Energy Demand Scheduling for Autonomous and Connected Vehicle Swarms in Smart Transportation System

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Abstract

In this paper, we study an energy demand scheduling with rationality for the autonomous and connected vehicle swarms problem. Therefore, the autonomous vehicles (self-driven) are capable of determining rational energy demand whereas the connected vehicles (human-driven) claim irrational energy demand. Thus, we formulate an optimization problem by employing the rationality of the energy demand between the autonomous and connected vehicles. Further, we propose an overlay network for gathering energy demand of the vehicles and available energy supply capacity of electric vehicle charging stations. To find the optimal solution of the proposed optimization problem, we develop a dynamic programming-based algorithm for energy demand scheduling with rationality. Finally, the experiment results ensure that the proposed solution approach outperforms the other baselines models with respect to utility gain and vehicle energy demand achieved rate.

1. Introduction

Nowadays, smart transportation system [1] is a promising enhancement of the on going technologies such as fifth-generation (5G) networks [2], smart city [3], renewable energy [4], [5], green communication networks [6], [7], artificial intelligence [8], and so on. In the smart transportation system, the electric vehicle is categorized into two types, 1) autonomous (i.e., self-driven) and 1) connected (i.e., human-driven) vehicles [9]. Therefore, the energy demand response (DR) [4], [6], [10] management is very challenging due to the randomness of energy demand and supply. Thus, energy demand scheduling for autonomous and connected vehicles is more challenging since irrational demand requests from the human-driven vehicles (i.e, connected). On the other hand, energy demand from the self-driven vehicles belongs to rational, where the decision comes automatically by the vehicles. Further, the EV charging stations have limited capacity to serve all of the demand by both autonomous and connected vehicles.

In this paper, we focus on an approach that provides a rational energy demand scheduling for the autonomous and connected vehicle swarms and the summary of the contributions are as follows:

- First, we propose a system model of the smart transportation system that provides an energy demand aggregator overlay network, which is capable of collecting energy demand of autonomous and connected vehicles, and supply-able energy information from EV charging stations.
- Second, we formulate an optimization problem, where rationality between the energy demand of autonomous and connected vehicles is considered. The objective of the formulated problem is to maximize the overall utility of EV charging stations.

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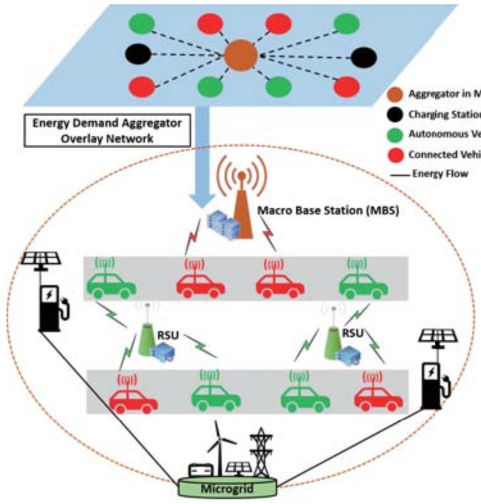

Figure 1: System model.

- Third, to solve the formulated problem, we propose a dynamic programming-based energy demand scheduling with rationality algorithm.
- Finally, our experimental analysis shows that the proposed solution approach provides the optimal solution and outperforms the baselines by increasing utility around 33% to 50%.

2. System Model and Problem Formulation

Considering a smart transportation system with microgrid platform that includes Macro Base Station (MBS), road side units (RSUs), and electrical vehicle (EV) charging station, as shown in Figure 1. In this system model, we consider two types of vehicles i) autonomous (i.e, self driving), and ii) connected (i.e., human driven). Let us consider a set of electrical vehicle (EV) charging stations $\mathcal{S} = \{1, 2, \ldots, S\}$ are serving energy demand for both autonomous and connected vehicles. We denote a set $\mathcal{A} = \{1, 2, \ldots, A\}$ to represent autonomous vehicles, and a set of connected vehicles is denoted by $\mathcal{C} = \{1, 2, \ldots, C\}$. Therefore, the energy scheduling of the vehicles are considered for 1 hour time slot t [6] and total demand (i.e., autonomous and connected) is defined as a set $\mathcal{D} = \{1, 2, \ldots, D\} \in \mathcal{A} \cup \mathcal{C}$. Further, we consider an energy demand aggregator overlay network to collect all of the energy demand and generation information. The aggregator cope with the demand from autonomous vehicles (i.e., rational decision using artificial intelligence) to tackle the irrational decision (i.e., demand) from human driven vehicles (i.e., connected).

In a one time slot t scheduling period, the energy total energy demand at the aggregator is ζ_t. The amount of energy supply scheduled from the aggregator to EV charging station s is ζ_s by satisfying the following constraint:

$$\sum_{s \in \mathcal{S}} \zeta_s \leq \zeta_t, \forall \zeta_s \geq 0. \tag{1}$$

We consider energy supply capacity of the EV charging station $s \in \mathcal{S}$ is fixed η_s at time slot t. Thus, the utility is defined as follows:

$$\Psi_s = \frac{\zeta_s}{\eta_s}. \tag{2}$$

The decision for the aggregator is to assign $\forall d \in \mathcal{D}, \mathcal{D} \in \mathcal{A} \cup \mathcal{C}$ with EV charging stations $\forall s \in \mathcal{S}$ for fulfilling the energy demand ζ_d of each vehicle d. Therefore, to fulfill $\forall d \in \mathcal{D}$ demand, we need to make a S-partition $\mathcal{S}_1 \cup \ldots \mathcal{S}_S \in \mathcal{S}$ of vehicles $\{1, 2, \ldots, D\}$ such that $\sum_{d \in \mathcal{S}_S} \zeta_d \leq \eta_s, \forall d \in \mathcal{D}$. To find the effectiveness of the demand decision from the autonomous vehicles we define the rationality function as follows:

$$\Phi = \frac{\sum_{c \in \mathcal{C}} \zeta_c}{|C|} \times \frac{|A|}{\sum_{a \in \mathcal{A}} \zeta_a}, \forall a \in \mathcal{A}, \forall c \in \mathcal{C} \tag{3}$$

where $\mathcal{D} \in \mathcal{A} \cup \mathcal{C}$, ζ_a denotes the energy demand of autonomous vehicle $a \in \mathcal{A}$, and ζ_c represents the energy demand of the connected vehicle $c \in \mathcal{C}$.

The problem formulation of the energy demand scheduling with rationality is as follows:

$$\max_{x_{sd} \in \mathbf{x}, y_s \in \mathbf{y}} \sum_{d \in \mathcal{D}} \sum_{s \in \mathcal{S}} \Psi_s x_{sd} \Phi + \Psi_s x_{sd}(1 - \Phi), \tag{4}$$

$$\text{s.t.} \quad \sum_{d \in \mathcal{D}} \zeta_d x_{sd} \leq \eta_s y_s, \forall d \in \mathcal{D}, \tag{4a}$$

$$\sum_{s \in \mathcal{S}} \zeta_s x_{sd} \leq \zeta_t, \forall \zeta_s \geq 0, \forall d \in \mathcal{D}, \tag{4b}$$

$$\sum_{s \in \mathcal{S}} x_{sd} = 1, \forall d \in \mathcal{D}, \tag{4c}$$

$$y_s \in \{0, 1\}, \forall s \in \mathcal{D}, \tag{4d}$$

$$x_{sd} \in \{0, 1\}, \forall s \in \mathcal{D}, \forall d \in \mathcal{D}. \tag{4e}$$

In problem (4), the objective is to maximize the total utility of the EV charging stations $\forall s \in \mathcal{S}$, where Φ represents the rational believe by the autonomous vehicles. The formulated problem (4) consist of two decision variables, first, $x_{sd} = 1 \in \mathbf{x}$ if demand d is fulfilled by EV charging station s, and $x_{sd} = 0$ otherwise. The second decision variable

Algorithm 1: Energy Demand Scheduling with Rationality based on Dynamic Programming

Input: $\mathcal{A}, \mathcal{C}, \mathcal{S}$
Output: **x**, **y**
Initialization: $\mathcal{D} \in \mathcal{A} \cup \mathcal{C}$, ζ_t ,**x**, **y**
1: **while** $\forall d \in \mathcal{D}$ **do**
2: **Calculate:** Φ using eq. (3)
3: **for** $\forall s \in \mathcal{S}$ **do**
4: **Procedure:**
5: **Procedure Start**
6: **if** $(\forall \zeta_s \geq 0)$ **then**
7: **Assign:** $x_{sd} = 1$ and $y_s = 1$
8: **Evaluate constraint:** (4a) and (4b)
9: **Calculate:** $\max(\Psi_s x_{sd} \Phi + \Psi_s x_{sd}(1 - \Phi))$ using eq. (4)
10: **Evaluate constraint:** (4a) and (4b)
11: **else**
12: *break*
13: **end if**
14: **Procedure End**
15: **end for**
16: **for** $\forall (d+1) \in \mathcal{D}$ **do**
17: *Recursion Call:* **Procedure**
18: **end for**
19: **end while**
20: **return** **x**, **y**

$y_s = 1 \in \mathbf{y}$ if EV charging station s is utilized, and $y_s = 0$ otherwise. Constraint (4a) ensures the upper bound of the supply-able energy for EV charging station $s \in \mathcal{S}$ and (4b) assures the scheduled vehicle energy demand is fulfilled by the EV charging station. Constraint (4c) determines the decision must be taken for each $x_{sd} \in \mathbf{x}$. Constraints (4d), and (4e) ensure $x_{sd} \in \mathbf{x}$ and $y_s \in \mathbf{y}$ are the binary decision variables. We solve the proposed energy demand scheduling with rationality problem (4) via a dynamic programming (DP) toward the optimal solution.

3. Solution with Dynamic Programming

We propose Algorithm 1 to solve energy demand scheduling with rationality for the autonomous and connected vehicle swarms. The Algorithm 1 runs by the aggregator of the energy demand aggregator overlay network in MBS. In Algorithm 1, line 2 calculates the rationality among autonomous and connected vehicles. Lines 5 to 14, we define a procedure to solve each subproblem $\forall d \in \mathcal{D}$ with the available EV charging stations $\forall s \in \mathcal{S}$, where line 8 validate the constraints (4a) and (4b). Further, we determine the objective of the problem (4) in line 9. The recursion call of the DP procedure is executed from lines 16 to 18 in Algorithm 1. Finally, we achieve the optimal solution in line 20. The computational complexity of the Algorithm 1 goes to $\mathcal{O}(\mathcal{D}^2\mathcal{S})$ whereas the space complexity leads to $\mathcal{O}(\mathcal{D})$.

Table I: Summary of Experimental Setup

Description	Value
No. of autonomous vehicles $\lvert\mathcal{A}\rvert$	$[100, 350]$
No. of connected vehicles $\lvert\mathcal{C}\rvert$	$[100, 350]$
No. of total vehicles $\lvert\mathcal{D}\rvert$	$[100, 700]$
No. of EV charging stations $\lvert\mathcal{S}\rvert$	4 with 8 stalls [11]
Each EV charging stations capacity ζ_t	7840 [11]
EV energy demand capacity	$[1, 100]$ KWh [12]

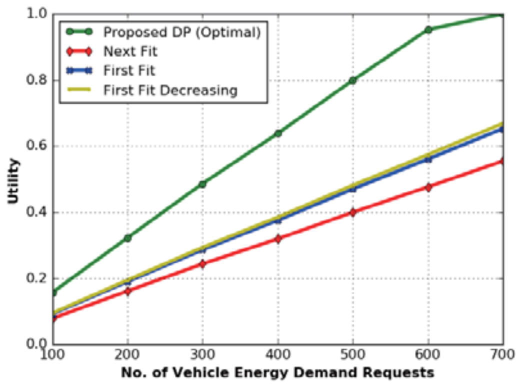

Figure 2: Overall utility achieved by the EV charging stations.

4. Experimental Result

We implement the proposed DP-based energy demand scheduling with rationality Algorithm 1 on the python platform and compared with the other three baseline approximation methods (i.e., next fit, first fit, and offline-first fit decreasing). Table I is shown the important parameters of the experiment setup.

First, we compare the overall utility by the EV charging stations in Figure 2, where the proposed DP-based method (circle mark green line) achieved a significant performance gain than that the next fit (diamond mark red line), first fit (cross mark blue line), and first fit decreasing (dot mark yellow line) methods since the proposed method guarantees the optimal solution. However, the trade-off between the Algorithm 1 and other baseline methods is computational complexity, where the computational complexity belongs to $\mathcal{O}(\mathcal{D}^2\mathcal{S})$, $\mathcal{O}(\mathcal{D})$, $\mathcal{O}(\mathcal{D}^2)$, $\mathcal{O}(\mathcal{D}\log\mathcal{D})$ for the proposed method, next fit, first fit, and offline first fit decreasing, respectively. Second, Figure 3 illustrates the demand achieved rate for the vehicles (i.e., autonomous and connected) by the EV charging stations. We show that for $\sum_{s\in\mathcal{S}}\zeta_s x_{sd} \leq \zeta_t, \forall\zeta_s \geq 0, \forall d \in \mathcal{D}$ the proposed method out perform the other baselines.

5. Conclusion

In this research, we have introduced an energy demand scheduling with rationality for the autonomous and connected vehicle swarms problem, where we proposed an energy demand aggregator overlay network. We have formulated an optimization problem by considering the rationality of the energy demand of both autonomous and connected vehicles. To achieve the optimal solution of the formulated problem, we have proposed dynamic programming-based energy demand scheduling with a rationality algorithm. Finally, the experiment result shows the higher performance gain in order to efficient energy demand scheduling for the autonomous and connected vehicle swarms with EV charging stations.

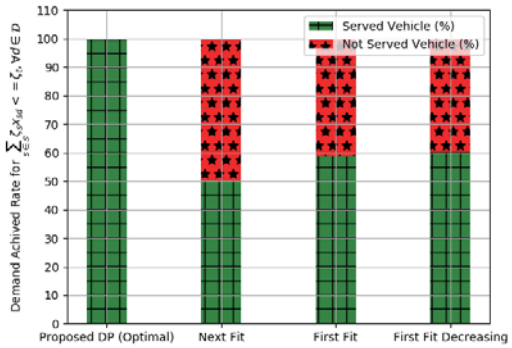

Figure 3: Demand achieved rate for the vehicles by the EV charging stations.

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