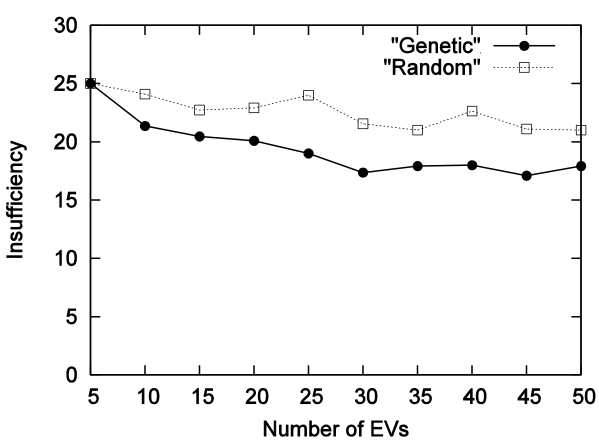


Figure 3 Insufficiency according to per-slot demand

Figure 4 shows the measurement result on the effect of population size. Large population accommodates more chromosomes, improving the diversity in mating two chromosomes. However, the execution time will get much longer as each genetic loop essentially includes selection and thus sorting steps. Figure 4 indicates that the trade performance largely gets better according to the increase in population size. When population size grows from 20 to 100, insufficiency decreases by 20 %. Beyond this point, the improvement is not so significant. We can set the population size in this range when the number of tasks is less than 30. Definitely, population size is a tunable parameter and can be adjusted according to the system requirement on response time and accuracy. Even in the case that population size is 100, the execution completes within 0.3 *sec*, guaranteeing a reasonable response time to EVs.

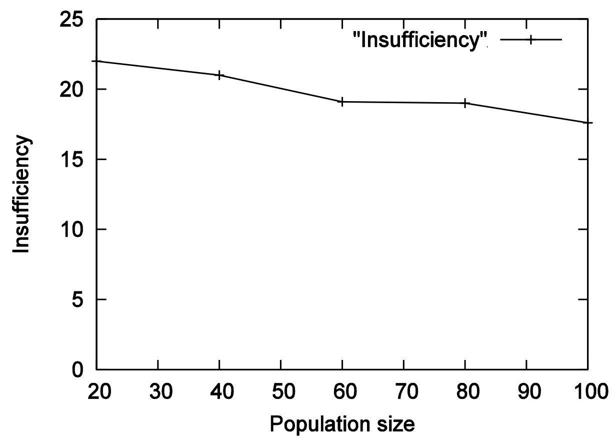


Figure 4 Insufficiency according to the population size

Figure 5 measures the number of EVs invited in the trade schedule. From the commercial microgrid aspect, it is more desirable to host more EVs, as they are potential customers, irrespective of the amount of electricity each EV can sell. The experiment changes the number of EVs submitting their requests-to-sell from 5 to 50. Until 10 EVs, all requesters are admitted. On the contrary, from 15 EVs, all EVs cannot be admitted. Here again, the random scheme shows rather unpredictable behavior while the genetic scheme curve changes quite slowly. The genetic scheme does not outperform its counterpart only on 2 cases, namely, for 30 and 45 EVs. The maximum enhancement from the random scheme reaches 28.5% when there are 35 EVs. The figure also indicates that the number of invited EVs does not exceed 12 even when totally50 EVs want to sell their electricity. That is, EV admission is limited by the total demand from the microgrid.

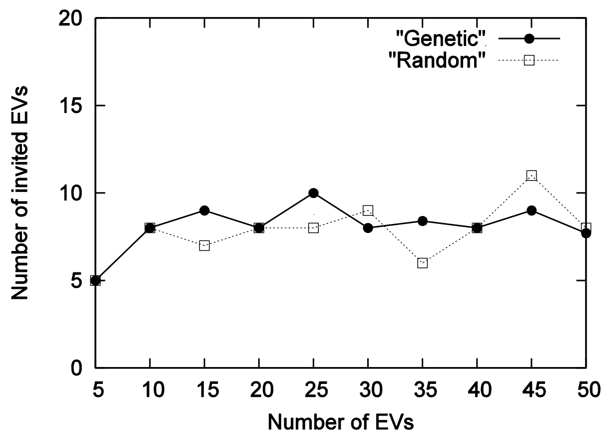


Figure 5 Experiment result on the number of invited EVs

Finally, Figure 6 plots the amount of electricity an EV can sell. From the EV side, it is better to sell more energy. The per-EV sales amount depends on the number of invited EVs and the total amount of sold electricity. For 5 EVs in our experiment setting, every electricity can be purchased and every EV is invited by both two schemes. In the case of 10EVs, the coordinator invites every EV, but does not buy the whole electricity. The genetic scheme, while inviting more EVs as shown in Figure 6, also allows an EV to sell more electricity. It outperforms the random scheme only except the cases of 15 and 35 EVs. The performance gap reaches33.7 % for 45 EVs. The genetic scheme shows about 20 %improvement in most points. Here, it must be mentioned that there exist cases in which the random scheme shows a better result. This is because we make the genetic algorithm take only the insufficiency in evaluating the fitness of a feasible solution. In addition, a sophisticated initialization of the population may lead to a better result.

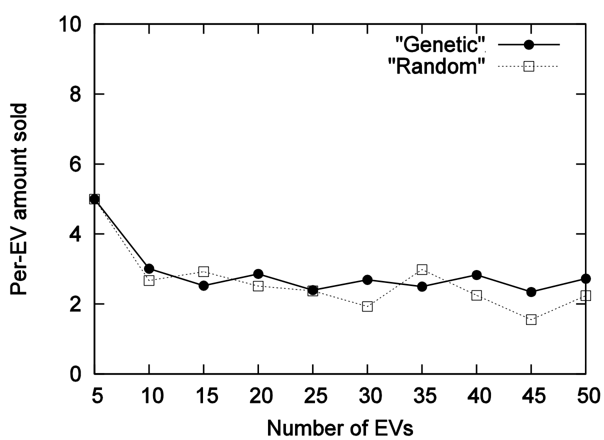


Figure 6 Measurement of the per-EV sales amount

6.0 CONCLUSIONS

In this paper, we have designed a V2G electricity trade coordinator between EVs and a microgrid to deal with a large number of EVs participating in the V2G trade. Agenetic algorithm is tailored to find a subset of EVs, mainly aiming at reducing insufficiency on the microgrid side. Here, the evaluation process has employed a heuristic-based unit scheduler whose execution time is just linear to the number of EVs in the trade process. The lightweight evaluation function, which also creates the on-off schedule for EV connections, leads to a reasonable response time, even in the large number of solutions to investigate. This admission test gives a chance for those EVs not admitted in the trade to contact with other microgrids. Its performance is measured via a prototype implementation, focusing on the insufficiency according to the number of tasks, demand density, and population size. The proposed scheme can efficiently work even in overload conditions, showing stable performance curves as well as achieving up to 20.8 % performance improvement.

As future work, we are planning to conduct an extensive analysis for data streams created from EVs and charging stations [18]. Particularly, an energy consumption model and the EV trip statistics will be exploited for V2G trade planning in a smart grid city. Specifically, our research team is now building a data processing framework consisting of Hadoop and R statistical packages, combined with geographic utilities.

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