

# Integrated Coordination of Electric Vehicle Operations and Renewable Energy Generation in a Microgrid

Junghoon Lee, Gyung-Leen Park

Dept. of Computer Science and Statistics, Jeju National University, 63243 Jejudaehakno 102, Jeju City, Republic of Korea

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## ABSTRACT

This paper designs a microgrid energy controller capable of creating a charging or discharging schedule for electric vehicles (EVs), aiming at leveraging the integration of renewable energy and shaving the peak load in the microgrid. Dynamically activated on each time slot to cope with the prediction error for the power consumption and the renewable energy generation, the controller calculates the number of EVs to charge or make discharge first. Then, a greedy algorithm-based scheduler selects EVs according to the expected energy potential during their stays. The potential is the integral of a supply-demand margin function from the current time to the expected departure time. A simulator is implemented for performance evaluation, comparing with uncoordinated scheduling, according to the number of EVs as well as the behavior of energy load and production. The experiment result shows that the proposed scheme can reduce the energy waste by 16.9 %, cut down the microgrid-level energy insufficiency by 12.2 %, and enhance the amount of electricity supplied to EVs by 37.3%, respectively, for given parameter setting.

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## Corresponding Author:

Junghoon Lee,

Jeju National University,

+82-64-754-3594, 63243 Jejudaehakno 102, Jeju City, Republic of Korea.

Email: [jhlee@jejunu.ac.kr](mailto:jhlee@jejunu.ac.kr)

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## 1. INTRODUCTION

Electric vehicles, or EVs in short, are a new type of vehicles, just consisting of motors and battery devices, as contrast to internal combustion engine vehicles stuffed with complex power generation machineries. The penetration of EVs brings a lot of environmental benefits such as pollution reduction, greenhouse gas cut-down, and noise minimization. Besides, they make the transport as a part of a power network, as EV batteries are charged basically by the electricity from the main grid, specifically, nuclear or thermal power plants. Nowadays, modern power systems, called the smart grid, are pursuing energy efficiency in power generation, transmission, and consumption, by integrating information and communication technologies [1]. Its main supporters are data communication channels and intelligent computer algorithms. EVs are considered one of the key components in the smart grid, as their digital nature provides a real-time interaction with other entities and makes it possible to co-work with a sophisticated control mechanism [2].

While the charging load imposes a significant burden on the power system, EV batteries can be used as spinning reserve for better frequency control [3]. That is, EVs provide massive capacity batteries when they are not moving and plugged-in to the grid. Moreover, the V2G (Vehicle-to-Grid) service can shave the peak load in energy consumption and distributes over the whole day. It allows us to avoid constructing a new power plant, achieving economic and environmental advantages. In addition, the energy storage has the potential of coping with the intermittency of renewable energy sources, as EVs can be charged even if the

energy supply is temporarily suspended and resumed. Hence, it can further reduce the nuclear and thermal energy generation, incorporating more solar or wind energies into our power system [4]. After all, the orchestration of the grid management, EV operations, and renewable energy generation is very important in modern energy networks. However, their control is essentially hard to design and apply to the real environment in practice.

The complexity of incorporated control for such heterogeneous grid entities mainly comes from the uncertainty of their behaviors [5]. Even though the complete prediction is available, the control mechanism must handle a lot of variables and thus suffers from severe time complexity [6]. This situation will get worse with the increase in the number of EVs to be managed. Practically, their coordination is executed in a microgrid level, not a system-wide grid level, due to hard-to-guarantee security reasons. A microgrid is an autonomous power system in buildings, shopping malls, university campuses, and the like [7]. It is typically made up of renewable energy generators, energy storage equipment, power connection to the main grid. Within a microgrid, the prediction of the future renewable energy amount and power consumption can be reasonably accurate [8]. EVs can be plugged-in to or disconnected from a microgrid according to their driving needs. While connected, they are part of the microgrid and under its coordination. From the microgrid's viewpoint, EVs are time-varying resources.

In this regard, this paper designs a coordination scheme for a microgrid having high renewable energy and EV penetration potential. This mechanism decides which EV to charge from renewable energy or discharge to the microgrid at each time slot. Here, the EV behavior, namely, when an EV arrives at or leaves the target microgrid, cannot be accurately predicted, thus the scheduler is invoked for each time slot to keep tracking of the currently appearing EVs. Our scheme will exploit a greedy algorithm approach taking into account the approximated probability an EV can acquire electricity from renewable energy generation during its stay time. The scheduling goal will be to avoid energy waste and better integration of renewable energy generation. It can be achieved by making EVs empty their batteries before the beginning of over production intervals as well as filling before insufficiency intervals, as much as possible [9].

The rest of the paper is organized as follows: After issuing the problem in Section 1, Section 2 reviews some related work. Section 3 describes the system model and designs the coordination scheme. Section 4 measures the performance of the proposed scheme via simulation and discusses the result. Finally, Section 5 concludes this paper with a brief introduction of future work.

## 2. RELATED WORK

Basically, the smart grid is an instance of a cyber-physical system in that a variety of entities keep generating a massive amount of monitoring records and appropriate timely reaction must be decided mainly by a sophisticated computer algorithm [10]. Its ideal control goal is to make power generation and consumption equal at all times [11]. However, in the real world, the goal is compromised to minimize the mismatch between them, overcoming unpredictable behaviors of grid entities. As an example of EV and renewable energy coordination, [12] proposes a control scheme which pursues the minimization of power imbalance within a microgrid. To make a charging and discharging schedule of EVs which may arrive at the grid early or late, this scheme employs a fuzzy approach, for the given bounded deviation on the arrival time estimation. They assume that the accurate prediction on power consumption and renewable energy generation is available.

In addition, [6] points out that the deregulation of power systems will bring new uncertainties, making their frequency control much more complex. This research designs an optimized fuzzy controller for the sake of deciding whether to charge or discharge batteries with respect to current grid frequency and battery SoC (State-of-Charge). It begins with the investigation of car availability during a day and assumes that a sufficient number of EVs are always plugged-in to the grid, while their arrival and departure time follows a normal distribution. In the controller, current frequency deviation is fuzzified into 7 levels from very low to very high. Battery SoC is also fuzzified into 5 linguistic variables. Next, whether to charge or discharge power is decided by the set of control rules. Besides, in determining the control action, [13] suggests SoC-based fairness. The fairness criteria claims that EVs having high SoC is selected for discharging but will be given precedence when it wants to be charged. Anyway, different coordination objectives are pursued on different assumptions especially in the EV behavior.

## 3. CONTROL MECHANISM

Figure 1 illustrates our system model. Basically, the microgrid gets electricity from the main grid according to the bi-party contract embracing price plans and power capacity provisioning. To the microgrid, EVs can be integrated by being plugged-in in parking lots. They are connected first to the on-off switch

control to be charged or discharge under the tight coordination of microgrid management agent. In addition, renewable energy generators, such as wind turbines or solar panels, are installed within the microgrid. The generated energy can be consumed by electric devices in the microgrid, possibly after being regulated in microgrid batteries, stored in the spinning reserve, or supplied to EVs. The data communication network, be it wired or wireless, makes it possible for the microgrid to interact with other information services such as power consumption prediction, weather forecast for renewable energy estimation, slot reservation requests from EVs. The control logic yields a switch control schedule along the time axis, which is divided by a series of fixed-size time slots.

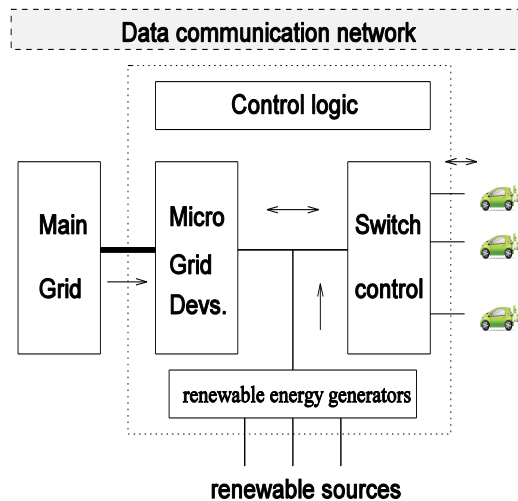


Figure 1. System model

The control application is executed just before the beginning of each time slot, so it takes only currently available EVs. The first scheduling goal is to reduce the waste of electricity excessively generated from the renewable energy sources due to their intermittent nature. To this end, it is important to make EV batteries empty when overproduction is anticipated. The second goal is to shave the peak consumption of electricity provided from the main grid. This can be achieved by filling EV batteries before the peak interval and making them discharge. We assume that the prediction mechanisms of acceptable accuracy for power load and renewable energy generation are available. A minor prediction can be adjusted by dynamically regenerating a control schedule slot by slot. The main focus lies in that when EV charging or discharging is scheduled in the future, the EVs must be connected to the microgrid. Hence, the scheduler must consider the time-dependent presence of respective EVs.

To begin with, the time axis is divided by fixed-size slots for manageable computation time. In spite of this setting, the schedule of respective EVs for a series of upcoming slots considering diverse factors will take quite a long time and it's hard to find an optimal solution for a given control goal. Here, each EV can be considered a real-time task [14]. Ultimately, the controller decides which EVs to charge when renewable energy is not consumed in the microgrid for the future use. On the contrary, during the interval of insufficient generation, the controller decides which EVs to make discharge. The difficulty lies in that an EV charged may leave the microgrid before the insufficiency interval. On the contrary, an EV may give electricity to the microgrid, but it cannot get it back. In this case, we assume that those EVs will be economically rewarded by cash or coupons for the sold electricity. It is essential for an EV to put a restriction on the minimal level and below this level no more injection is allowed.

The main idea of our scheduling scheme is depicted in Figure 2. According to the prediction on renewable energy generation and power consumption, we can estimate the supply-demand margin along the time axis. An EV may stay at the microgrid and its departure time can be estimated, even not completely accurate. When the margin is positive, that is, renewable energy exceeds the demand, the remaining amount is stored in EV batteries. Generally speaking, the electricity flow capacity through the regular power cable is 3 kWh. Hence, the number of EVs to select is decided by the total over production. If there is not sufficient number of EVs, the generated energy will be wasted. For EV selection, we order EVs by the expected charging potential. It is defined by the sum of margins during the staytime of an EV. Namely,

$$\int_c^d f(x)dx \quad (1)$$

where  $f(x)$  is the curve fitting function of the supply-demand margin. while  $c$  and  $d$  are the current time slot and the estimated departure time.

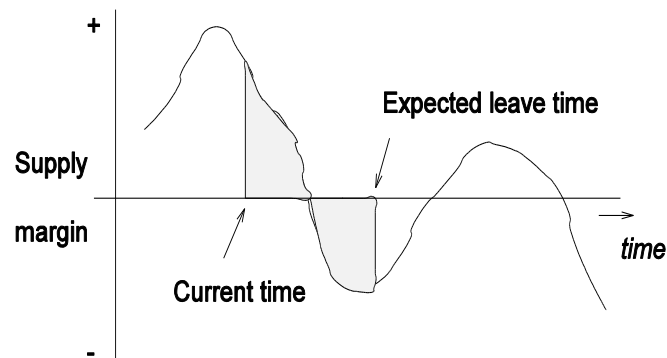


Figure 2. Selection criteria

An EV having negative potential will be also asked to discharge its electricity to the grid. Hence, it is advantageous to make them be charged as much as possible whenever a chance is given. At the beginning of a time slot having positive margin, the controller first decides the number of EVs to charge considering the amount of over production and the maximum flow amount through the power line and selects EVs to charge from the one having the least potential. If the number of EVs to charge is smaller than the number of chargeable EVs, the surplus energy will be wasted. Here, EVs already in their full charge will be removed. The operation on negative margin slots is just opposite to this. Those EVs having positive potential will be selected first. EVs reaching the minimum bound will be eliminated from the discharging list. If the energy insufficiency cannot be covered by EV-stored electricity, the microgrid cannot but purchase more electricity from the main grid.

#### 4. PERFORMANCE MEASUREMENT

This section measures the performance of the proposed control scheme via simulation discretely tracing the events. V2G is important during the period of intensive energy consumption, mainly daytime and work hours. Hence, the experiment assumes that the scheduler runs during 12 hours a day, while the time slot length is 15 minutes. A dailytime window consists of 48 slots. EVs arrive at the microgrid randomly from Slot 0 to Slot 44. The stay time distributes uniformly from 4 to 24 slots. The maximum battery storage is 18 *kwh*, while the SoC at the arrival time of an EV is 6 to 18 *kwh* [15]. At this stage, this experiment takes a virtual power consumption and renewable energy generation data. For each day, average daily supply-demand margin can be set to  $\alpha$  *kwh*, then its maximum and minimum values are  $\alpha-50$  to  $\alpha+50$  *kwh*. Each slot has a random value out of this range. The total power consumption in a microgrid can be much larger than this range. For each parameter setting, 50 sets are generated and the results are averaged.

The main performance metrics are wasted energy, EV-charged energy, and energy insufficiency, respectively. We compare the performance with an uncoordinated scheduler which randomly selects EVs to charge or make discharge. In the subsequent figures, this scheme is marked as *random* while ours as *proposed*, respectively. The two performance parameters are the number of EVs and the supply-demand margin. Actually, if the margin is too large or too small, the V2G schedule has little effect, as all of the energy can be either wasted or spent by the microgrid. The first experiment measures the effect of the number of EVs to the performance metrics and the results are shown from Figure 3 to Figure 5. The number of EVs is changed from 30 to 180, while the center of the margin is set to 0 *kwh*. According to Figure 3, when the number of EVs is smaller than 40, the amount of wasted energy is almost same, as all or no EVs are selected, showing the improvement of less than 3.1 %. Beyond this point, in spite of some fluctuation, the wasted energy is cut down by up to 16.9 %. The performance enhancement is essentially influenced by supply-demand margin dynamics.

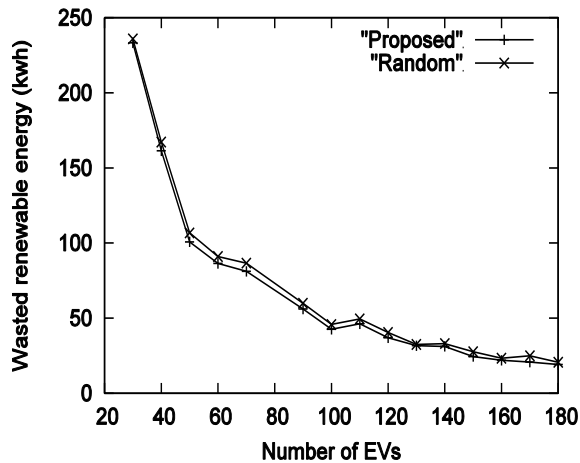


Figure 3. Wasted energy vs. number of EVs

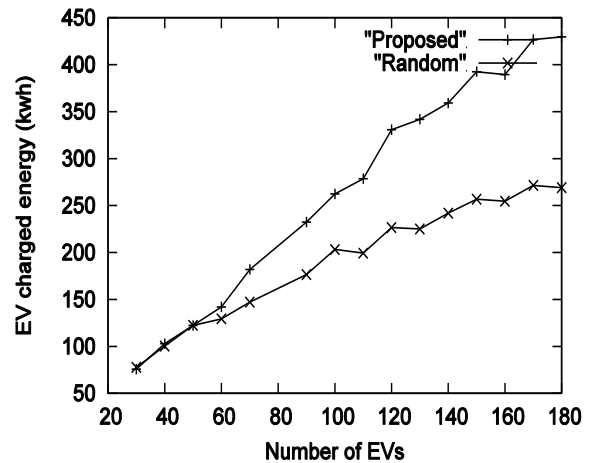


Figure 4. EV-charged energy vs. number of EVs

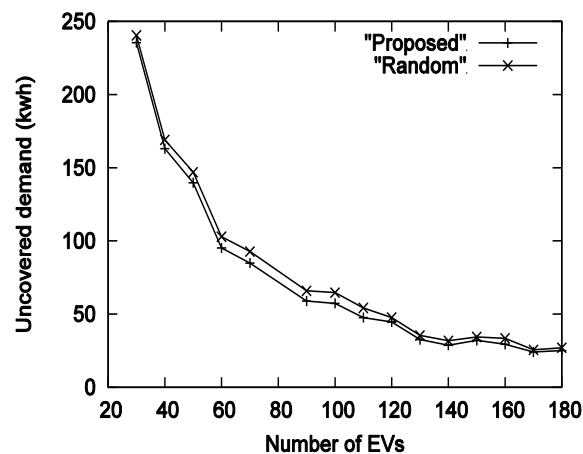


Figure 5. Insufficiency vs. number of EVs

Next, Figure 4 plots the amount of renewable energy used for EV charging. The experiment measures the SoC level difference at the arrival time and the departure time of an EV. With more EVs, more renewable energy can be absorbed by EVs. According to the figure, the performance gap gets larger along with the increase in the number of EVs, reaching 37.3 % in case of 180 EVs. Figure 5 shows the insufficiency in the microgrid. When there are smaller amount of energy obtainable from EVs, the microgrid must buy from the main grid. The price will be different by the time-of-use. The performance behavior looks similar to the case of Figure 3. The insufficiency is reduced by from 2.0 to 12.2 %. This result indicates that EVs charged with renewable energy leave before the stored electricity can be used. Actually, the EV-stored energy can be exploited below the supply-demand margin, due to the constant consumption in the microgrid.

The second experiment measures the effect of the supply-demand margin to the performance metrics and the results are shown from Figure 6 to Figure 8. In these figures, the x-axis is the average supply-demand margin, while the distribution range is fixed to 100 kWh. For example, if the x-axis value is -10, the supply-demand margin ranges from -60 to 40 kWh. Here, the number of EVs is set to 100. Figure 6 shows that the energy waste cannot be avoided. However, our scheme can reduce it by up to 25.1 % when the margin is 100 kWh. Next, Figure 7 plots the EV-charged amount when the center of the margin ranges from -30 to 30 kWh. According to the experiment result, the proposed scheme can more efficiently charge EVs compared with the uncoordinated selection scheme by up to 33.2 % when the demand is slightly more than the supply. Finally, Figure 8 shows the energy insufficiency for the given parameter set. Here again, the proposed scheme reduced the insufficiency over the uncoordinated scheme maximally, namely, by 24.2 %, when the margin center is -10.0 kWh.

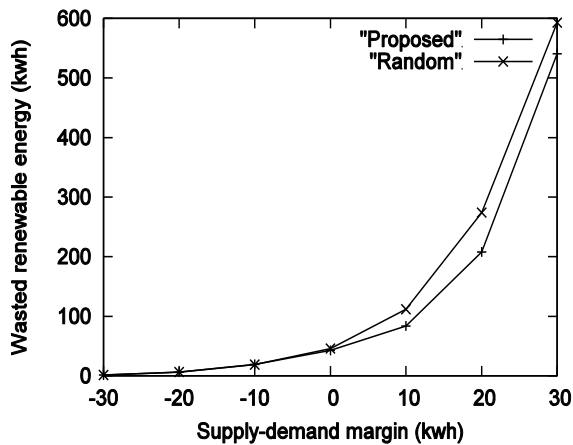


Figure 6. Wasted energy vs microgrid load

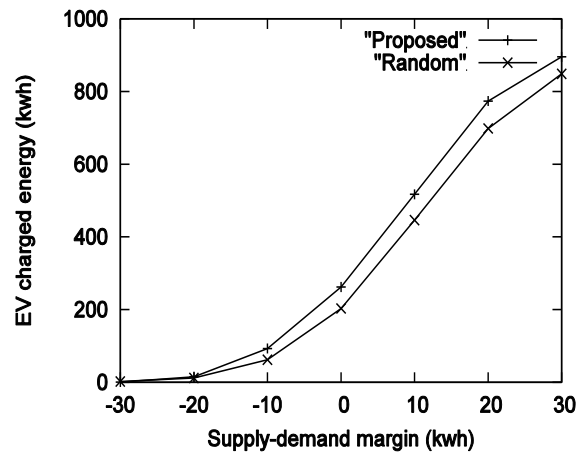


Figure 7. EV-charged energy vs microgrid load

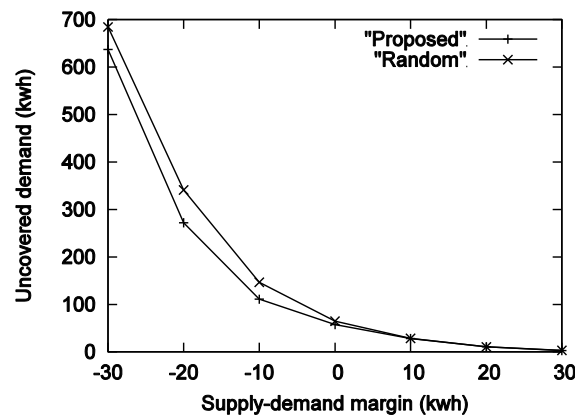


Figure 8. Insufficiency vs. microgrid load

## 5. CONCLUDING REMARKS

In this paper, we have designed a microgrid energy controller which creates an EV charging or discharging schedule. The scheduling goal is to absorb the overproduced electricity from intermittent renewable energy sources for EV charging as well as to shave the peak load in a microgrid. For the sake of minimizing the effect of misprediction for the power consumption and the renewable energy generation, the scheduler is executed just before the beginning of each slot. It first calculates the number of EVs to charge or make discharge based on the power line capacity as well as the amount of over production or power lack in the upcoming slot. Then, EVs of that number are selected according to the energy potential, which denotes the expected availability or insufficiency an EV will experience during its stay time. A simulation study shows that the proposed scheme can reduce the energy waste by 16.9 %, and enhances the amount of energy supplied to EVs by 37.3 %, compared with the uncoordinated scheduling scheme. Particularly, it cuts down the microgrid-level energy insufficiency, which leads to the additional energy purchase from the main grid, by 12.2 %.

As future work, we will model the behavior of the supply-demand margin in an actual microgrid. To this end, power consumption records are acquired from the utility company and its model is being developed, tested, and adjusted. In addition, our target microgrid installs some solar energy generators, whose operation logs are also available. Now, the analysis process evaluates the correlation between the amount of energy generation and a set of climate parameters. It is also considered to estimate the SoC level for an EV based on the route it has taken to make a more efficient schedule of EV operations. In upgrading the scheduling algorithm, the time-dependent fluctuation between the overproduction and power lack will be integrated to select the EVs to charge or make discharge. A slot assignment may regulate the priority in the subsequent slots for a compensation purpose. Such requirements will be integrated in our microgrid energy controller.

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