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Modeling Key Players of Highway EMS as MetaMAS™ Agents that Interact with Traffic and Power Simulators

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Abstract

With the spread of electric vehicles (EVs), it will be necessary to find an effective way of charging EVs on highways. Otherwise, the problem of many EV drivers trying to charge at the same time and at the same place may arise, with the result that the EV drivers may have to wait for hours before charging at a public EV charging station. Therefore, a highway energy management system (highway EMS) is required that controls EV charging. In order to evaluate EV charging strategies, a simulator is needed that can model how the highway EMS affects EV drivers' decision-making. Using a multi-agent simulator (MAS), individuals' decision-making and activities can be described. However, a traffic simulator and a power simulator are also required. In this paper, we focus on a new general-purpose meta-level multi-agent simulator, MetaMAS™. Unlike conventional MASs, MetaMAS™ can use several external domain-specific simulators. Our MetaMAS™ agents, such as EV driver agents, communicate with other agents and interact with traffic and power simulators. In other words, individuals (agents) connect different simulation worlds (traffic and power simulators) from the bottom up. The main contributions of this paper are the modeling of the key players of the highway EMS as MetaMAS™ agents and the evaluation of some strategies of the highway EMS: the digital signage strategy, the energy reduction strategy, the digital signage and energy reduction strategy, the power reduction strategy, and the energy and power reduction strategy. We evaluate these strategies from the viewpoints of "average waiting time for charging and queuing per charge" and "average waiting time for charging and queuing per unit of energy."

Keywords: *Multi-agent Simulation; Co-simulation; Integration of Traffic and Power Simulators; EV Charging Management; Highway EMS*

1. Introduction

With the spread of electric vehicles (EVs), various problems will arise. First, EVs cannot run for a long distance without charging the batteries at service areas (SAs) or parking areas (PAs). Second, it takes tens of minutes to charge EVs even if quick chargers (QCs) are available. Third, if many EV drivers try to charge at the same time at the same place, they might wait for hours before using QCs. Therefore, a highway EMS that controls EV charging is required.

There are many strategies to control EV charging. Ideally, it would be best if we could evaluate the strategies by means of social experiments. Unfortunately, it is difficult to conduct social experiments and collect enough real data at the moment since few EVs are

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currently running on highways and few QCs are deployed at SAs and PAs. Therefore, simulation is vital for doing research on future highway EMSs.

Highway EMSs control EV drivers' charging activities. In simulation, we also need to model how highway EMSs affect individual drivers. In MASs, autonomous agents sense the simulation environment, communicate with other agents, make their own decisions, and act on the simulation environment. Therefore, it is natural to use a MAS to evaluate the charging strategies of highway EMSs. Since the 1990s, there has been growing recognition of the value of MASs in the social sciences where the relationships between individuals' behaviors and social phenomena have to be analyzed [1, 2]. However, in addition to a MAS, two domain-specific simulators are needed: a traffic simulator to calculate when each EV arrives at an SA/PA and a power simulator to understand how the power usage changes. We use a new general-purpose meta-level multi-agent simulator, MetaMAS™, to integrate a traffic simulator and a power simulator. Unlike previous MASs, MetaMAS™ integrates domain-specific simulators through agents' activities. In this paper, we show how to model key players of the highway EMS as agents that communicate with the traffic and power simulators.

This paper evaluates five kinds of EV charging strategies of the highway EMS: the digital signage strategy, the energy reduction strategy, the digital signage and energy reduction strategy, the power reduction strategy, and the energy and power reduction strategy. In the digital signage strategy, we place digital signs just before the access road to each SA/PA, and inform the EV drivers of the numbers of EVs that are waiting for charging at the next three SA/PAs. In the energy reduction strategy, we reduce the maximum charging amount of EVs. In the digital signage and energy reduction strategy, we combine the digital signage strategy and the energy reduction strategy. In the power reduction strategy, the charging power of QCs at an SA/PA is reduced so that it will not exceed the contract power of the SA/PA. In the energy and power reduction strategy, we combine the energy reduction strategy and the power reduction strategy. Since these strategies are fundamental and important to shorten the waiting time of queuing EVs or to keep the power usage below the contract power, it is vital to evaluate the effects.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 explains simulation scenarios. Section 4 shows how to model MetaMAS™ agents. Section 5 explains domain-specific simulators: a traffic simulator and a power simulator. Section 6 shows simulation results. Section 7 is the conclusion.

2. Related Work

According to a review [3] of agent technologies in transportation, most agent-based applications focus on modeling and simulation, and multi-agent simulation is used to investigate traffic-related problems, such as route guidance, urban traffic management and control, collaborative driving, railway traffic control, combined rail/road transport, air traffic control, and the optimization of airport operation. And according to a survey [4] of agent-based modeling and simulation in transportation, agents are used to model decision-making underlying drivers' behaviors based on rule-based reasoning. It also points out that agent-based simulation is used to optimize distributed control systems for which cooperative agent techniques are important. In [5], the authors try to optimize the locations of public EV charging facilities on Awaji Island, Japan to reduce the number of EVs that run out of electricity. They use an agent-based traffic simulator to evaluate where and how many EVs run out of electricity. Unlike our simulator, the domain of these agent-based simulators is restricted to transportation.

In public EV charging facilities, it is important to cut the peak power usage to avoid instability of the power grid. Some scheduling or optimization techniques [6-9] are used to decide when and with how much energy each EV is charged. It is important to note that they analyze the simulation results from the viewpoint of power usage, and they do not consider the movement of EVs between charging stations along a highway.

There is a general-purpose simulator integration architecture called "high-level architecture (HLA)" defined under IEEE Standard 1516. In HLA, multiple simulators share common data (called a federation object) via run-time infrastructure (RTI). A tutorial on HLA is available in [10]. Unlike MetaMAS™, RTI itself is not a simulator.

3. Simulation Scenarios

We compare the effects of some highway EMS strategies by means of simulation. In our simulations, vehicles run one-way on the Tomei Expressway in Japan (346.8km) towards Komaki interchange (IC). We create an origin-destination (OD) profile of the vehicles based on the data [11] of Central Nippon Expressway Co. Ltd. (2012). 214535 vehicles start trips per day. 75% of the vehicles run less than 80 km per trip. 18% run between 80 and 200 km per trip. 7% run more than 200 km per trip. The simulation will end at 345596 simulation seconds (≒ 4 simulation days). The ratio of EVs to gasoline cars is 3:97 or 5:95. Although we use publicly available real data, in the present work it is not our aim to recreate actual traffic flow of the Tomei Expressway on our simulator. The purpose of this paper is to evaluate the effects of highway EMSs.

The energy consumption rate of each EV is 7.5 km/kWh. The initial state of charge (SOC) of each EV is between 12 and 15kWh. We do not expect that EVs are fully charged when entering the highway because the EVs consume some energy when driving on local roads before reaching the highway and we expect that QCs will be placed at each SA/PA (every 20 kWh) in the near future. Since there will be sufficient charging stations, EV drivers may not be particularly careful about the remaining energy. There are 3 types of EV drivers: optimistic, normal, and cautious EV drivers who try to charge the battery at the next SA/PA when the SOC becomes below 4, 7, and 10 kWh, respectively. The ratio of optimistic, normal, and cautious EV drivers is set at 4:5:3 based on the data [12-15] of the EV drivers who actually run on Japanese highways. The EVs never run out of electricity when QCs are set at every SA/PA. Gasoline car drivers sometimes stop at an SA/PA with the probability of 10% and restart the trip after 30 minutes.

10 QCs are placed at each SA/PA. The distance between 2 adjacent SA/PAs is around 20 km. Based on the specification [16] of a QC, the maximum power of each QC is set at 50 kW. When all QCs are used, EVs wait in line in front of the QCs. After charging the battery, EV drivers resume the trip immediately.

We simulate the digital signage scenario, the energy reduction scenario, the digital signage and energy reduction scenario, the power reduction scenario, and the energy and power reduction scenario that are explained in the following subsections.

3.1. Base Case Scenario (1 scenario)

In the base case scenario, the SOC of an EV will be 19.2 kWh at the end of a charge. No information is given to EV drivers through digital signs. Optimistic, normal, and cautious EV drivers charge the battery at the next SA/PA when the SOC becomes below 4, 7, and 10 kWh, respectively.

3.2. Digital Signage Scenarios (4 scenarios)

Even when many EVs are queuing for charging at some SA/PAs, the charging stations at other SA/PAs might not be busy. Therefore, we would like to distribute the locations of EV charging. If the EV drivers know the queue length of each SA/PA, they can choose to charge the EV at less crowded SA/PAs.In the digital signage scenario, EV drivers obtain information about the length of the queue of EVs that are waiting for charging at the next three SA/PAs through digital signs. By this strategy, we can expect that "the average waiting time for charging and queuing per charge" will be reduced accordingly.

A digital sign is placed just before the access road to each SA/PA. Based on the information, each EV driver chooses the least congested SA/PA when they need to charge the battery. The queue-length information recognition probability is set at 10, 40, 70, or 100%. The queue-length information recognition probability of x% means that EV drivers recognize and use queue-length information on the digital signage for decision-making with the probability of x%. When the SOC is below 10 kWh, the EV driver uses the queue-length information of the next three SA/PAs and chooses the least congested SA/PA for the next charging. When the SOC is below 7 kWh, the EV driver uses the queue-length information of the next two SA/PAs and chooses the least congested SA/PA for the next charging. Even if the EV driver does not recognize a digital sign, the EV driver uses the previously obtained queue-length information. Without any queue-length information, optimistic, normal, and cautious EV drivers charge the battery at the next SA/PA when the SOC becomes less than 4, 7, and 10 kWh, respectively.

3.3. Energy Reduction Scenarios (2 scenarios)

When many EVs are queuing for charging, if the charging amount of each EV is reduced, we can expect that the "average waiting time for charging and queuing per charge" will be reduced accordingly. In the energy reduction scenarios, if 10 or more EVs (= 1 or more EVs per QC) are queuing in front of the 10 QCs at an SA/PA, the maximum charging amount of the next EV (the first EV in the queue) will be restricted to 4 or 8 kWh. Otherwise, the SOC of the EV will be 19.2 kWh at the end of a charge.

This strategy might be effective to reduce the time for charging and queuing. However, EV drivers might be dissatisfied because the charging amount is limited. Therefore, we introduce a new evaluation criterion "average waiting time for charging and queuing per unit of energy." In this evaluation criterion, not only the waiting time but also the charging amount is taken into consideration.

3.4. Digital Signage and Energy Reduction Scenarios (8 scenarios)

In the digital signage and energy reduction scenarios, we combine the digital signage scenario and the energy reduction scenario. In these scenarios, first, we try to distribute the charging locations of EVs by means of the digital signage strategy. However, even after leveling the charging locations of EVs, some EV drivers might need to wait for charging and queuing. In this case, we try to reduce the waiting time by means of the energy reduction strategy.

The probability of information recognition from a digital sign is set at 10, 40, 70, or 100%. The maximum charging amount will be restricted to 4 or 8 kWh when 10 or more EVs are queuing. We expect that both "waiting time per charge" and "waiting time per unit of energy" will be reduced.

3.5. Power Reduction Scenarios (2 scenarios)

When many EVs are charging at the same time at the same SA/PA, the power usage might exceed the contract power, turning on the breaker (when the total demand power of all the QCs in operation is higher than the contract power).In the power reduction scenarios, the default maximum power usage of each QC is also set at 50 kW. However, the highway EMS reduces the maximum power of QCs when necessary so that the total power usage will not exceed the contract power. We change the contract power to 300 or 400 kW. The SOC of an EV will be 19.2 kWh at the end of a charge.

In these scenarios, the maximum power usage of each QC is restricted to the contract power (300 or 400 kW) divided by the number of charging EVs at the SA/PA when the total power usage would be above the contract power otherwise. The maximum power usage is dynamically adjusted every time the number of charging EVs changes.

Since the charging power will be reduced, this strategy will reduce the charging speed, resulting in longer charging time, which will then dissatisfy EV drivers. Therefore, we need to evaluate the charging strategy in terms of "average waiting time for charging and queuing per charge."

3.6. Energy and Power Reduction Scenarios (4 scenarios)

In the energy and power reduction scenarios, we combine an energy reduction scenario and a power reduction scenario. In these scenarios, we expect that the energy reduction strategy would shorten the "average waiting time for charging and queuing per charge" that is increased by the power reduction strategy. The charge amount will be restricted to 4 or 8 kWh when 10 or more EVs are queuing. The contract power is set at 300 or 400 kW. As in the case of the energy reduction scenarios, it is important to evaluate the "average waiting time for charging and queuing per unit of energy" as well because the charging amount is restricted.

4. Modeling MetaMAS™ agents

MetaMAS™ is a new general-purpose meta-level multi-agent simulator that integrates domain-specific simulators. Figure 1 shows the architecture of the MetaMAS™ simulator. MetaMAS™ agents correspond to independent decision-makers such as individuals, organizations, devices, and systems. MetaMAS™ agents sense some events that are happening on the domain-specific simulators, communicate with other agents, make decisions according to the situation, and act to control domain-specific simulators. In order to evaluate highway EMSs, we plug a (mesoscopic) traffic simulator and a power simulator into MetaMAS™ and model the key players as agents. The controller synchronizes the times of the simulators. MetaMAS™ agents conduct rule-based reasoning periodically. They also conduct rule-based reasoning when detecting an event from a domain-specific simulator or receiving a message from another agent.

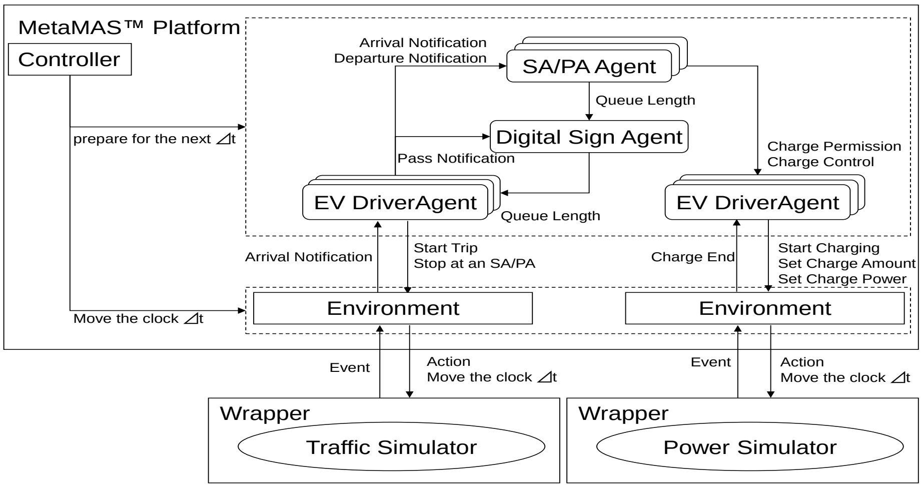


Figure 1. MetaMAS™ Architecture

4.1. Driver agents

EV and gasoline car driver agents are created in MetaMAS™ when they start driving. When the driver agents start or stop driving, they also start or stop the corresponding cars on the traffic simulator. When a car on the traffic simulator arrives at a point of interest (POI), the traffic simulator notifies the corresponding MetaMAS™ driver agent of the event. Gasoline car driver agents sometimes stop at an SA/PA with the predefined probabilities and restart the trip after staying there for the predefined time.

When arriving at an SA/PA, the EV driver agent communicates with the SA/PA agent. When all QCs are used, the EV driver agent waits until it gets the permission for charging from the SA/PA agent. When the EV driver agent starts charging the battery, it controls the QC component on the power simulator. When the battery charge finishes, the power simulator notifies the MetaMAS™ EV driver agent of the event. After charging the battery, the EV driver agent notifies the SA/PA agent of the departure event, and resumes the trip immediately.

When approaching an SA/PA, the EV driver agent decides whether or not to stop at the next SA/PA to charge the battery. This decision-making algorithm of the EV driver agent is defined as follows. (Note that the EV consumes around 3kWh to move from an SA/PA to the next SA/PA, which is around 20 km away. Also recall that the following thresholds of optimistic, normal, and cautious drivers are based on the real data.)

Charge decision-making algorithm of EV driver agents

1. *[Emergency Charge] If the SOCis below4 kWh, then the charge alert lamp is on and the EV driver agent decides to stop at the next SA/PAto charge the battery. (This is also the threshold of* ***optimistic*** *EV drivers.)*
2. *[Charge Planning Based on the Queue-length Information] Else if the EV driver agent recognizes a digital sign with the predefined possibility (0, 10, 40, 70, or 100%) and obtains the queue-length information, then:*
   - *If the SOCis below 7 kWh, then:*
     - *If the queue length of the next SA/PA is the shortest of the next two SA/PAs, then the EV driver agent decides to stop at the first SA/PAto charge the battery.*
     - *Otherwise the EV driver agent plans to stop at the second SA/PA.*
   - *Else if the SOCis below 10 kWh, then:*
     - *If the queue length of the next SA/PA is the shortest among the next three SA/PAs, then the EV driver agent decides to stop at the next SA/PAto charge the battery.*
     - *Otherwise the EV driver agent plans to stop at the SA/PA where the queue length is the shortest.*
3. *[Previous Charge Plan Execution] Else if the EV driver agent previously planned to stop at the next SA/PA and has not cancelled the plan, then the EV driver agent decides to stop at the next SA/PAto charge the battery.*
4. *[Charge by Free Will] Else if the EV driver agent is* ***normal*** *and the SOCis below the threshold of normal drivers (7 kWh), then the EV driver agent stops at the next SA/PAto charge the battery.*
5. *[Charge by Free Will] Else if the EV driver agent is* ***cautious*** *and the SOCis below the threshold of cautious drivers (10 kWh), then the EV driver agent stops at the next SA/PAto charge the battery.*
6. *[Charge Plan Cancelling] If the EV driver agent decides to stop at the next SA/PA, then the EV driver agent cancels the plan to stop at another SA/PA. The charge alert lamp becomes off after charging the battery.*

4.2. SA/PA Agents

SA/PA agents communicate with EV driver agents and count how many QCs are used and how many EVs are queuing or charging at the SA/PA. EVs wait for charging in line (M/M/S queue). When a QC becomes available, the SA/PA agent gives permission for charging at the QC to the first EV driver agent in the queue. SA/PA agents also give the queue-length information to digital-sign agents upon request.

The SA/PA agents also play the role of EMS. In the energy reduction strategy, if an EV driver agent starts charging the battery when more than or equal to the predefined number (10) of EVs arequeuing, the SA/PA agent restricts the maximum charging amount of the EV to the predefined amount (4 or 8 kWh). Once an EV driver agent starts charging the battery, the SA/PA agent will not change the maximum charging amount of the EV. The SA/PA agents change some parameters of the power simulator via EV Driver Agents when limiting the maximum charging amount of the EVs.

Each SA/PA agent sets the maximum power usage of each QC at the pre-defined default value (50 kW) if the total power usage of QCs at the SA/PA is below the contract power. (When the contract power is 500 kW, the total power usage at the SA/PA is always below the contract power.) Otherwise, in the power reduction strategy, the SA/PA agent sets it at the contract power (300 or 400 kW) divided by the number of charging EVs at the SA/PA, so that the total power usage will be below the contract power. The SA/PA agent dynamically changes the maximum power of each QC every time an EV agent starts or ends charging.

4.3. Digital-sign Agents

A digital sign is placed just before the access road to each SA/PA. **Digital-sign agents** communicate with the SA/PA agents and obtain the queue-length information of the next three SA/PAs. When an EV passes a digital sign, the EV driver agent communicates with the digital-sign agent and obtains the queue-length information of the next three SA/PAs with the predefined possibility (0, 10, 40, 70, or 100%).

5. Domain-specific Simulators

This section briefly explains the domain-specific simulators with which MetaMAS™ agents interact. We use two domain-specific simulators: the traffic simulator and the power simulator. MetaMAS™ synchronizes these simulators every 1 simulation second.

5.1. Traffic Simulator

In general, there are three levels of granularity in traffic simulation: macroscopic, mesoscopic, and microscopic. In macroscopic traffic simulation models, the traffic flow of each road is simulated. However, the movement of each vehicle is not described. In the microscopic traffic simulation models, the movement of each vehicle is described in detail. However, the simulation speed is slow. Mesoscopic traffic simulation models have an intermediate level of granularity and are gaining popularity. Some mesoscopic traffic simulation models describe the movement of each vehicle. However, the simulation speed is fast because they do not describe the movement of each vehicle in detail. For example, in microscopic traffic simulation models, the interactions between vehicles are described: each vehicle accelerates, decelerates, or changes lane following other vehicles in front. On the other hand, in mesoscopic traffic simulation models, these interactions are not represented.

Since we need to describe the decision-making of each EV driver agent in the MetaMAS™ layer, we also need to describe the corresponding individual vehicle in the traffic simulator. This is important because the decision-making of each EV driver depends on the location and the remaining energy of the EV, which are calculated based on the information from the traffic simulator. However, we need to repeatedly simulate the movements of a large number of vehicles and it would take a lot of time if we use a microscopic traffic simulator. Therefore, we chose a mesoscopic traffic simulator.

Our traffic simulator is a mesoscopic traffic simulator that simulates the movements of individual vehicles based on the model of Greenshields[17] with minimum speed. In this model, the speed v(km/h) of each car is calculated as follows:

$$v=\begin{cases} v_f\left(1-\frac{k}{k_j}\right) & (if\ v > v_0) \\ v_0 & (otherwise) \end{cases}$$

where the free speed v_f is 100 km/h, the minimum speed v_0 is 10 km/h, and the jam density k_j is 140 vehicles/km/lane. The density k (vehicles/km/lane) is calculated from the number of vehicles on the link, the number of lanes on the link, and the length of the link. The speed v of a vehicle decreases as the number of vehicles running on the same link increases, which simulates traffic jams. The speed v of the vehicle also changes when it moves to the next link and the density changes. Unlike microscopic traffic simulators, this mesoscopic traffic simulator does not simulate acceleration, deceleration, and lane changing. As shown in Figure 1, when a car starts from, passes, or arrives at a POI (SA, PA, IC, *etc.*), the traffic simulator sends an event to the corresponding MetaMAS™ driver agent. In addition, the MetaMAS™ driver agent can start and stop the corresponding vehicle in the traffic simulator.

5.2. Power Simulator

The power simulator simulates the power demand or supply of various types of power equipment, such as QCs, stationary storage batteries (SSBs), photovoltaics (PVs), and grid power of the highway power system, and EVs in charging and calculates the net power at each root power node assuming the hierarchical structure of the highway power system. Though the charging facilities of an SA/PA consist of several types of power equipment, in this paper we consider only QCs and power from the grid as the charging facilities of an SA/PA. The net power demand at an SA/PA at each simulation step is calculated by summing the charging power demand of all the EVs connected to the QCs of the SA/PA. Each SA/PA agent of MetaMAS™ can change the maximum charging amount or the maximum charging power of each EV at an SA/PA.

As a basic quick charging model, we use the model mentioned in [18] with the specification specified in [16]. To simulate the quick charging of an EV using this model, first, the maximum charging current and voltage are calculated taking into account the specifications of the QC and the battery of the EV, and the maximum charging power set by the SA/PA agent. Then, the charging of the EV is performed. At each simulation step of the simulator, the charging of the EV takes place in two steps. In the first step, taking into account the remaining energy of the EV, specification of the battery of the EV, and the maximum charging current and voltage, the terminal voltage and charging current are calculated. In the second step, the EV is charged with the terminal voltage and charging current, the remaining capacity (in Ah) is calculated, and the remaining energy of the EV is updated using the remaining capacity and nominal voltage of the battery of the EV. These two steps continue until either the remaining energy of the EV reaches 80% SOC or the maximum charging amount set by MetaMAS™ is supplied to the EV. At each simulation step of the simulator, the power demand for an EV charging is calculated taking into account the terminal voltage and charging current, and power conversion efficiency of the QC. After the charging of an EV is finished, the power simulator notifies the corresponding EV driver agent of MetaMAS™ about the completion of charging.

In this paper, we assume that each QC conforms to the specification in [16], having maximum 50 kW of output power capacity, maximum 500V of output voltage, and maximum 125A of output current. The power conversion efficiency of a QC is set to 1.0, and the specification of the battery of each EV is set as follows: nominal battery capacity=24 kWh or 66.2 Ah, nominal voltage=364.8V, charging cut-off voltage=403.2V, number of cells=96, adjusting parameter (α) of quick charging model=10, and internal resistance= 0.192Ω.

6. Simulation Results

We simulated 21 scenarios: 1 base case scenario (signage recognition probability of 0% and unlimited charging amount[1]), 4 digital signage scenarios (signage recognition probability of 10, 40, 70, or 100% and unlimited charging amount), 2 energy reduction scenarios (signage recognition probability of 0% and maximum charging amount of 4 or 8 kWh), 8 digital signage and energy reduction scenarios (signage recognition probability of 10, 40, 70, or 100% and maximum charging amount of 4 or 8 kWh), 2 power reduction scenarios(contract power of 300 or 400 kW and unlimited charging amount), and 4 energy and power reduction scenarios (contract power of 300 or 400 kW and the charging amount of 4 or 8 kWh). The EV penetration rate is either 3% or 5%. In the following simulation results, we used only the data of EVs that finished the trips before the end of the simulation.

6.1. Average Waiting Time per Charge

Figure 2 shows the average waiting time (minutes) for charging and queuing per charge when changing the probability of signage recognition and the energy reduction amount. It is clearly seen that in the digital signage scenario, the average waiting time per charge becomes shorter as the probability of signage recognition becomes higher.

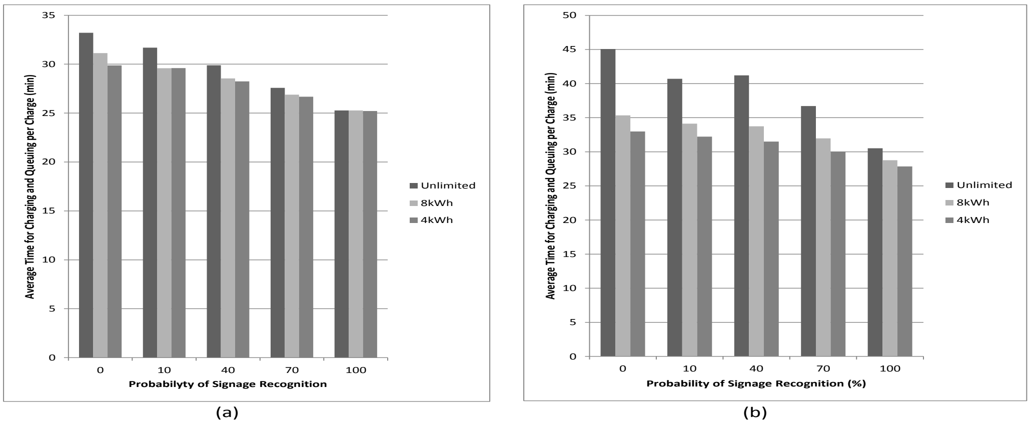


Figure 2. Average Waiting Time per Charge 1 (a) EV Rate 3%; (b) EV Rate 5%

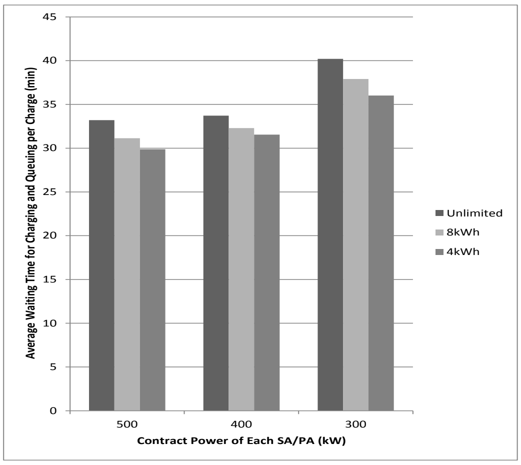
Figure 2 also shows that in the energy reduction scenario where 10 QCs are placed at each SA/PA, the more we limit the maximum charging amount when 10 or more EVs (= 1 or more EVs per QC) are queuing, the shorter the average waiting time per charge becomes. However, when changing the maximum charging amount from 8 kWh to 4 kWh, the average waiting time per charge is not reduced much.

It can also be understood that the best strategy to reduce the average waiting time per charge is to combine the signage strategy and the energy reduction strategy when the signage recognition probability is 100% and the maximum charging amount is 4 kWh.

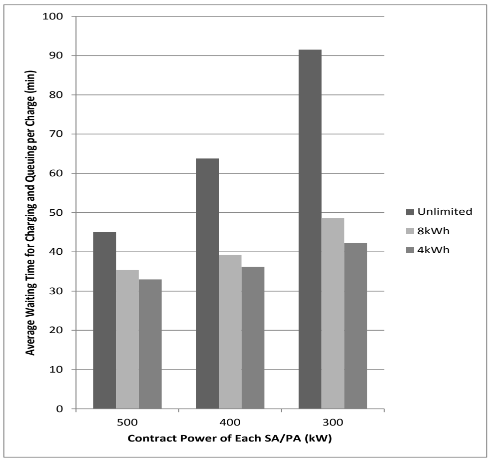
[1]When the charge amount is *unlimited*, the remaining energy of EVs will be 19.2 kWh at the end of the charge.

Figure 3 shows the average waiting time (minutes) for charging and queuing per charge when changing the contract power and the energy reduction amount. It can be seen that the average waiting time per charge becomes longer as we set the contract power smaller. It can be understood that too much contract power reduction would significantly dissatisfy EV drivers.

Figure 3 also shows that the average waiting time for charging and queuing per charge becomes shorter as the charging amount becomes smaller when 10 or more EVs are queuing. In particular, in Figure 3 (b), the average waiting time per charge becomes nearly half when the maximum charging amount is restricted to 4 or 8 kWh and the contract power is 300 or 400 kW. This means that the energy reduction strategy is particularly effective when the waiting time per charge is long.



(a)



(b)

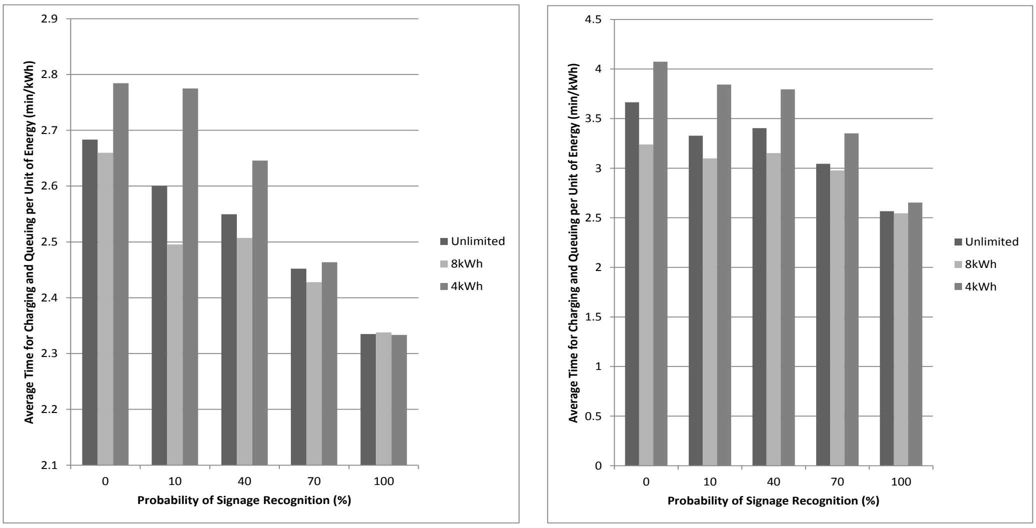
Figure 3. Average Waiting Time per Charge 2 (a) EV Rate 3%; (b) EV Rate 5%

6.2. Average Waiting Time per Unit of Energy

The average waiting time for charging and queuing *per charge* does not reflect the fact that EV drivers are more (less) satisfied if they can charge more (less) energy when the waiting time is the same. Therefore, we introduce a new evaluation criterion: the average waiting time per unit of energy. Figure 4 shows the average waiting time (minutes) for charging and queuing *per unit of energy* (kWh)when changing the probability of signage recognition and the energy reduction amount. As can be seen from Figure 4, in the digital signage scenario, the average waiting time per unit of energy decreases greatly as the signage recognition probability increases. This result is very similar to the result for the average waiting time per charge that is shown in Figure 2.

However, it is noteworthy that the average waiting time per unit of energy becomes the shortest when the maximum charging amount is limited to 8 kWh in the energy reduction scenario. Before obtaining this simulation result, we guessed that the average waiting time per unit of energy would become the shortest when the maximum charging amount is restricted to 4 kWh, which was not the case. On the contrary, the average waiting time per unit of energy becomes even longer than the base case scenario when the maximum charging amount is limited to 4 kWh. This means that the average waiting time could not be reduced sufficiently compared to the reduced charge amount when changing the maximum charging amount from 8 kWh to 4 kWh.

It can also be understood that the best strategy to reduce the average waiting time per unit of energy is to combine the signage strategy and the energy reduction strategy(8 kWh). However, the maximum charging amount should not be reduced too much (to 4 kWh). It is also very effective to increase the signage recognition probability.

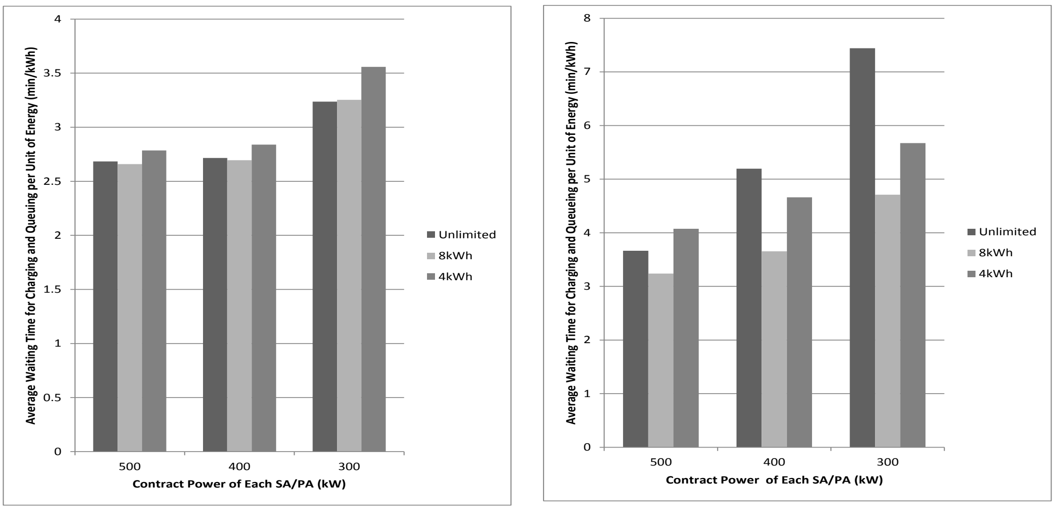


(a) (b)

Figure 4. Average Waiting Time per Unit of Energy 1
(a) EV Rate 3%; (b) EV Rate 5%

Figure 5 shows the average waiting time (minutes) for charging and queuing per unit of energy (kWh) when changing the contract power and the energy reduction amount. The average waiting time per unit of energy becomes longer as the contract power is set smaller. In Figure 5 (a), the average waiting time per unit of energy does not increase much even if the contract power is changed from 500 kW to 400 kW. However, it increases much if the contract power is changed from 400 kW to 300 kW. This means that the contract power reduction is acceptable to some extent from the viewpoint of waiting time per unit of energy. However, too much contract power reduction would significantly dissatisfy EV drivers.

It is interesting to see that the average waiting time per unit of energy generally becomes the shortest when limiting the charging amount to 8 kWh. This result is very similar to the result that is shown in Figure 4. The maximum charging amount should not be reduced too much (to 4 kWh).



(a) (b)

Figure 5. Average Waiting Time per Unit of Energy 2
(a) EV Rate 3%; (b) EV Rate 5%

7. Conclusions and Future Work

We have shown how to model key players of a highway EMS using MetaMAS™, a new general-purpose multi-agent simulator. We can intuitively understand the role of each agent because each MetaMAS™ agent corresponds to a key player in the real world. Unlike previous multi-agent simulators, MetaMAS™ agents communicate with domain-specific simulators such as traffic simulators and power simulators. Therefore, in our simulation model, it is individuals (agents) who connect different worlds (domain-specific simulators). This approach is essential for bottom-up simulation of smart communities where different domains, such as traffic, electric power, gas, water, education, and medical services, are connected by people, organizations, devices, and systems.

Using the integrated simulators, we evaluated the digital signage strategy, the energy reduction strategy, the digital signage and energy reduction strategy, the power reduction strategy, and the energy and power reduction strategy, which are fundamental and important strategies for the future highway EMS. In order to evaluate these strategies, we modeled the key MetaMAS™ agents such as EV driver agents, SA/PA agents, and digital-sign agents.

From the simulation results, it can be seen that the digital signage strategy significantly reduces the average waiting time for charging and queuing per charge and the average waiting time for charging and queuing per unit of energy. The closer the signage recognition probability is to 100%, the more effective this strategy becomes.

It can also be understood that the energy reduction strategy is effective from the viewpoint of average waiting time per charge and the average waiting time per unit of energy. However, too much energy reduction deteriorates average waiting time per unit of energy.

The best strategy to reduce the average waiting time for charging and queuing per charge is the combination of the digital signage strategy and the energy reduction strategy. Again, from the viewpoint of average waiting time per unit of energy, it is very important not to reduce the maximum charging amount too much. It is also important to increase the signage recognition probability.

The power reduction strategy is effective for keeping the power usage below the contract power. From the simulation results, it can be understood that the power reduction strategy is acceptable to some extent. However, too much contract power reduction significantly increases the average waiting time for charging and queuing per charge.

In addition, the combination of the energy reduction strategy and the power reduction strategy has been tested. The energy reduction strategy can reduce the average waiting time for charging and queuing per charge that is increased by the power reduction strategy. Again, it is very important not to greatly reduce the maximum charging amount and the contract power.

In this paper, we examined some near-future scenarios, which are the most important and urgent issues for the highway owners who have to pay for the charging facilities. In future work, it will be necessary to come up with new highway EMS strategies as the EV penetration rate rises and the battery charging technologies are improved. For example, when EV penetration rate significantly rises, we need to install more QCs. If many EVs have batteries of high capacity, the frequency of charging will be lower. However, it will take a lot of time to fully charge such high-capacity batteries. Even if it becomes possible to quickly charge high-capacity batteries, *e.g.*, within 30 minutes, such super QCs will consume much higher power in a short time, leading to instability of the power grid. If in-motion wireless EV charging technologies are embedded in highways, we need to consider different highway EMS strategies. We would like to investigate these scenarios in future work.

The limitation of our simulation approach is that we cannot predict and list up all the new technologies and their future costs. In general, it is possible to make agent-based models and evaluate "what-if" scenarios in many cases. However, we need to carefully choose what we should evaluate. For this purpose, we need to not only watch the current trend but also listen to the voices of stakeholders who pay for the highway EMS.

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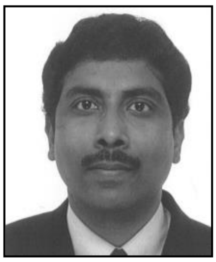

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