Stochastic Optimization of Electric Vehicle Charging Stations

Στοχαστική Βελτιστοποίηση της Διαδικασίας Φόρτισης Ηλεκτρικών Οχημάτων

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Dedicated to my family.

Abstract

With range anxiety becoming the every day problem for Battery Electric Vehicles (BEVs) owners, even more research is being conducted in the field of BEV charging and Charging Stations (CSs) scheduling optimization. In this context our work addresses the problem of BEV charging in an urban environment with no a-priori knowledge of vehicle arrivals. Our system is modeled as a $M/G/K$ queuing system. Two adaptive charging algorithms are proposed, both of them relying on queue stability. The first one charges BEVs up to a percentage of their maximum capacity when charging queues become unstable. The second one when detects instability charges BEVs sufficiently enough to reach their next destination. Both algorithms can be used in combination with an admission control algorithm that does not allow BEVs that do not fulfill certain criteria into the charging stations. The First-Come-First-Serve algorithm is directly compared to our proposed algorithms, with prominent improvement concerning congestion in charging stations and waiting time of electric vehicles.

Περίληψη

Με το άγχος της απόστασης να μετατρέπεται σε ένα καθημερινό πρόβλημα για τους ιδιοκτήτες ηλεκτρικών αυτοκινήτων, όλο και περισσότερες έρευνες δημοσιεύονται στους τομείς της φόρτισης ηλεκτρικών αυτοκινήτων και του προγραμματισμού από τους σταθμούς φόρτισης. Σε αυτό το πλαίσιο η παρούσα διπλωματική εργασία ασχολείται με το πρόβλημα της φόρτισης ηλεκτρικών αυτοκινήτων σε ένα αστικό περιβάλλον χωρίς πρότερη γνώση των αφίξεων. Το σύστημα μπορεί να μοντελοποιηθεί ως ένα $M/G/K$ σύστημα ουρών. Όσον αφορά την επίλυση του προβλήματος προτείνονται δύο προσαρμοστικοί αλγόριθμοι, οι οποίοι βασίζονται στη σταθερότητα των ουρών. Στον πρώτο αλγόριθμο ο σταθμός φορτίζει τα ηλεκτρικά αυτοκίνητα έως ένα συγκεκριμένο ποσοστό όταν οι ουρές φόρτισης γίνουν ασταθείς. Στον δεύτερο αλγόριθμο όταν υπάρχει αστάθεια στις ουρές, ο σταθμός φορτίζει τα ηλεκτρικά αυτοκίνητα τόσο ώστε να φτάσουν στον επόμενο προορισμό τους. Και οι δύο αλγόριθμοι μπορούν να χρησιμοποιηθούν σε συνδυασμό με έναν αλγόριθμο ελεγχου εισόδου, ο οποίοις περιορίζει όσα ηλεκτρικά αυτοκίνητα δεν πληρούν συκγεκριμένα κριτήρια να εισέλθουν στον σταθμό φόρτισης. Ως μέτρο σύγκρισης χρησιμοποιείται ο αλγόριθμος $First - Come - First - Serve$, με τα αποτελέσματα να φανερώνουν μία εμφανέστατη βελτίωση όσον αφορά στη συμφόρηση των σταθμών φόρτισης αλλά και του χρόνου αναμονής των ηλεκτρικών αυτοκιητων στην ουρά.

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Chapter 1

Introduction

As of 2017 a total of 3 million Electric Vehicles (EVs) have been sold worldwide with an increase of 50% in the sales just between 2016 and 2017. The predictions, based on the legislation voted and the constraints imposed by the European Union and other developed countries, are that by 2030 more than 130 million EVs will have made their way in the market [1]. The turn of the automotive industry in the all-electric car is unprecedented [2] and as a result a vast amount of resources is being invested in the development of Battery Electric Vehicles (BEVs). The market is still growing and there are many opportunities for innovation and profit. The impact of this turn is obvious in terms of Electric Vehicle Supply Equipment (EVSE) increased availability and rapid battery development. The fact that all major automotive companies have set the goal for electrification of vehicles can also be seen by the fact that the development of Internal Combustion Engines (ICE) has dramatically slowed down, with some companies soon retiring them completely. This shift will drastically change the driving habits of millions of people as both the range and charging time of EVs are still not comparable to those of an ICE vehicle.

To address this issue, in this work we attack the problem of EV charging in urban environments, by reducing the time an EV is waiting to be charged. We adopt an adaptive queuing-based approach by scheduling in a way that keeps all the charging queues stable [3]. We propose two algorithms for this purpose. The first algorithm adjusts the target charging percentage of each EV when the queue grows more than the service rate of the charging station. However, when the queue backlog is stable, each EV battery is charged at its maximum capacity. The second algorithm considers the distance that EVs need to cover for their next trip. Every time we observe queue growth the system enters what we call a

Next-Trip-Mode where each EV is charged just enough to reach its next destination. As in the first algorithm, when the queue backlogs are normal charging takes place at the maximum EV battery capacity. The main advantage of our approach is that we use an adaptive technique, while at the same time we model the system based on realistic assumptions.

The rest of this thesis is organized as follows. In Chapter 2 we provide a thorough analysis of the relevant bibliography on the field of EV charging. In Chapter 3 we describe the fundamental principles on which our model is built. In Chapter 4 we formulate our optimization problem and set the constraints needed. A detailed explanation of our proposed algorithms is provided in Chapter 5, while the results of computer simulations are presented in Chapter 6. Finally, Chapter 7 concludes this work.

Chapter 2

Related Work

This rise in interest of both the society and the automotive industry has led into considerable research in the field of BEV charging and its integration into the existing infrastructure, as can be seen in [4] and [5]. Those detailed articles review the literature in BEV Charging Scheduling Optimization and present the problem formulation adopted in every case.

In [6] the authors focus on optimizing the driving range of EVs by deploying several mobile CSs beyond the static CSs. They formulate an optimization problem and due to its complexity they solve deterministic formulation of it that leads to significant extension of the driving range. In [7] the authors propose two techniques that exploit BEV charging during their workplace parking and utilize it through both Vehicle-to-Grid (V2G) and Grid-to-Vehicle (G2V) technologies. Their two strategies minimize daily cost and Peak-to-Average Ratio (PAR) respectively. In [8], the authors propose a predictive management technique in order to allocate optimally the BEV deployment into a community micro-gird. With day-ahead energy prediction and real-time optimal allocation they achieve a reduction in netload ramping and total energy cost as in the previous work. However both of these works do not consider the BEV owner and his convenience, something which is accomplished in [9], where a bi-objective optimization problem is formulated that jointly minimizes operation cost of the charging station and maximizes the convenience of the BEV owners. Despite the effectiveness of the proposed algorithm the authors did not take into account the diversity of BEV batteries, and the stochastic nature of the BEV arrivals. Similarly in [10] while a queuing model with V2G communication is proposed, the BEV arrival rate is considered steady, the number of BEVs in the system is predefined and there is no diversity in BEV battery capacity or Charging Station (CS) charging rate. A very interesting technique that involves BEV admission control and optimal charging is studied in [11]. The authors propose a two-stage process that ensures both CS owner profit and customer satisfaction. Several researchers have tried a game-theoretic approaches in dealing with BEVs Charging Scheduling [12] [13]. A notable effort in the same field, is [14] where an on-line distributed game-theoretic approach has been proposed that minimizes waiting time of BEVs in CSs.

Chapter 3

System Model

Our system consists of N CSs co-located in an urban environment, each having K chargers. We adopt a queuing model for characterizing the behavior of a CS. The system is modeled as a $M/G/K$ queuing system. In each CS the incoming EVs are serviced in order of their arrival (FIFO). Charging time is divided into T time slots each having a duration τ seconds. These time slots are indexed by t, that is $t \in \{1, 2, ..., T\}$.

3.1 Electric Vehicle Arrivals

As mentioned in Chapter 2 the literature typically assumes a steady arrival rate in the models to capture vehicle behavior. This may result in large deviations between simulation and reality [11,15]. In real life vehicle arrivals in refueling stations (both electric and conventional) are more frequent in some intervals of the day and less frequent in some others. Thus, in our work EV arrivals in CSs are modeled as a *Poisson* stochastic process, with a variable, i.e. time-dependent, mean arrival rate $\lambda_N(t)$. As a result the number of EV arrivals during t is $a_N(t) \sim Poiss(\lambda(t))$.

3.2 Electric Vehicle Model

Each EV $i \in I$, arrives with a state-of-charge $SOC_{in}^i \in [0, 1]$ which is a normally distributed random variable, where a value equal to 1 indicates full battery and a value equal to 0 indicates empty battery. Its battery capacity is modeled by a discrete random variable B in kWh that follows the distribution shown in Figure. 3.1. This probability mass function results from the market shares each EV type occupies as mentioned in

EV Type	Battery Capacity (kWh)	EE (kWh/Km)
Small	25	0.1897
Mid-Size	50	0.1757
Large	75	0.2008
SUV	100	0.2487

Table 3.1: EV Efficiency

[16]. The Electric Efficiency (EE) per Kilometer is presented in Table 3.2 and was extracted from [17], which contained the latest data on EE of All-Electric Vehicles as of 2018. Finally, every EV knows the information about the distance of its next trip. This is modeled as a continuous normally distributed random variable $T_i \in [0, 120]$ given in Km.

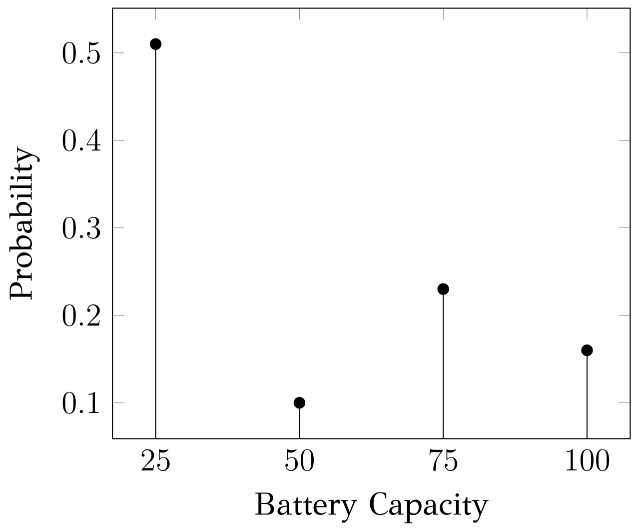

Figure 3.1: Battery Capacity Probability Mass Function

3.3 Charging Station Model

Every CS has a Central Control Unit (CCU). This CCU monitors the charging procedure in every charger and is responsible for gathering the charging information from the recently arrived EVs as described in Section 3.2. Every charger has its charging rate L_k and a queue $Q_k(t)$ which represents the amount of energy the charger has to deliver to the EV charging in time t. The charging rate depends on the type of the charger [1]. The charger types we use in our model are summarized in Table 3.3. Also a binary variable $x_k(t) \in \{0, 1\}$ is used to indicate whether the k_{th} charger is available at time t ($x_k(t) = 0$), or not ($x_k(t) = 1$). Finally each CS has a cumulative queue $U_n(t)$ for unallocated EVs, which in turn represents the amount of energy the charging station has to give to the EVs currently waiting to be charged.

Charger Type	Charging Rate (kW)
Level-1	5
Level-2	15
Level-3	30
Tesla Super Charger	$<$200

Table 3.2: Types of Chargers

3.4 EV Allocation

Every CS has an Allocation Matrix H_N^t that contains all $x_K(t)$ variables. Every time slot the CCU checks if there are any arrivals $a(t)$, and whether any charger is available. If there is an available charger, the CCU allocates the i_{th} EV to the k_{th} charger by queuing its battery requirement $R_i^{in} = SOC_i^{in} * B_i$ into the Q_k. If there is no charger available the CCU queues R_i into queue U_n. The allocation procedure is explained in detail in Algorithm 1.

Algorithm 1 EV Allocation Algorithm

Input: H_N^{t-1}, $a(t)$, and SOC_{in}^i, B_i for currently arrived EVs
Output: H_N^t and Q_k, U_N for every CS

for $i = FirstArrived$ to $LastArrived$ **do**
  for $n = 1$ to N **do**
    if $a_n(t) > 0$ **then**
      for $k = 1$ to K **do**
        Check $x_k(t)$
        if $x_k(t) = 0$ **then**
          $Q_k \leftarrow Q_k + R_i^{in}$
          $x_k(t) = 1$
        else if $x_k(t) = 1$ **then**
          $U_k \leftarrow U_k + R_i^{in}$
        end if
      end for
    end if
  end for
end for
Recalculate H_N^t
return H_N^t

Chapter 4

Problem Formulation

Having clarified our system model, we will now formulate our optimization problem. First we define the charging time to be the sum of the time an EV waits in the queue to be charged w_i^q and the time it takes to charge w_i^c.

$$w_i = w_i^q + w_i^c \tag{4.1}$$

Also by average waiting time we will be referring to:

$$\overline{w_i} = \frac{\sum\limits_{m=1}^{M} w_i(m)}{M} = 0, m \in (1, 2, ..., M) \tag{4.2}$$

where M is the set of EVs that have been charged and have left the station.

Our main objective is to minimize the waiting time w_i for each EV i. The original problem can be formulated as follows:

$$\min \quad \sum_{i \in I} w_i \tag{4.3}$$

$$\text{subject to} \quad R_i^{in} \leq B_i \quad \forall\, i \in I \tag{4.4a}$$

$$R_i^{in} \leq w_i^c * L_k \leq (B_i - R_i^{in}) \tag{4.4b}$$

$$\lim_{t \to \infty} \frac{\sum\limits_{n=1}^{N} (U_n + \sum\limits_{k=1}^{K} Q_k)}{t} = 0 \tag{4.4c}$$

With constraint (4.4a) we ensure all EVs will have an initial charging requirement lower than their battery capacity. In constraint (4.4b) charging time is bound to a maximum of a full battery charge. Finally constraint (4.4c) ensures queue stability of the system [3].

The queuing dynamics of the system are defined as:

$$Q(\tau + 1) = Q(\tau) + a(\tau) - l(\tau) \tag{4.5}$$

Where $Q(\tau + 1)$ and $Q(\tau)$ are the charging queue backlogs in respective time slots, $a(\tau)$ is the new energy demand and $l(\tau)$ is the energy demand that was satisfied during the current time slot. As a consequence the above constraint (4.4c) can be fulfilled only when $a(\tau) \approx l(\tau)$. However, this will result in some EVs having to stop charging and leave the system even though they do not have enough battery charge to reach another CS.

Chapter 5

Proposed Algorithms

In order to issue with the inequity described above, we propose two algorithms that both minimize the waiting time but at the same time do not force EVs out of the system in a way that is sub-optimal for them and the system overall.

5.1 Adaptive Percentage Charging Algorithm (APCA)

In this first algorithm we modify our optimization problem (4.3) - (4.4c) so that the CCU adjusts the charging percentage up to which every EV charges, if the current charging queues become unstable. To achieve that we introduce a constraint variable $p_i(\tau)$. So our optimization problem now is reformulated as follows:

$$\min \quad \sum_{i \in I} w_i \tag{5.1}$$

$$\begin{aligned} \text{subject to} \quad & R_i^{in} \leq B_i \quad \forall\, i \,\in\, I && (5.2a)\\ & R_i^{in} \leq w_i^c * L_k \leq p_i(t) * (B_i - R_i^{in}) && (5.2b)\\ & \lim_{t\to\infty} \frac{\sum\limits_{n=1}^{N}(U_n + \sum\limits_{k=1}^{K} Q_k)}{t} = 0 && (5.2c)\\ & p_i(t) \pm dp \in [0,1] && (5.2d) \end{aligned}$$

When the current queuing time becomes greater than the average queuing time then the charging percentage drops by dp. Respectively when the current queuing time is smaller than the average queuing time, charging percentage grows by dp. The APCA is explained in detail in Algorithm 2.

Algorithm 2 Adaptive Percentage Charging Algorithm

Input: $w_i^q, Q_k(t), U_N(t)$
Output: $p_i(t)$

1: **if** $\sum_{i=1}^{I} w_i^q > \overline{w_i}$ **then**
2: $\quad p_i(t) = p_i(t-1) - dp$
3: **else if** $\sum_{i=1}^{I} w_i^q < \overline{w_i}$ **then**
4: $\quad p_i(t) = p_i(t-1) + dp$
5: **end if**
6: **return** $p_i(t)$

5.2 Adaptive Next Trip Charging Algorithm (ANTCA)

In the second algorithm we propose, when the CCU detects queue instability, it changes its charging policy, so that EVs are charged sufficiently enough to reach their next destination. Our optimization problem is again slightly modified as shown in Eq. (5.3) - (5.4c) next:

$$\min \quad \sum_{i \in I} w_i \tag{5.3}$$

$$\text{subject to} \quad R_i^{in} \leq B_i \quad \forall\, i \in I \tag{5.4a}$$

$$R_i^{in} \leq w_i^c * L_k \leq p_i(t) \tag{5.4b}$$

$$\lim_{t \to \infty} \frac{\sum_{n=1}^{N} (U_n + \sum_{k=1}^{K} Q_k)}{t} = 0 \tag{5.4c}$$

$$p_i(t) \in [0, 1] \tag{5.4d}$$

As in Algorithm 2, when waiting time exceeds the queue average waiting time, the charging station charges EVs sufficiently enough to reach their next destination, based on the information they provide about the distance they have to drive. When the current queue waiting time does not exceed the queue average waiting time EVs are charged to maximum percentage. The ANTCA is described in in Algorithm 3.

Algorithm 3 Adaptive Next Trip Charging Algorithm

Input: $w_i^q, Q_k(t), U_N(t)$
Output: $p_i(t)$

```
if \sum_{i=1}^{I} w_i^q > \overline{w_i} then
    p_i(t) = T_i * EE_i / B_i
else if \sum_{i=1}^{I} w_i^q < \overline{w_i} then
    p_i(t) = 1
end if
return p_i(t)
```

5.3 Admission Control Algorithm (ACA)

We designed an Admission Control Algorithm (ACA) that minimizes charging demands in CSs, when EV arrivals increase. Specifically with ACA, CSs have the option of rejecting some EVs whose charging demands are smaller than those of other EVs. Let us assume, for example, that a CS is currently charging its EVs at a maximum of 60% of their maximum battery. When an EV arrives with a $SOC_{in}^i > 60\%$ it is rejected. This obviously minimizes waiting time observed in CSs and is an additional technique used in conjunction with either of the algorithms described in this Chapter.

Algorithm 4 Admission Control Algorithm

Input: $Q_k, U_N, p_i(t), SOC_{in}^i, B_i$
Output: H_N^t

```
if p_i(t) > SOC_{in}^i then
    Allocate EV per Algorithm 1
end if
return H_N^t
```

Chapter 6

Simulation Results

Our simulation is conducted in an urban environment in a full 24-hour cycle. During this cycle there are periods with difference in frequency of arrivals as can be seen in Figure 6.1. We consider CSs that have three chargers, two of them are Level-2 and one is Level-3. The total EVs entering each CS are average to 450. This happens because we opted for an arrival process which is of stochastic nature.

Our algorithms are put to comparison with the First-Come-First-Serve (FCFS) algorithm which is the basic serving algorithm of Queuing Systems.

6.1 APCA & ANTCA Queue Congestion Evaluation

Here we evaluate the effect the proposed algorithms have on the system. As we can see in Figure 6.2 with ACPA we achieve almost a 25% reduction in waiting time over FCFS algorithm. However, there is still room for improvement, something that ANTCA achieves, practically eliminating waiting time when queues are unstable.

Concerning the average queue backlog we can see in Figure 6.3 that the results were similar as above. In FCFS it is expected that the average queue backlog will keep growing as no EV is leaving until it is fully charged. With APCA we see that, when the queue starts growing so that the system becomes unstable, some EVs leave the system because they are charged not at 100% as in FCFS but at a lower percentage. Finally ANTCA is the algorithm that burdens the least the CS as when it detects instability starts charging EVs sufficiently enough for their next trip.

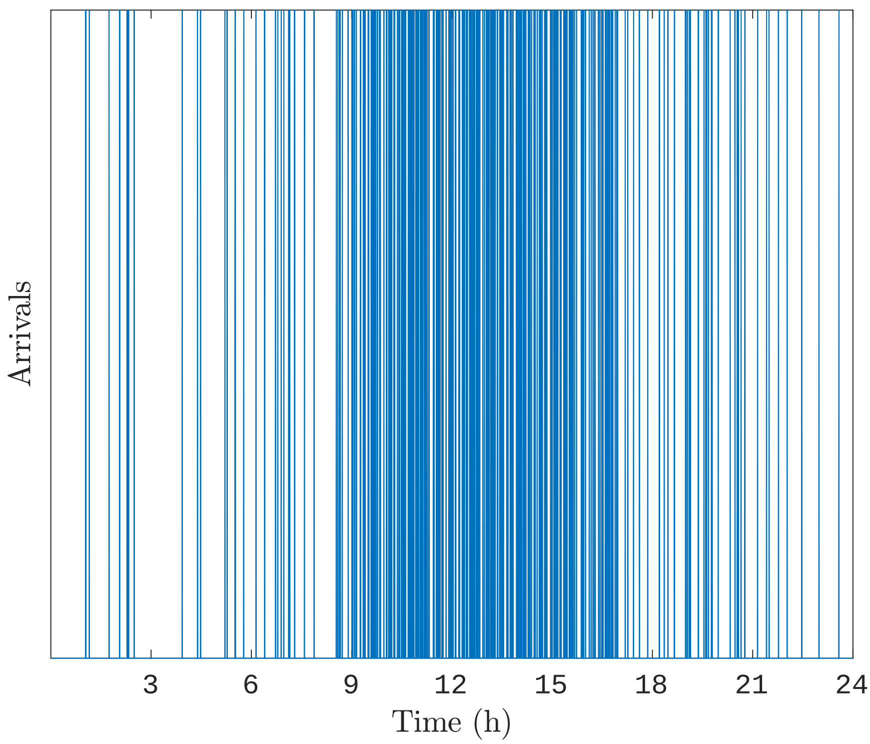

Figure 6.1: EV Arrivals versus time.

We observe the same behavior in the number of total EVs in the system as seen in Figure 5. It is worth noticing that both APCA and ANTCA have almost identical behavior concerning both Average Backlog and Total EVs in the system as the have the same notion of a stable system embedded in them.

As mentioned in Section 5.3, another way to decongest CSs is via ACA. The results, shown in Figure 6, reveal an obvious reduction of the average waiting time EVs experience for APCA and in Figure 6.6 for ANTCA.

Table 6.1 provides a summary on the evaluation of our algorithms. It can be seen that neither of the proposed algorithms is superior in every way to the others. APCA does offer a higher SOC^{out} but it charges 20% less EVs than ANTCA in the same time period. On the other hand, we see that the application of ACA on both the proposed algorithms does reduce the load from the CSs but does not increase SOC^{out} dramatically. This can be explained by the fact that EVs that are not rejected have such a low SOC^{in}, that it does not suffice for their next trip.

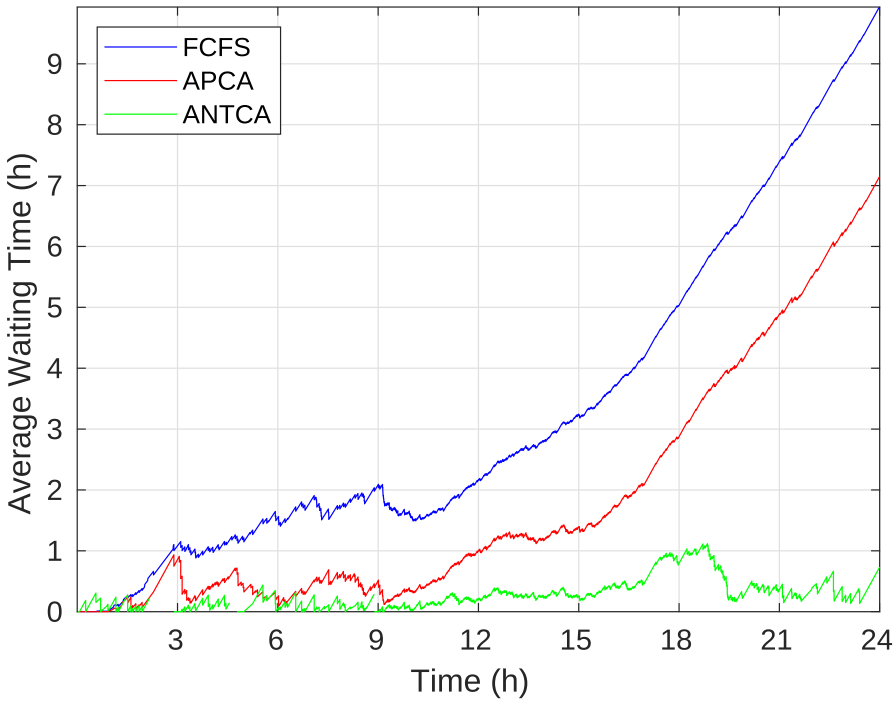

Figure 6.2: Average waiting time versus time.

Table 6.1: Algorithm Evaluation Summary

Algorithm	FCFS	APCA	APCA+ACA	ANTCA	ANTCA+ACA
Rejection Probability	0	–	0.75	–	0.7
EVs Charged (%)	14	40	25	20	30
Mean SOC^{out}	1	0.58	0.60	0.48	0.50

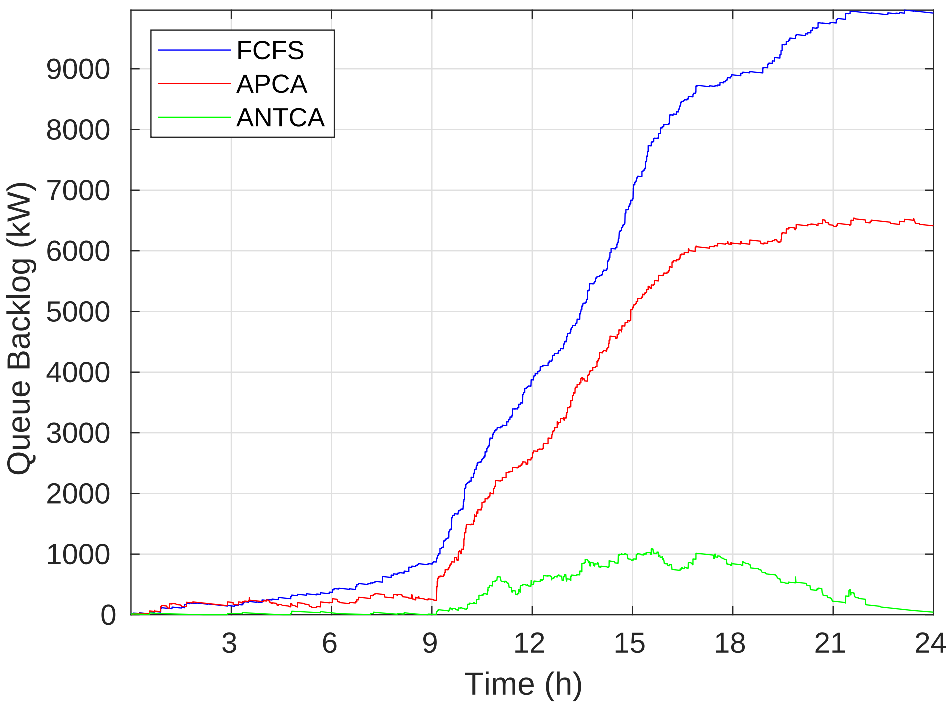

Figure 6.3: Average queue backlog

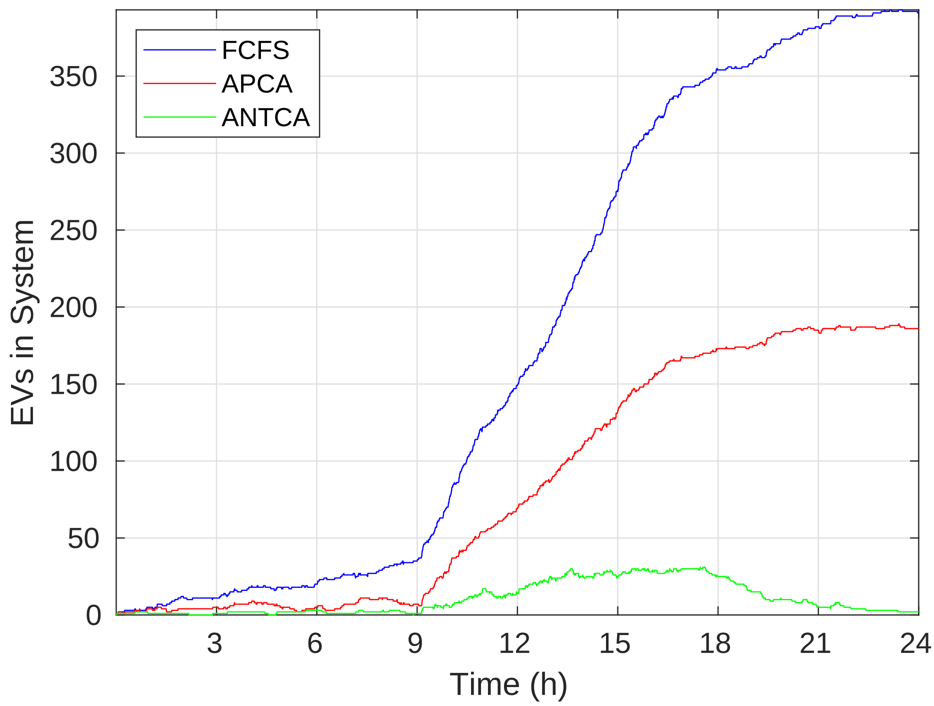

Figure 6.4: EVs in the system

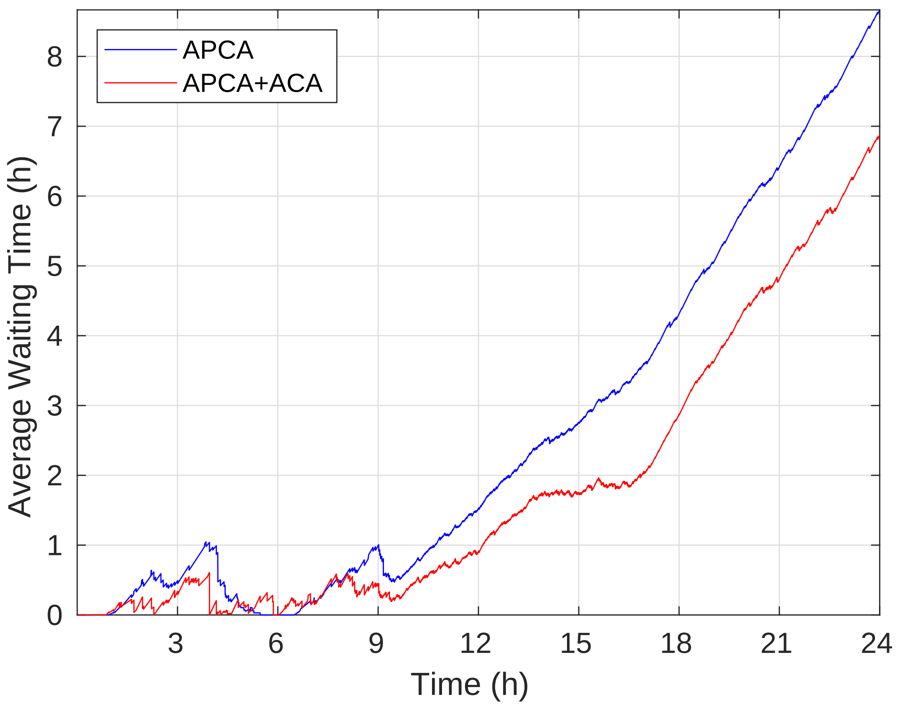

Figure 6.5: Effect of ACA on APCA

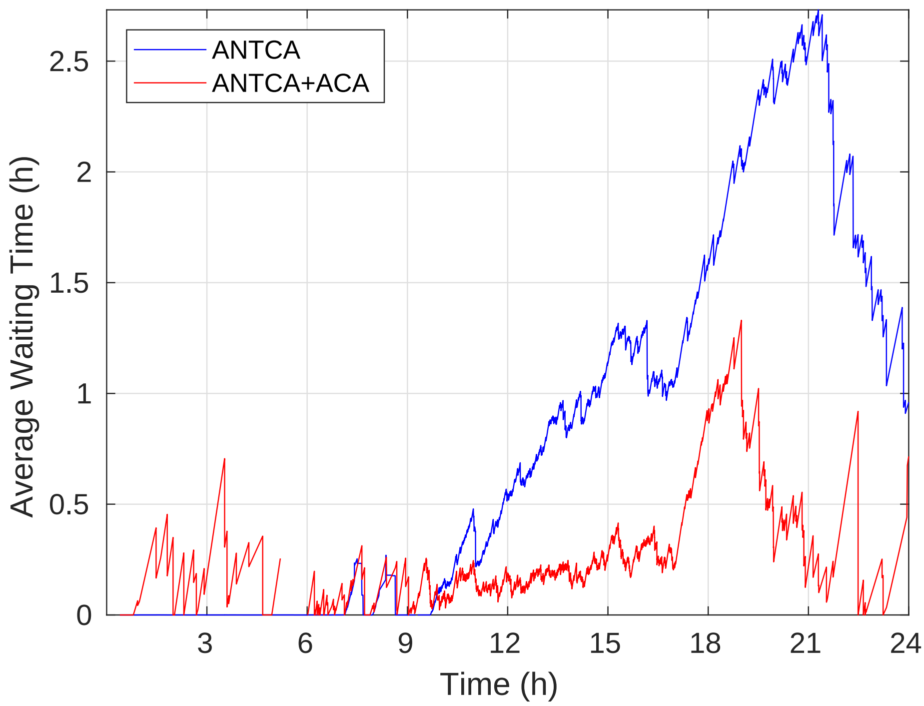

Figure 6.6: Effect of ACA on ANTCA

Chapter 7

Conclusion

In this work, we proposed two adaptive algorithms for optimizing the waiting time of EVs in charging stations. Our algorithms and our results in Chapter 6 we suggest that both algorithms can be applied in charging stations located in urban environments, with a fraction of charging stations adopting APCA and another fraction of them ANTCA. We believe that in combination those two algorithms can handle charging rush hours, without any modification to the charging stations or the power grid. A detailed exploration of such a combined approach is part of our future work. Furthermore, we also plan to evaluate our approach over networks of CSs.

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