Distributing Power to Electric Vehicles on a Smart Grid

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***Abstract*—Electric vehicles create a demand for additional electrical power. As the popularity of electric vehicles increases, the demand for more power can increase more rapidly than our ability to install additional generating capacity. In the long term we expect that the supply and demand will become balanced. However, in the interim the rate at which electric vehicles can be deployed will depend on our ability to charge these vehicles in a timely manner. In this paper, we investigate fairness mechanisms to distribute power to electric vehicles on a smart grid.**

We simulate the mechanisms using published data on the current demand for electric power as a function of time of day, current driving habits for commuting, and the current rates at which electric vehicles can be charged on standard home outlets. In the simulations we assume that there is sufficient excess power, over the current demand to charge all the electric vehicles, but that there is not sufficient power to charge all the vehicles simultaneously during their peak demand. We use information collected on the smart grid to select which vehicles to charge during time intervals. The selection mechanisms are evaluated based upon the fraction of the vehicles that are forced to leave late in order to acquire sufficient charge, and the average time that those vehicles are delayed. We also compare the techniques with conventional pricing mechanisms that shift demand by charging less during off peak hours.

We have found that simple strategies that only use measurements on battery levels and arrival times to select the vehicles that will be charged may delay a significant fraction of the vehicles by more than two hours when the excess capacity available for charging vehicles exceeds their requirements by as much as a factor of three. However, when we can use reliable information on departure times and driving distances for the electric vehicles, we can reduce the delays to a few minutes when the capacity available for charging exceeds their requirements by as little as 5%.

Keywords-Fair Allocation, Min-max Fairness, Electric Vehicles, Smart Grid

I. INTRODUCTION

An emphasis on green technologies and the price of gasoline is causing the number of electric vehicles to increase rapidly. However, the time to approve and construct new generating facilities is considerable. Therefore, it is likely that there will be times when the generating capacity will not be sufficient to meet the power demand created by electric vehicles. To allow the use of electric vehicles to increase as rapidly as possible, it's necessary to find techniques to manage electric vehicle charging so that their owners are not inconvenienced.

An important difference between charging electrical vehicles and operating other appliances is that the demand need not be serviced immediately. The vehicle is likely to be plugged in for a longer period of time than it takes to recharge the battery. At present, there are several proposals to shift power consumption from peak hours by charging less for power during non-peak hours [1][5]. However, this strategy depends on a customer's financial status rather than their requirements, and reduces the usefulness of electric vehicles for a large portion of the population. In addition, if most of the vehicles are on timers to take advantage of the price at a certain time, the generating capacity will not be fully utilized during the times when power is more costly. An example is shown in Section IV, A.

In this paper, we investigate using fairness mechanisms that have been used in communication networks [6] to allocate power to electric vehicles. We simulate a system that uses the fairness mechanisms and test the system using real world data.

The power company has a limit on the number of electric vehicles that can be charged simultaneously by using the power that is not currently being used for other appliances. When the number of vehicles that request charging exceeds the limit, the power company does not increase the number of vehicles that receive power. The power is distributed to specific vehicles by operating an on/off switch associated with the vehicle's charging station. Time is divided into five minute intervals, and during each interval the power company selects the subset of the vehicles that will receive charge. This strategy is straightforward to implement and should operate with any battery charging system that can be plugged into a standard outlet.

Our objective is to compare rules that the power company may use to select the charging stations that are actuated during specific five minute intervals. The first two rules are a round robin (RR) technique that cycles through the list of vehicles requesting charge, so that all of the vehicles receive the same amount of charge, and a first come first serve (FCFS) rule that charges the vehicles in the order that they arrive. These rules use information that the power company can measure directly. The results of simulating these rules with actual power and commuting data are shown in Section IV, C. Even when the power network has three times as much excess power as the vehicles require, some vehicles will be delayed by more than 100 minutes beyond their required departure time. If users need their vehicles to commute to work, these delays will not be acceptable.

To improve the usefulness of electric vehicles, we investigate charging rules that measure the power levels in the vehicle batteries, and information of expected departure times and commuting distances that are supplied by the users. The battery levels of all of the vehicles are used to minimize the maximum power required by any vehicle by charging the vehicles with the lowest battery level first. This technique is also combined with user supplied expected driving distances to charge the vehicles that require the most energy to reach their destinations first. This technique is referred to as min-max Energy Requirement (MinmaxER). We find that this technique does not work as well as RR or FCFS because the vehicles that arrive later and require the most energy start charging before completing the charging of vehicles that have been charging for a longer time and are nearly fully charged. As a result, many more vehicles are delayed for long periods of time.

In the final allocation rule we use both the expected driving distance and required departure time, supplied by the user, and minimize the maximum delay that will be experienced by any user. We refer to this rule as min-max Delay Time (MinmaxDT). By this rule, none of the vehicles will be delayed by more than a few minutes, even when the total power available to charge electric vehicles barely exceeds their requirements. MinmaxDT will make electric vehicles more useful and allow them to be deployed more quickly than the alternatives.

The problem with MinmaxDT is that it depends on users being truthful. Users may ask for an earlier departure time than they need to make it less likely that they will be delayed when they would really like to leave. They may exaggerate their expected driving distances to guarantee that they have a surplus of energy for side trips. If this technique is adopted, we must also develop penalty or pricing methods to encourage drivers to be truthful. For instance, the power company may compare predicted departure times and driving distances with actual values and add a penalty time to the drivers expected departure time on future charging episodes. Alternatively, the power company may charge more when drivers request quicker charging for an earlier departure or a longer driving distance. This paper will not investigate the mechanisms that may be used to encourage drivers to be truthful.

The above charging rules are evaluated based upon the fraction of the vehicles that are forced to leave late in order to receive sufficient charging and the average time that those vehicles are delayed. We have a number of simulation results generated by using data collected from the real world.

The main conclusions we found in this paper are as follows:

1) The pricing strategy may not fully utilize the generating capacity during the times that power is more costly (see in Section IV, A).
2) With insufficient information simple attempts at fairness don't work as well as FCFS and RR; especially, the proposed MinmaxER may delay a significant fraction of the vehicles by more than two hours when the excess capacity available for charging vehicles exceeds their requirements by a factor of three.
3) Fairness mechanisms work best when they can get reliable information on departure times and driving distances; especially, the proposed MinmaxDT scheme needs only 5% more than the power demanded to ensure all the vehicles departing with delay in a few minutes.
4) The proposed MinmaxDT scheme is not sensitive to the distribution of plugged-in time, the number of total arrivals per day and the charging rate.
5) Higher charging rate decreases the number of electric vehicles that are impossible to complete charging before users' expected departure time (see in Section IV, B).
6) Increasing charging rate helps to enhance the performance of all schemes we investigated except our proposed MinmaxDT scheme. Therefore, effective fairness schemes play a more crucial role under a relative low charging rate than under a relatively higher charging rate.

The rest of this paper is organized as follows: real world data used in our system and the basic fairness schemes will be presented in section II. In section III, we first formulate the problem of the electric vehicles charging on a smart grid, and then present two fairness mechanisms, which are MinmaxER and MinmaxDT. In section IV we compare the fairness mechanisms with conventional pricing mechanisms and evaluate different fairness mechanisms in our model by using real world data. We conclude the paper in section V.

II. Real World Data and Basic Fairness Schemes

In this section, we introduce real world data that are used in the system and demonstrate the basic fairness schemes.

A. *Real world data*

We use real world data to build our system. We assume that the arrivals of vehicles for charging follows a Poisson distribution and the arrival rate λ changes as a function of time of day. We also assume most vehicles arrive during the early evening hours. In 2009's American Community Survey Reports [2], we collected the distribution for the number of workers leaving home to go to work as a function of time. We shifted the time axis by 10 hours, *i.e.*, 8 a.m. corresponds to 6 p.m., to get the distribution for the arrival. Note that the total number of vehicles is scaled to around 3,000 in our system. This is appropriate for a medium-sized city based on President Obama's goal of putting one million electric vehicles on the road of U.S by 2015 when it is assumed that there are 80 large-size cities with 5000 electric vehicles each and 200 medium-sized cities with 3000 electric vehicles each. We also assume the plug-in time, which is also the time available for charging, satisfies Normal distribution. The reason we use Normal distribution is we regard the desired plug-in time of each vehicle as an independent and identically distributed event. Based on the average working hours of 8, the mean for the distribution is set as 14 hours and the standard deviation is 4 hours. Any generated plug-in time which is less than 6 hours or more than 22 hours (for a probability of 4.55%) is truncated. The desired departure time for each vehicle could be obtained by the arrival time plus the plug-in time.

We assume that all vehicles are charging at home. The electric vehicles are plugged into a 120 volt, 15 amp circuit, the electrical vehicles, such as Nissan LEAF, FORD 2012 Focus Electric, BMW Mini E, THINK City, Mitsuibishi iMeiv and SMART. Then we set the battery to be charged fully as 28kwh and the range for a fully charged battery as 100 miles, which requires 186.7 units of 5-minute interval charging.

The commuting distances are generated based on Omnibus Household Survey [3] by US Department of Transportation. They surveyed how many miles one-way people travel from home to work on a typical day. We doubled their figures for a round-trip consideration and fitted it to Exponential distribution with λ for 1. The generated data which is more than 70 miles are truncated. This is because we consider extra 20 miles for other purposes excluding working and 10 miles for emergencies. Vehicles are supposed to arrive with battery levels uniformly distributed from 0% to 30%. The minimum energy required for charging is then obtained by the expected energy minus the current energy.

The power available for charging (*TPA*) during a day is the amount of power supplied minus the power consumption which is based on available statistics [4]. It's assumed that the power supplied by power companies remains constant for each day, but will be set to different value according to the supply and demand ratio (*SDR*) we pick. *SDR* is defined as follow.

$$SDR = TPA / TPD \tag{1}$$

where *TPA* denotes the total power available for charging electric vehicles and *TPD* denotes the total power demand for charging electric vehicles.

B. Basic Fairness Schemes

The intuition for fairly charging electric vehicles is giving every vehicle the same amount of energy. Thus, we develop the Round Rabin (RR) fairness as a basic fairness scheme. It charges every vehicle by round without considering the battery and the driving information.

The RR operates as follows.

```
do every 5-minute interval{
update the list of the plug-in vehicles,
calculate the number of vehicles that could be charged during this time interval, record it as m,
charge m EVs in the list by an ascending order and update the status of charged EVs,
move the charged EVs to the end of the list,
remove the EVs that complete charging,
add the new arrivals during this time interval to the end of the list}
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Similarly, we develop the First Come First Serve (FCFS) system and First Depart First Serve (FDFS) systems. We regard the FCFS system as the baseline system.

III. Fairness Mechanisms

In this section, we first formulate the problem that fairly apportioning the power available for the charging of plug-in electric vehicles on a smart grid. Then, we introduce two fairness mechanisms, *i.e.*, Min-Max Energy Requirement fairness (MinmaxER) and Min-Max Delay Time fairness (MinmaxDT).

A. Problem Formulation

The problem that fairly apportions the power available for the charging of plug-in electric vehicles on a smart grid could be regarded as a resource allocation problem [7]. Generally, our resource is the power available and our task is to complete the charging for expected driving distance before the expected departure time. Compared with the classic resource allocation problem, there are two key differences for our problem. Firstly, our task is time dependent; the fairness mechanisms are not only evaluated by the number of completed task but also whether the task is completed by the deadline. Second, the power available for charging is time varied. It is hard to make exact schedules for the tasks.

Note that when $SDR < 1$, no distribution mechanism is useful. When $SDR > 3$, all the distribution mechanisms work well. And when $1 \leq SDR \leq 3$, different distribution mechanisms perform significantly differently. We focus on looking for the mechanisms that perform well in this range.

To evaluate the proposed fairness mechanisms, we define two evaluation metrics, *i.e.*, fraction of delayed vehicles (*FOD*) and average delay for delayed vehicles (*ADFD*), as follows.

$$FOD = NOD / NOA \tag{2}$$

where *NOD* denotes number of delayed vehicles and *NOA* denotes number of arrived vehicles.

$$ADFD = \sum DT_i / NOD \tag{3}$$

where DT_i denotes delayed time for the *i*th vehicle.

B. Min-Max Energy Requirement

In min-max fairness we charge the vehicles that require the most energy first. That is, we minimize the maximum amount of energy required by any of the plugged-in vehicles.

We define the charging system as being MinmaxER fair if we cannot provide any vehicle more energy without decreasing the energy provided to a vehicle that requires more charging. This is similar to the max-min fairness in communication networks. The objective is to distribute energy as much as possible without exceeding user's expected power.

The metric for MinmaxER is defined as follows.

$$ER_1 = (ED/FR) \times BC - CR \tag{4}$$

$$ER_i = ER_{i-1} - UnitE \times CS_{i-1} \tag{5}$$

where *i* denotes the *i*th charging process, *ED* denotes the expected driving distance, *FR* denotes the range for a fully charged battery, *BC* denotes the capacity of a full battery, *CR* denotes the current energy for the battery, *UnitE* denotes the energy for 5-minute interval charging and *CS* denotes the charging status, 1 for charged, 0 for non-charged.

MinmaxER fairness charges the vehicle that has a larger value of *ER* first.

C. Min-Max Delay Time

If a vehicle does not have sufficient charging for its expected travel, it will be delayed until it has the required charge. Delay time is then defined as the difference between the completion time of charging and the expected departure time. In MinmaxDT, we try to minimize the maximum delay time. We define a system is MinmaxDT fair if we cannot shorten the delay time of a vehicle without increasing the delay time of other vehicles with longer delay time.

In order to realize the fairness, we want delayed vehicles to be charged first. However, by simply putting high priorities to delayed vehicles can't decrease the fraction of cars that are delayed. To address this problem, we propose a new metric Spare Time (*ST*) to minimize the maximum delay time by using the expected energy and expected departure time.

ST associated with each car is defined as follow.

$$ST_i = (Dt\text{-}Ct)/5 - N_{c,i} \quad (6)$$

$$N_{c,i} = N_{c,i-1} - 1 \times CS_{i-1} \quad (7)$$

where i denotes the ith charging process, Dt denotes the expected departure time, Ct is the current time and Nc is number of 5-minute intervals that a car must charge before it can leave. When a vehicle is not delayed, *ST* is positive and can be regarded as the spare time that is not used for charging. This mechanism is to minimize the maximum spare time in order to prevent the vehicle from finishing charging many hours before the desired departure time so that more time/energy can be saved for other vehicles. While a vehicle is delayed, *ST* will be negative. According to the formula (6)(7), the more a vehicle is delayed, the smaller is it's ST and the higher is it's priority.

IV. Evaluation

In this section, we first compare the fairness mechanisms with conventional pricing mechanisms and then evaluate different fairness mechanisms in our model by using real-world data. Our baseline system is the FCFS system and we assume that all the users are truthful.

A. Pricing Mechanisms Vs Fairness Mechanisms

Obviously, fairness mechanisms are trying to fully utilize the generating capacity. The pricing solutions, however, will not be pareto efficiency when there is not sufficient power for charging electric vehicles during the times when power is less costly. For example, assume that the generating capacity is just sufficient to meet the demand of the appliances other than electric vehicles, and that the power company encourages electric vehicles to recharge their batteries during non-peak hours by reducing the price for charging electric vehicles whenever the power being used by other appliances is less than 75% of the generating capacity. Then the power between the peak value and the power use curve below the 75% points is what is available for charging electric vehicles. This power is referrred to as the lower price for electric vehicles, *LPER*. The total energy that could be used for charging electric vehicles is defined as *TER*. We assume that few people would like to charge their electric vehicles at normal price, while most people would like to take advantage of lower charging rate. We also assume *TER* is 20% of the total power and *LPER* is 15% of the total power. In this case, we cannot charge all the electric vehicles at lower charging rate without increasing the available capacity if the electric vehicles require more than 15% of the total power. Nearly 5% of the total power which is priced at the normal rate during peak hours is not used by the electric vehicles and is hence wasted due to the pricing scheme. In additional, as we increase the rate of (electric vehicle power consumption)/(Other power consumption), the power wasted by pricing increases. What this shows is that when electric vehicles require a small fraction of the power being used, pricing mechanisms can encourage electric vehicle users to charge at non-peak hours, but that as electric vehicles become more popular, more power will be wasted by pricing.

B. Simulation Setup

The smart grid based electric vehicles charging management system is simulated in MATLAB R2011a with three changeable parameters: supply and demand ratio (*SDR*), number of days *(n)*, and total arrival vehicles per day (*N*). The essential purpose of the simulation is to compare the two types of fairness schemes proposed with the basic fairness systems and to find out how the information provided by the users could improve the performance of charging schemes in terms of two different metrics: the fraction of delayed vehicles and the average delay of delayed vehicles. Except for FCFS, Round Rabin (RR) and First Depart First Serve (FDFS), are also included in the real simulation. RR tries to give every vehicle the same priority for charging; FDFS gives higher priority to the cars that expect to depart earlier.

For each applied metric, *SDR* is ranging from 1 to 3 (increasing in steps of 0.05 from 1 to 1.1; increasing in steps of 0.2 from 1.2 to 2; increasing in steps of 1 from 2 to 3). *N* is around 3000 in the simulation. To obtain accurate simulation results, number of days, n is set to be 15. However, the measurements are not taken until the 4th day so that the initializations are accurate enough and insensitive to variations. In addition, the measurements end up on the (n-2)th day to ensure all electric vehicles have departed by the nth day.

Note there is a case that the cars request a lot of energy on their arrivals while their expected departure time is too early to complete charging process, even if they were always given the highest charging priority, the available energy for expected departure will be more than sufficient. However, when the charging rate increases, there will be fewer samples whose expected departure time is earlier than the time that it is charged for the highest priority. For example, when the circuits for being plugged into are a 110 volt, 15 amp circuit, the full charging for a 28kwh battery will cost 15.5 hours, and 5% can not possibly complete charging in time even the vehicles can charge continuously. If the circuits for being plugged into are a 220 volt, 30 amp circuit, only 3.9 hours are needed to fully charge the battery, and all vehicles can complete charging in time if they can charge continuously. Thus, higher charging rate decreases the number of electric vehicles that are impossible to complete charging before users' expected departure time.

Since we are interested in when insufficient power causes a vehicle to be delayed, we would like to remove the part of delay when evaluating our charging schemes. *ET* denotes the earliest time that the vehicle can leave if it charges continuously, *DT* is the declared time that driver would like to leave, *AT* being the actual departure time. Then, the Delay caused by Inadequate Power (*DIP*) is

$$DIP = AT - \max(ET, DT) \quad (8)$$

DIP separates the delay caused by power distribution from the delay caused by unreasonable driver expectations.

C. Results Analysis

The four important conclusions are as follows.

1. With insufficient information simple attempts at fairness don't work as well as FCFS and RR.

As is demonstrated in Figure 1 and Figure 2 that, when *SDR* ⩽1.6, MinmaxER fairness scheme has the largest fraction of delayed vehicles (over 50% cars are delayed when *SDR* <1.2) and the largest amount of average delay for delayed cars (over 3.5 hours when *SDR* <1.2), all of which are totally unacceptable in practice. The reason is that MinmaxER charges the cars that require most energy first. So after a period of time, these particular cars' requested energy become less and their charging priority become lower accordingly. Instead, the newly arrived cars obtain high priority for charging and prevent the cars that arrived earlier from completing their charging process. Figure 3 proves the above explanation to be reasonable by showing that a large fraction of cars that can depart in advance in the RR or FCFS system are delayed, though not much, by applying the MinmaxER fairness scheme. Moreover, the *ADFD* of applying MinmaxER increases a lot compared with the RR or FCFS system.

2. Fairness mechanisms work best when they can get reliable information on departure times and driving distances.

a) Using additional information (*i.e.*, departure time) greatly improves the performance of charging system. For FDFS and MinmaxDT charging schemes which take into account the information of departing time, we observe a general improvement on both metrics. In particular, as in Figure 1, FDFS and MinmaxDT ensure more than 90% cars departing without delay as long as *SDR* >1.1, compared with the FCFS system of the same performance which requires *SDR*⩾1.6. The goal of FDFS and MinmaxDT can account for the drop in the fraction of delayed vehicles. An interesting exception happens at *SDR* <1.05, where the fraction of delayed vehicles using MinmaxDT fairness scheme is much larger than that of the FCFS system. The problem is similar to MinmaxER which we have explained before.

Moreover, the average delay of delayed cars when employing the additional information (*i.e.*, departure time) drops down to a great extent in the FCFS system for the whole range of values for *SDR*. Typically, as in Figure 2, around 109.9 minutes delay of the delayed cars in FDFS and no delayed cars is observed for MinmaxDT at *SDR* =1.1, in comparison with 169.3 minutes delay for the FCFS system with the same *SDR*. This indicates a significant decrease by employing the additional departure time.

b) MinmaxDT fairness scheme achieves the best performance when the available energy barely exceeds the required energy; when there is very little extra power, MinmaxDT delays a large number of vehicles for a small amount of time, rather than a smaller number of vehicles a larger amount of time. Here we would like to compare FD and MinmaxDT, both of which take advantage of the information of departure time. It is shown in Figure 1 that MinmaxDT fairness scheme always performs better than FDFS charging scheme in terms of the fraction of delayed Electric vehicles when *SDR*⩾1.05. This is because MinmaxDT compromises between the advanced departure time and the delayed departure time. Put it in another way, for the cars that can depart many hours earlier than their expected using FDFS, MinmaxDT fairness scheme deliberately defers their departure to a later date. This can be seen clearly from Figure 3, which is the delay distribution of different schemes at *SDR* =1.2. Note that a negative delay occurs when a vehicle completes charging before the expected departure time. It could be regarded as a positive *ST* as we defined and explained in Section III, C.

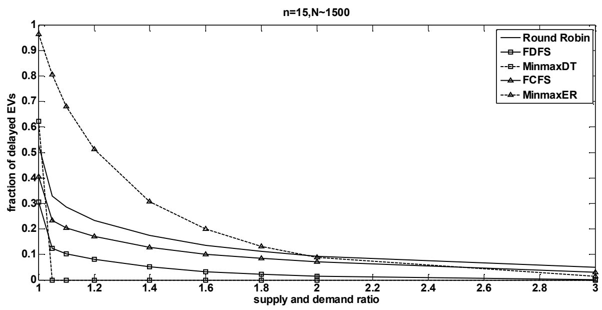

Figure 1. Fraction of delayed vehicles for different charging schemes

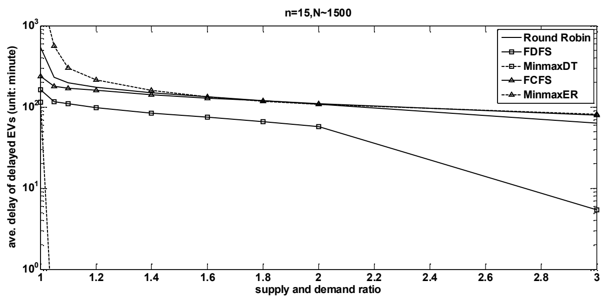

Figure 2. Average delay of delayed vehicles for different charging schemes

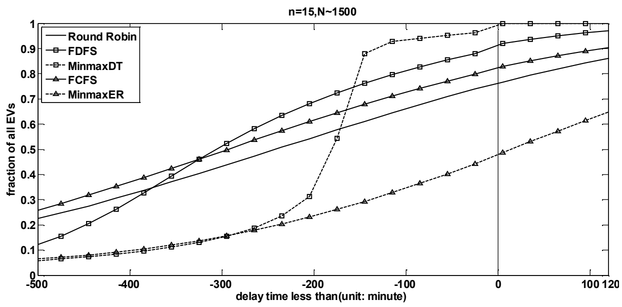

Figure 3. The delay distribution for five charging schemes

3. The proposed MinmaxDT scheme is not sensitive to the distribution of plugged-in time, the number of total arrivals per day and the charging rate.

a) MinmaxDT also works very well when we generalize the system model to uniformly distributed desired plugged-in time. Since the distribution of desired plugged-in time plays an important role in our project, we try the uniform distribution rather than normal distribution. The results shown in Figure 4 demonstrate that our proposed MinmaxDT fairness scheme still obtains the best performance when the available energy is 10% more than the required energy. The *ADFD* result is similar.

b) Increasing the number of total arrivals per day will not affect the performance of our proposed MinmaxDT fairness scheme. We compare our proposed MinmaxDT fairness scheme to other four charging schemes, Round Robin, FCFS, MinmaxER and FDFS by doubling total arrivals of electric

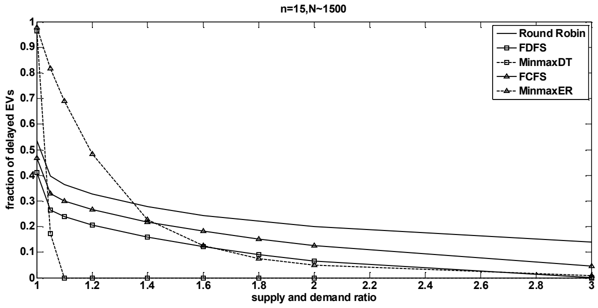

Figure 4. Fraction of delayed vehicles for a uniform plugged-in time

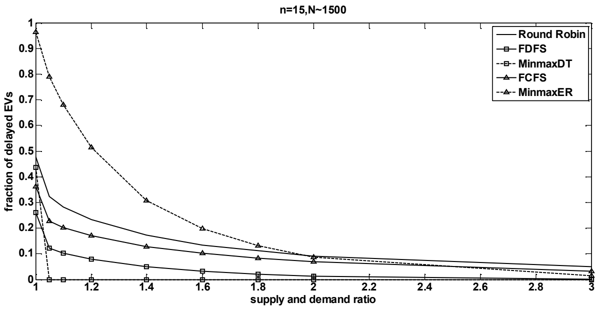

Figure 5. Fraction of delayed vehicles for doubled total arrivals

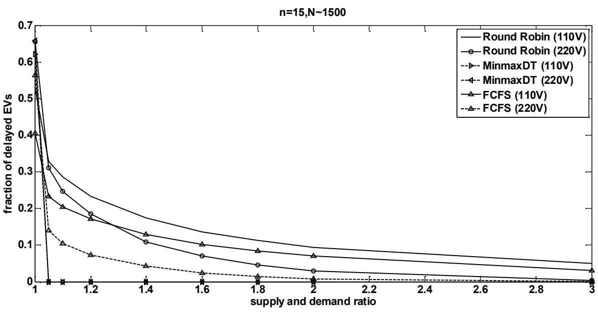

Figure 6. Fraction of delayed vehicles for two kinds of plugged-in circuits

vehicles per day. Figure 5 show the *FOD* result. The *ADFD* result is similar. It is found that all conclusions obtained previously could be directly applied here.

c) MinmaxDT is not sensitive to the charging rate and works well under a relative low charging rate (e.g., 110Vx15A). In order to quantify the impact of the charging rate on our results, we try the 220 volt, 30 amp circuit rather than the 110 volt, 15 amp circuit. The results shown in Figure 6 demonstrate that the MinmaxDT scheme is not sensitive to the charging rate. The ADFD result is similar. Based on these results, there is little differences between the performance for 220Vx30A and that for 110Vx15A. So MinmaxDT could work well under a relatively low charging rate. A higher charging rate doesn't benefit our system with MinmaxDT scheme.

4. Increasing charging rate helps to enhance the performance of all schemes we investigated except our proposed MinmaxDT scheme. Therefore, effective fairness schemes play a more crucial role under a relative low charging rate than under a relatively higher charging rate.

Figure 6 shows that, when the power available is the same, charging faster will decrease the delay time for all the fairness schemes to some extent except the MinmaxDT scheme. However, the MinmaxDT scheme performs almost the same when the charging rate decreases. Thus, well scheduled schemes are more important for improving the performance of fairness charging when there is a lower charging rate.

V. CONCLUSION

In this paper, we investigate different fairness mechanisms that have been used in communication networks to power allocation on a smart grid. We defined a range of fairness metrics that require different amounts of information and studied how the information provided by the users could improve the performance of charging schemes. From numbers of results, we have made several important conclusions. Defending against dishonest information (*e.g.*, desired departure time and expected driving distance) remains a challenging task and we will investigate it in future.

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