An Agent-based Negotiation Scheme for the Distribution of Electric Vehicles Across a Set of Charging Stations

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Abstract

We consider the problem of scheduling Electric Vehicle (EV) charging within a set of multiple charging stations. Each station aims to maximize the amount of charged energy and the number of charged EVs. We propose an agent-based simulation scheme, where the EVs announce their requests to the stations and each station computes an optimal solution using Integer Linear Programming (ILP) techniques. We propose two variations of the problem, namely the Offline Mode and the Online Mode. In the first one, all the EVs send their charging requests simultaneously at the beginning of the simulation and the stations compute their charging schedules at once, while in the second one each EV may send a charging request at whichever time point and the stations compute their charging schedules incrementally. Moreover, we apply agent-based negotiation techniques between the stations and the EVs to service EVs when the ILP problem is initially unsolvable due to insufficient resources at some stations. Finally, we insert delays in the Online Mode, meaning that an EV that came to an agreement with a station may cancel this agreement and request charging anew. We test our scheme for both variations, Offline and Online, for a diverse set of stations and EVs and show the outcomes of the different scenarios in the system.

Keywords: electric vehicle, charging station, optimal charging schedule, negotiation, intelligent agents, agent-based simulation

1. Introduction

The increasingly negative impact of climate change on society has forced several countries to instigate national plans to reduce carbon emissions [1]. The electrification of transport is one of the main pathways to significantly reduce CO_2 emissions, improve quality of driving and reduce running costs for owners [2]. However, the successful introduction of EVs into the market lies upon the acceptance of the new type of vehicle by the customers. Currently, three main problems prevent the spread of EVs: 1) the relatively small driving range, 2) the long charging times and the unavailability of charging stations, and 3) the higher cost of buying an EV compared to a conventional car [3]. Given that these limitations demand several years before they can potentially be removed, ways of making EVs attractive to customers given the current situation must be developed. For example, the flexible charging of many EVs given the available stations and the balanced distribution of them across the stations, can soften limitations 1 and 2.

Moreover, in order to ensure that the large-scale deployment of EVs results in a significant reduction of CO_2 emissions, it is important that they are charged using energy from renewable sources (e.g., wind, solar). Crucially, given the intermittency of these sources, mechanisms (e.g., [4], [5]), as part of a Smart Grid [6], need to be developed to ensure the smooth integration of such sources in our energy systems. EVs could potentially help by storing energy when there is a surplus, and feed this energy back to the grid when there is demand for it [7], [8].

In this paper, we study an agent-based simulation scheme in which agents try to optimally satisfy their needs. In our setting, a number of charging stations with limited chargers and available energy exist. In this domain, EVs send requests to the charging stations and need to charge. The stations reply by accepting or declining the EVs' requests. For the scheduling of EVs to charging stations, Integer Linear Programming (ILP) techniques are being used. In case the ILP problem is initially unsolvable due to insufficient resources at some stations, a negotiation procedure between the EVs and the station takes place. In so doing, the stations propose changes (i.e., offers) to the EVs' initial preferences and EVs can accept or reject these offers. As [9] states, usually, different classes of agents are used to represent those actors in such systems. In our case, we assume that each EV carries its own intelligent agent which autonomously communicates the EV's initial preferences, and later participates in the negotiation with the stations. In this domain, the EVs are self-interested agents that need to maximize their utility (i.e., maximize energy charged and minimize charging time), while the charging stations aim to maximize the number of serviced EVs and the utilization of the available (renewable) energy.

We advance the state of the art as follows:

1. We propose a multi-agent system which consists of multiple stations, that receive charging requests from EVs and compute a schedule, trying to reach their goals, and maximize the EVs' utility.
2. We present a simulation scheme, which consists of two modes, one offline, where all the EVs send their requests simultaneously and the stations have full knowledge on the data, and one online, i.e. stohastic, where the requests may arrive at any time point at a station.
3. We propose a negotiation scheme, where the stations make alternative proposals to the EVs that could not fit in their initial optimal schedule.
4. Finally, we insert the notion of delays in our system, which means that an EV that accepted to charge in a station may change its requirements and ask to move its charging in the future. By doing so, we showcase how our algorithms are affected when EVs delay, which is a possible scenario in a real-world deployment.

The rest of the paper is structured as follows: In Section 2 we present related work to our problem. We continue, in Section 3 by defining our problem and giving details about the multi-agent system we propose. In Section 4, we present several algorithms used by our simulations, such as the Linear Model, that the stations solve in order to compute their local schedule or to compute the alternative offers. In Section 5, we present the two execution variations of our system, namely the *Offline Mode* and the *Online Mode*. Finally, we present our experimental study, in Section 6, and conclude our paper in Section 7.

2. Related Work

To date, a number of papers trying to solve similar problems exist in the literature [10]. For example, Bayram et al. [11] assume a large number of charging points, each of them having pre-ordered a certain amount of energy. They use a centralized mathematical programming algorithm to optimally allocate the energy to EVs, so as to service the maximum number of EVs. The authors evaluate the mechanism in a setting where both selfish (want to charge at the nearest charging point), and cooperative EVs exist, and verify the performance of their algorithms. In turn, [12] propose dynamic programming algorithms that schedule the charging of EVs according to the availability of energy while guaranteeing the intended journeys can be completed. They also show that their solutions can adapt to fluctuations in energy generation from renewable sources thus increasing EV penetration to the grid. In a similar vein, [13] propose an optimal charging decision making framework for connected and automated electric vehicles. The authors use a large scale electric vehicle data set to establish a stochastic energy consumption prediction model with consideration of realistic uncertainties. Based on this model, multi-stage optimal charging decision making models are introduced. Later, a dynamic programming algorithm is used to calculate the optimal charging strategies. In [14] the authors are taking a more complete approach, trying to schedule EVs' charging in the Smart Grid, while taking into consideration other components of the system, such as power plants and storage systems. A problem is formulated, where the cost relevant to the delay of the satisfaction of the EVs' and the income from the service provided is optimized. Finally, the authors in [15] are taking into consideration the load of the grid and the cost of the electricity at each time interval, which may be dynamic. In their scenario an aggregator tries to schedule EVs, while minimizing the energy cost. In doing so, they propose a Pursuit algorithm and a Reinforcement Learning algorithm, in combination with a simple offline placement algorithm, so the schedule will adapt in the fluctuations of the energy cost, while using past knowledge.

Instead, in [16] agents state time windows within which they will be available to charge, and bid for units of electricity in a periodic multi-unit auction (one auction per time step). In order to ensure truthfulness, the authors developed a mechanism that occasionally leaves units of electricity unallocated (burned), even if there is demand for them. In a similar vein, Chung et al. [17] study the problem of the distribution of a set of EVs across several charging stations. In so doing, they model the (possibly contradicting) preferences of the stations and the EVs as a bi-objective optimization one and the Pareto optimality of the proposed solution is proven. In addition, using more traditional agent-based negotiation techniques, Gan et al. [18], implement an iterative procedure to allow EVs to negotiate the charging rate (at different time points) with a utility company (that broadcasts a price signal to control charging). Crucially, they show that, should the charging characteristics of all EVs be known, an optimal solution is reached in a decentralized fashion. Furthermore, the authors in [19] study a setting where EV charging stations participate in energy, reserve and regulation distribution markets by optimally managing their EVs. In doing so, the technical constraints in the distribution networks are met and the overall system cost is minimized. In [20], the authors suppose a day-ahead market and using a Mixed Integer Programming (MIP) technique and a bidding strategy, they try to minimize the charging costs and satisfy the EVs' need for charging. Finally, the authors in [21] propose a mechanism to increase the social welfare of the EVs in a self-interest agent system. Specifically, it is pledged that an EV will charge by its departure, but the time points that will be allocated to it are flexible. In contrast, in our work, a fixed schedule for each EV is decided and cannot change.

Additionally, research based on simulations also exist. In [22], the authors create a multi-agent simulation EV charging which consists of a suite of modules that simulate vehicle traffic, electric vehicles, charging stations and the electrical power grid. Moreover, they take into consideration the impact of the temperature on the discharging of the EVs during their trips. For the charging of the EVs, two types of strategies are compared, one uncontrolled where the EVs charge without limitations as long as they are connected in the grid and one limited to the maximum energy used from the grid, which is more efficient and exploits V2G charging. In the same vein, [23] suggests a centralized algorithm that optimizes electric vehicle charging, combining V2G and G2V, while paying special attention to the energy coming from renewable resources. Forecast data for the power demand as well as the renewable energy generation is used along with the preferences of the drivers about their charging schedule. By running a simulation of their system the efficiency of the algorithm is proved in terms of power imbalance. [24] proposes an algorithm to facilitate the construction of an optimal micro-grid in terms of CO2 emissions. To do so, the authors assume several EV charging schemes and use the load curves generated in order to find the best parameters for the micro-grid. Moreover, the authors in [25] simulate an e-carsharing scenario, supported by a fast-charging station, to provide technical specifications about their system. Finally, tools have been developed which simulate a wide range of EV charging such as the EVLibSim ([26]). EVLibSim is a simulation tool with efficient user interface that covers a lot of functions for EV charging in a station like slow and fast charging, battery exchange etc. The tool is based on the EVLib library ([27]), written in JAVA, which is used to create and manage charging events in a station. The authors provide a simple algorithm for scheduling, however more sophisticated algorithms can be combined with it. Simulation-based approaches are a feasible way of testing systems without investing valuable resources and, also, facilitate in the avoidance of design errors in time [28].

The common characteristic of the majority of the work in this field is that the preferences of the EVs, once communicated to the charging station(s) do not change. The main difference of our approach is that here, we propose an agent-based scheme where in case an EV's preferences cannot be fulfilled, a station can negotiate with it and propose a different charging plan. In contrast to [18], charging characteristics of all EVs are not assumed to be known.

Negotiation between intelligent agents is a very common procedure amongst multi-agent systems. When agents negotiate, they may change their local plans or relax their constraints so as to come to an agreement with other agents in the system. Agent negotiation is used in various problems such as the assemblance of a supply chain [29] as well as the allocation of routes to cars in order to alleviate the traffic on the streets [30]. Negotiation techniques have already been considered as an efficient method to increase the participation of various actors within the Smart Grid [31] as well. Specifically, in [32] agents negotiate energy over a peer-to-peer overlay in order to schedule the energy flows between producers and consumers.

Due to the nature of the problem, most of the papers, described above, differ in the way they model the distribution of energy to EVs, thus an explicit comparison between metrics is meaningless. In terms of an abstract comparison, the negotiation layer we propose improves the metrics of serviced EVs in a station as well as the energy utilization, however, this can lead to additional load on the Smart Grid. Compared to our previous work [33], where we assumed that there is a unique station in the system, which computes an optimal charging schedule, in this paper we consider multiple charging stations. In addition, the negotiation phase is more efficient from the perspective of a station and the EVs have more sophisticated strategies.

3. Problem Definition

In this paper, we study a setting where several EVs send requests for charging in multiple charging stations over time. We assume that each EV is modeled as an agent which communicates to the charging stations the EV's needs and constraints and tries to satisfy them in the best possible way. An intelligent agent is a computer system that is capable of flexible autonomous action in some environment in order to meet its design objectives [34]. In this case, the EV agent receives as input the demand and constraints of the driver and acts autonomously in terms of communicating with the charging station, which is also represented by an agent, and reach the best agreement based on the availability of the stations and the demand of other EV agents. In a real scenario, such an agent could reside on the on-board computer of the electric vehicle. Each station receives requests from the EVs and aims to achieve its goals, which are maximizing its own profit as well as maximizing serviced EVs. The first goal is linked to the amount of energy that will be charged to the EVs and the second goal is linked to the number of the EVs that the station will charge. In so doing, each station takes into consideration its available resources (i.e., chargers and available energy), as well as the EVs' constraints. Each EV agent will choose at most one station to charge. After the decision is made, the pilot of the vehicle is informed and drives to the destination.

In more detail, we denote the set of EV-agents $i \in I \subseteq \mathbb{N}$ and the set of charging station agents $j \in J \subseteq \mathbb{N}$. Each station j has a number of chargers $s_j \in S_j \subseteq \mathbb{N}$. Moreover, we assume a set of discrete time points $t \in T \subseteq \mathbb{N}$ to exist. At each time point each charging slot has one energy unit e_{s_j} (note that energy storage is not supported). The number of chargers constraints the maximum number of EVs that can charge simultaneously. Now, the agent type for each EV is a tuple $p_i = \langle t_i^{inf}, t_i^{arr}, t_i^{dep}, e_i, u_i \rangle$. In more detail, each EV sends a charging request to the stations at t_i^{inf} (inform time) about its arrival time at $t_i^{arr} \geq t_i^{inf}$, the preferred departure time t_i^{dep} as well as the e_i energy that needs to charge. Additionally, each EV i has utility of u_i value, which shows how much of its needs are satisfied.

Now, once the stations receive the requests, containing the EVs' preferences, they apply a scheduling algorithm to decide on their local charging schedules and finally, each station j produces an offer $o_{j,i}$, if possible, for each EV i that requested charging from it. The procedure continues in rounds: In the first round, each station j sends to each EV i that requested charging from it the offer $o_{j,i}$, or in case that given the EV's and station's constraints, an offer is impossible to be computed, the station informs the EV about its unavailability. Each EV evaluates its incoming offers and has two available options: 1) either to accept a station's offer, and in that case it notifies the rest of the stations to stop sending offers to it, or

2) in the case that an acceptable offer has been made by none of the stations it asks for a better offer from them. In the next round, the stations recompute their schedules, considering solely the EVs that accepted their offer and those that demanded a better offer in the previous round. If a station, still cannot charge an EV, it computes an alternative proposal which is as close as possible to the EV's initial preferences. We should note that an alternative proposal is an offer, but not within the initial preferences of an EV. The EV, based on the bounds that are set within its own strategy $str_{p_i} = \langle t^{arr}_{i,min}, t^{dep}_{i,max}, window_{i,max}, e_{i,min}, rounds_{i,max}\rangle$, which is unknown to the stations, evaluates the offers and alternative proposals. In more detail, an EV will not accept any proposal $prop = \langle t^{arr}_{prop}, t^{dep}_{prop}, e_{prop}\rangle$ with $t^{arr}_{prop} < t^{arr}_{i,min}$, $t^{dep}_{prop} > t^{dep}_{i,max}$, $e^{prop} < e_{i,min}$ or $t^{dep}_{prop} - t^{arr}_{prop} > window_{i,max}$. Additionally, an EV i will reject any incoming alternative proposal after $rounds_{i,max}$ of the negotiation and will notify the stations to stop sending offers to it. This procedure lasts one time point and goes on until there are no pending EVs which means, each EV has accepted an offer, or rejected all possible stations.

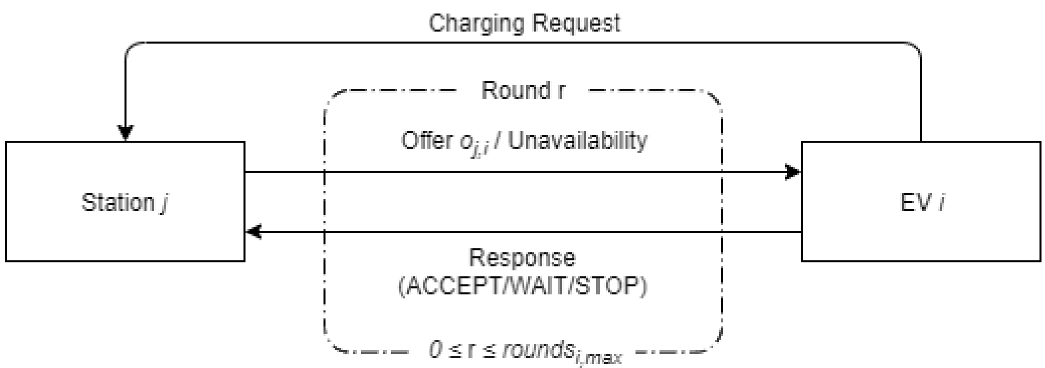

Figure 1: Agent Communication

Based on the categorization of agents architecture, described in [35], both types of our agents can be characterized as *Utility-Based Agents*, as all of the stations and EVs choose actions that maximize their utility. As mentioned before, a station's utility is a combination of how many charging slots are used and how many EVs are serviced. Moreover, an EV's utility is computed by the difference between its initial preferences and the deal made with a station. Furthermore, the station agents can be described as *Limited Rational Agents*, due to the fact that the ILP problem may be complicated and require long computational time, so a suboptimal solution may emerge. On the other hand, the EV agents can be considered *Perfect Rational Agents*, because their decisions depend on simple if-then rules, hence are always the best possible.

4. Algorithms

Here, the basic algorithms of our solutions are described. We begin with the algorithm that the stations use to compute their initial schedule, followed by the algorithm that the stations use to compute the alternative proposals. Additionally, we present how the EVs make a choice on whether they accept the offer of a station or not and how their utility is computed. Finally, more information is provided on the delays.

4.1. EV Scheduling Algorithm

Each station j computes its optimal schedule of EV charging using an optimal Integer Linear Programming (ILP) formulation of the problem (developed using IBM ILOG CPLEX 12.6.2). The aim of this formulation is to find the optimal charging plan such that it leads the station closer to its goal. Thus, the formulation contains two decision variables and an objective function that is maximized under a number of constraints. The fact that the decision variables in our problem take integer values and the objective functions and constraints are all linear, renders ILP as the most appropriate technique to be used. Each part of the formulation is presented thoroughly below.

4.1.1. Decision Variables

Here, we present the two decision variables, that the objective functions and the constraints may use. The first variable, denoted as $a_{i,t} \in \{0, 1\}$, represents if the EV i will charge in the specific time point t. Its type is Boolean and it receives the value 1 if i will charge at t, or 0 in the opposite case. The second variable is denoted as $b_i \in \{0, 1\}$ and represents whether an EV i is serviced or not. Again, if i is serviced the variable b_i receives the value 1 and the value 0 in any other case. From now on, we are going to call the first variable *profit variable*, because each time a charging slot is used in a station its monetary income is increased, and the second one *service variable*, because it represents how many EVs will be serviced.

4.1.2. Objective Functions

A charging station uses the Objective Function given by equation 1. The objective function makes use of the *profit variable* as it tries to maximize its profit, which means use as many charging slots as possible. We should note that a charging slot represents a charger at a specific time point. This, also, increases the number of the serviced EVs while keeping the profit high. In the case where the second variable was used as well in the objective function the station would choose EVs with smaller energy demand in order to achieve its goal (service as many EVs as possible), which may lead to smaller profit, which is the station's main goal.

$$maximize\{\sum_{i\in I}\sum_{t\in T} a_{i,t}\} \tag{1}$$

4.1.3. Constraints

As for the constraints, every vehicle i must charge the number of energy units that it needs between its preferred time points (Equation 2), while the number of vehicles that charge simultaneously must not exceed the total number of charging slots (Equation 3). In the first constraint, the amount of energy e_i the EV requested is multiplied by *service variable* for the EV, because if there is not enough energy for the station to charge the EV for the demanded energy, the sum in the left side of the equation must be equal to zero and thus b_i becomes equal to zero so as to make the linear problem solvable.

$$\forall i \in I, \sum_{t=t_i^{arr}}^{t_i^{dep}} a_{i,t} = e_i \times b_i \tag{2}$$

$$\forall t, \sum_{i\in I} a_{i,t} \leq |S_j| \tag{3}$$

4.2. Alternative Proposals Computation

As mentioned before, stations compute alternative proposals when they cannot fit an EV in their schedule using their initial preferences. In this subsection, we present in detail how a station calculates alternative proposals. Each station's objective is to use as many as possible charging slots by changing as little as possible the initial preferences of the EVs. To achieve this, the stations solve the Linear Programming problem, presented below:

$$profit\_sum = \sum_{i \in I} \sum_{t \in T} w1 \times z \times a_{i,t} \tag{4}$$

$$closeness\_sum = \sum_{i \in I} \sum_{t \in T} w2 \times d_{i,t} \times a_{i,t} \tag{5}$$

$$maximize\{profit\_sum - closeness\_sum\} \tag{6}$$

constrainted to:

$$\forall i \in I, 1 \times b_i \leq \sum_{t=t_i^{arr}}^{t_i^{dep}} a_{i,t} \leq e_i \times b_i \tag{7}$$

where at a time point t, for an EV i, if $t < t_i^{arr}$ then $d_{i,t} = t_i^{arr} - t$ and if $t > t_i^{dep}$ then $d_{i,t} = t - t_i^{dep}$, is the distance of the time point from the initial window. The problem is also constrained by the inequation 3. In more detail, the station tries to fill as many remaining chargers as possible (Equation 4) giving priority to the time points with the smallest distance from the EVs' initial window (Equation 5), while trying to give to each EV less or equal energy to the initial demand (Inequation 7). The two weights, w_1 and w_2, are used so that the two sums are transformed to the same scale. To compute each weight, we first calculate the maximum value of the corresponding sum and then we divide a constant number with this value. By multiplying each sum with its weight we make sure that the two sums in the objective function are going to be of equal importance. Then we multiply the first sum with $z > 1$ to make maximizing profit the first priority.

4.3. EVs Strategy

In this section we present the algorithm (Algorithm 1) that the EVs use in order to produce the answers they provide to the stations. An EV receives offers from the stations and sorts them from best to worst (line 1). Then it picks the first offer in the list (line 2). If the rounds of the conversation are less or equal to the EV's $rounds_{max}$ and the selected offer is within its initial preferences or the rounds of the conversation are equal to the EV's $rounds_{max}$ and the selected proposal is an alternative to its initial preferences (but inside the bounds of the EV's strategy) it accepts the offer and rejects all other stations (lines 5-7). In contrast, if the number of rounds of the conversation is less than the EV's $rounds_{max}$ (but there is not an offer within the initial preferences), the EV asks for a new offer (lines 8-9). Finally, if the rounds of the conversation are equal to the EV's $rounds_{max}$ and there is no available offer (i.e., out of acceptable bounds of EV's strategy, or station could not find one) the EV rejects all the stations (lines 10-12).

Algorithm 1 EV Strategy

1: ev.sort(incoming offers)
2: $first \leftarrow ev$.offers.first
3: $st \leftarrow first$.getStation
4: Define ev's patience as $rounds_{max}$
5: **if** ($first$.withinInitial **and** $rounds_{conv} \leq rounds_{max}$) **or** ($first$.isAltProposal **and** $rounds_{conv} == rounds_{max}$) **then**
6:    ev.send("ACCEPT", st)
7:    ev.send("REJECT", {allStations - st})
8: **else if** ($first$.notAvailable **or** $first$.isAltProposal) **and** $rounds_{conv} < rounds_{max}$ **then**
9:    ev.send("PENDING", allStations)
10: **else if** $rounds_{conv} == rounds_{max}$ **then**
11:    ev.send("REJECT", allStations)
12: ev.offers.clear

4.4. Utility Computation

At this point, we should present how the utility of an EV is computed, after it accepts an offer from a station. An EV will have utility of 1 if it is scheduled to be charged with its initial preferences, while if it rejected all the stations its utility is equal to 0. However, if an EV accepted an alternative proposal, then it means that it had to compromise and alter its initial preferences. In that case, the utility of the EV is computed as shown below:

$$u_i = 1 - (w_3 \frac{energyDif}{maxEnergyDif} + w_4 \frac{windowDif}{maxWindowDif}), \tag{8}$$

where $energyDif$ is how much energy the EV sacrificed, $windowDif$ is the count of how many time points the arrival and the departure time points were moved out of the initial window, $maxEnergyDif$ represents how much is the worst loss of energy (all the energy asked minus 1) and $maxWindowDif$ is computed in the same way as $windowDif$ when the window has undergone maximum displacement. Below, an example computation of the utility of an EV is presented:

In a system with 5 time points, an EV demands 2 energy units and would like to charge at time window $[2-3]$. A station proposes to the EV to charge for 2 energy units, but in a different time window. The new time window is $[1-2]$. The EV accepts the proposal. The utility of the EV then is computed this way: First the $energyDif$ is computed. The EV has not sacrificed any energy units so $energyDif$ is equal to 0. Also, $maxEnergyDif$ is equal to 1 (maximum loss of energy). After that, $windowDif$ is computed. The new arrival time point differs 1 time point form the initial time window. The new departure time point remains into the initial time window, making its distance equal to 0. So, $windowDif$ is the sum of those two numbers and it is equal to 1. Then, $maxWindowDif$ is computed, in the same way, except that the distance between the initial and the worst time window is computed. The worst time window for the EV, is $[0-1]$ (the initial window is slided the furthest distance to the left. If the slide to the right is larger, then that window will be considered). The worst arrival time point differs 2 time points and the worst departure time point differs 1 time point form the initial time window. So $maxWindowDif$ would be equal to 3. The utility then is:

$$u_i = 1 - (0.5 \times \frac{0}{1} + 0.5 \times \frac{1}{3}) = 0.83 \tag{9}$$

4.5. Delays

Finally, in the Online Mode there is a possibility that an EV delays its arrival to the station with which it came to an agreement about its charging. When an EV knows that it is going to delay, it informs the station about this change by communicating its new preferences. The station, then, removes the EV from its schedule and treats it like a totally new entry. The delayed EV will not have priority over the other EVs, meaning that it may end up altering its preferences or not being charged at all. Continuing, we provide information about EV delays and how the delayed EVs calculate their new preferences.

At a random time point $t_i^{inf} < t < t_i^{arr}$, an EV that reserved charging slots in a station at time point t_i^{inf} may announce its inability to be punctual. When this happens, the EV sends a new charging request with its updated preferences only to the station in which it was about to charge. The new preferences result from the initially accepted charging preferences slided to the right for a random number of time points. The energy demand remains the same unless $|T| - t_i^{arr'} < e_i$, where $|T|$ is the total number of the time points in a simulation and $t_i^{arr'}$ is the new arrival time point. This means that if the EV arrives at the station on its new arrival time point, there will not be enough time points until the end of the simulation to satisfy its initial energy demand. Thus, in that case energy demand is equal to $|T| - t_i^{arr'}$ in order for it to be as close a possible to e_i. Apart from their new preferences, the EVs also update their strategy by simply sliding the acceptable time window by the same amount of time points as the one of the initial preferences. We assume that each EV can declare one delay, maximum.

5. Offline & Online Mode

The scheme described in Section 3 has two modes - Offline and Online. In the Offline Mode, the negotiation between the stations and the EVs runs only once after all the EVs have informed the stations about their requests. In our implementation of the Offline Mode we assume that the negotiation takes place in $t = 0$, including $t = 0$ in the generated schedules, because when the requests were accumulated is not of importance. In the Online Mode, the EVs send charging requests at any time point $t = t_i^{inf}$.

The Offline Mode is used as a benchmark to evaluate the results of the Online Mode. However, a realistic scenario for the Offline mode is that the stations gather the charging requests for a day d at day $d-1$ and calculate their schedules at the end of $d-1$. In the next subsections the two alternative variations are presented in algorithmic manner.

5.1. Offline Mode

At the beginning of the simulation ($t = 0$), and as can be seen in Algorithm 2, each EV broadcasts a charging request (lines 1-2) to the stations. Each station receives its requests and adds the EVs requested charging into its pending list (lines 3-4). While there are pending vehicles in the system (line 6), which means that there are EVs waiting for a better offer from the stations, each station computes its optimal charging schedule for the EVs in its pending list, as described in Section 4.1 (line 8). If there are any EVs that could not fit in the optimal schedule of a station, then this station informs them about its unavailability (line 10). Continuing with the algorithm, each station, sends a message containing its offer to each EV that requested charging from it (line 12). Each EV sends an answer based on its strategy (lines 14-15). Then, the stations receive the answers of the EVs. Each station, having cleared its pending list, (line 13) fills it again with the EVs that asked for a better offer (lines 19-20). Also, the EVs that accepted a station's offer are locked into the schedule, so the decision of their charging will not change (lines 21-23). If there are still pending EVs, then the conversation rounds count is increased by 1 (line 24) and the procedure is repeated (lines 6 - 24).

Algorithm 2 Offline Mode Algorithm

1: **for all** $ev \in A$ **do**
2:     *ev*.request(stations)
3: **for all** $station \in C$ **do**
4:     *station*.pendingList.addAll(EVs requested)
{Conversation part}
5: Define rounds of conversation as $rounds_{conv} = 0$
6: **while** pendingEVs **do**
7:     **for all** $station \in C$ **do**
8:         Optimal(*station*.pendingList)
9:         **if** Not charged **then**
10:             *station*.informUnavailable (not Charged EVs)
11:             *station*.pendingList.remove(not Charged EVs)
12:         *station*.sendOffers(*station*.pendingList)
13:         *station*.pendingList.clear
14:     **for all** $ev \in A$ **do**
15:         Send *answers* based on *Algorithm 1*
16:     **for all** $station \in C$ **do**
17:         *station*.receive(*replies*)
18:         **for** (r of EV: ev) $\in$ *replies* **do**
19:             **if** r equals "PENDING" **then**
20:                 *station*.pendingList.add(*ev*)
21:             **else if** r equals "ACCEPT" **then**
22:                 *station*.lock(*ev*)
23:                 *station*.updateResources
24:     Increase $rounds_{conv}$ by 1

5.2. Online Mode

In the Online Mode (Algorithm 3), charging requests can arrive at the stations at any time point t. We define a set of time points that the simulation is going to last (line 2). While the current time point t_c of the execution is less than the total number of time points (line 4), EVs that their t^{inf} is equal to t_c send requests to the stations. Additionally, EVs which have already made a reservation at a station, however, in t_c realize that they will delay, also inform the corresponding station (lines 5-7). Each station receives its requests and adds the EVs that requested charging into its pending list (line 9). Stations, then, are going to make offers at that time point and the *Conversation Part* of the *Offline Mode Algorithm* takes place but only for the EVs that requested at this time point (line 12). So that means that the *Conversation Part* is going to run more than one time, but using only a little proportion of the EVs in the system. The decision for the EVs that have accepted an offer at some time point and are scheduled to be charged in a station, won't change when new EVs arrive and a new optimal schedule is computed by the stations. So, the new optimal schedule in a station will be computed using only the resources that haven't been allocated yet.

Algorithm 3 Online Mode Algorithm

1: Define slot of the execution as $currentTimeSlot = 0$
2: Define total time slots of the execution as $timeSlots$
3: Define an empty set of stations as $activeStations$
4: **while** $currentTimeSlot \leq |T|$ **do**
5:     **for all** $ev \in A$ **do**
6:         **if** $ev.t_{inf} == currentTimeSlot$ **then**
7:             ev.request(Stations)
8:     **for all** $station \in C$ **do**
9:         $station$.pendingList.addAll(EVs requested)
10:         **if** $station$.makesOffers **then**
11:             $activeStations$.add($station$)
12:     Execute Offline *Conversation Part* with only $activeStations$
13:     $activeStations$.clear
14:     Increase $currentTimeSlot$ by 1

6. Evaluation

In this section we present simulations which demonstrate the way the EVs distribute to stations, at which point stations achieve their goals, what impact the alternative proposals have on the outcome and how the delays affect the goals of a station. Additionally, we report the execution time for various simulations. The evaluation begins by running Offline and Online Mode simulations of a system with a single station and observing the difference between the two variations as well as the effect of the alternative proposals and delays on the metrics. Then another station is added and various metrics are monitored. Finally, a large scale simulation with a system of four stations takes place.

The parameters used in our experiments are based on the specification of the well-known Nissan Leaf[1] and its four variants. In more detail, the battery capacity of the four Nissan Leaf models ranges from $40kWh$ (Accenta, N-Connecta, Tekna) to $62kWh$ (e+ Tekna) and they all use a $6.6kW$ charger[2], therefore, we assume that the chargers in our experiments output the same power in kWs. We define that all of the charging EVs consume the same amount of energy at each time point and this amount equals to one energy unit. Moreover, we assume that the time is divided in discrete time points and the experiments simulate the duration of one day, so we have 288 time points each of which represents 5 minutes, making an energy unit equal to $0.55kWh$. This means that a single station can offer at maximum $7920kWh$ in the duration of a day. In each experiment, the EVs require heavy charging, so their energy demand ranges in $[50, 75]$ energy units and their preferences are drawn from a Uniform Distribution (other distributions can be used too) because we want the stations to be agnostic about possible traffic patterns. In addition, we should state that in the experiments containing negotiations, for each station, we study the utility of the EVs that accepted an offer. The weights for the utility computation are 0.5 for the energy difference and 0.5 for the window difference. Finally, in experiments with more than one station, we assume that all the stations are on close locations on the map.

[1] `https://europe.nissannews.com/en-GB/releases/release-426214149-the-new-nissan-leaf-the-world-s-best-selling-zero-emissions-electric-vehicle-now-most-advanced-and-accessible-on-the-planet`

[2] `https://www-europe.nissan-cdn.net/content/dam/Nissan/gb/brochures/Vehicles/Nissan_Leaf_UK.pdf`

[36] proposes a mathematical model to place the stations optimally on a map. However, in our work, we want to compare the traffic attracted in each station based on its strategy and not on its location (some stations might be out of the maximum distance an EV is willing to traverse).

6.1. Single Station

In this section we present the results obtained with simulations ran on a single station to point out the differences between our various approaches. We compare the Offline and Online Mode on how many EVs are serviced and how many charging slots of the station are used. For the Online Mode we consider a case where the suggestions of alternative proposals do not take place and another case where they do. By doing so, we show the impact of the alternative proposals in our system. Finally, the utility of the EVs in our third scenario is presented. The station contains 50 chargers and there are 250 EVs in the system.

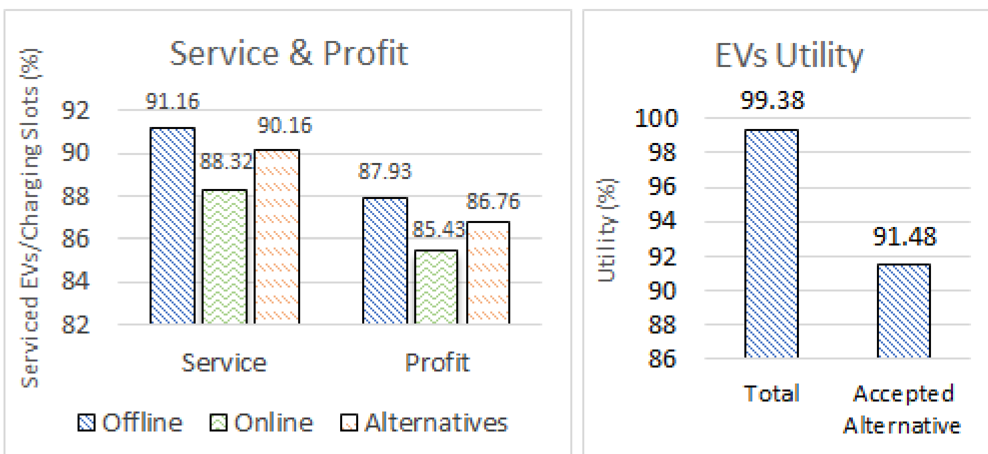

Figure 2: Single Station - Service, Profit & EVs Utility

As seen in Figure 2, the Offline Mode dominates the other two on both of our metrics. The Online Mode without alternative proposals comes last, as expected, charging 2.84% less EVs and using 2.5% less charging slots than the optimal solution. By applying the alternative proposals technique the station manages to increase these values and achieve a better result, which is closer to the optimal one. Specifically, the station charges 1.84% more EVs and uses 1.33% more charging slots than the simple Online Mode. So, alternative proposals improve the service and profit of a single station.

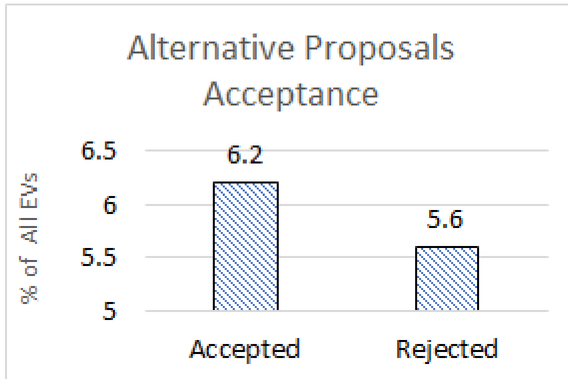

Figure 3: Single Station - Alternative Proposals Acceptance

Another point worth mentioning is why the stations do not use more of their charging slots. Because the arrival time of the EVs is randomly generated there is not much concentration in single time points so the earlier time points of the execution have not been demanded by many EVs. However, the following time points are requested by both EVs that informed earlier than their arrival time and EVs that demanded charging slots in early time points but their energy needs required many of the future slots, too. In Figure 4 the usage of chargers in each time point for the three simulations is showcased. In parallel with Figure 2 it is noticed that the Offline Mode makes the best usage of charging slots, the Online Mode the worse and the Online Mode with alternative proposals lies in the midst of the other two.

When an EV accepts an offer which diverges from its initial preferences, it loses some of its utility. In Figure 2 we notice that the overall utility of the EVs - that is, the utility of all the EVs that charged in the station either using an alternative proposal or not - remains high at 99.38%. However, the isolated utility of the EVs that their preferences were altered have a lower utility 91.48%, which is still satisfactory. From the total number of EVs in our system, 6.2% accepted an alternative proposal, while 5.6% rejected one (Figure 3). As one can notice, even though 6.2% of the EVs accepted an alternative proposal, the overall service was not increased by this number. This happens because an EV that altered its preferences in order to charge may occupy future charging slots that were going to be used by another EV. So the improvement in service is not absolutely equal to the number of EVs with altered preferences.

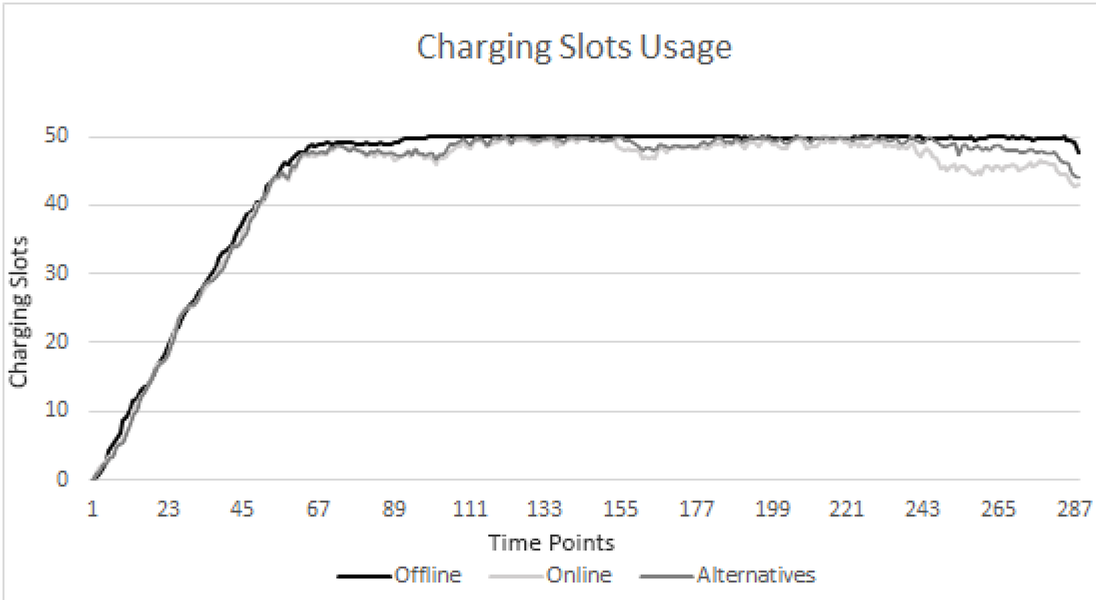

Figure 4: Single Station - Slots Usage

6.2. Delays

Here, we present the impact that the delays of EVs have on a station. As mentioned before, EVs that came to an agreement about their charging at a station, may eventually be unable to arrive to the station on time so they declare delay and request charging with their new preferences. To show that, we run experiments for different quotas of EVs that declare delay. In more detail, we start by setting 10% of EVs to delay. Then, we increase this percentage by 10, until we reach 50% of the EVs in the system. However, these percentages are not absolute because an EV that is set to declare delay may not be charged by the station in the first place so it will never have the possibility to do it.

As one can notice in Figure 5 when there are delays in the system the two metrics tend to diminish. In the Online Mode without alternatives the difference is initially insignificant starting from 0.3% for service and 0.08% for profit at 10% delays but reaching 12.88% for service and 12.7% for profit at 50% delays. However, when the station suggests alternative proposals it attains higher metric values increasing service by 1.82% and profit by 1.74% in average. Additionally, Figure 6 shows that the total number of alternative proposals is increased. Moreover, the number of the acceptance of alternative

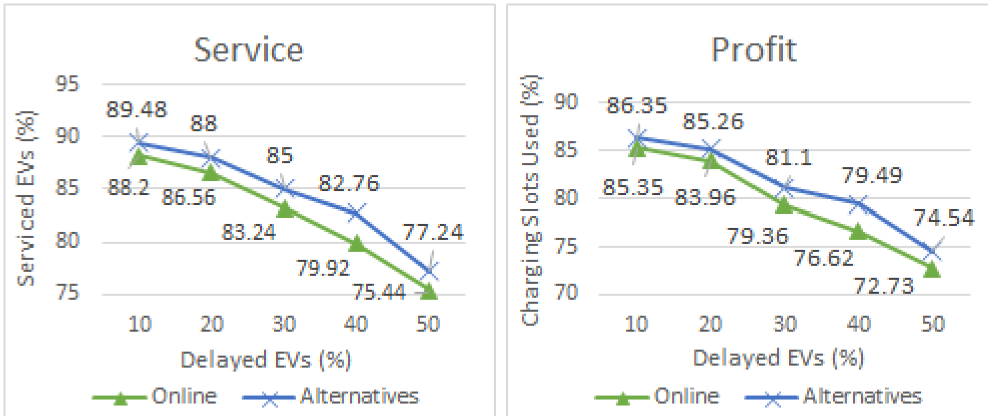

Figure 5: Single Station - Delays: Service & Profit

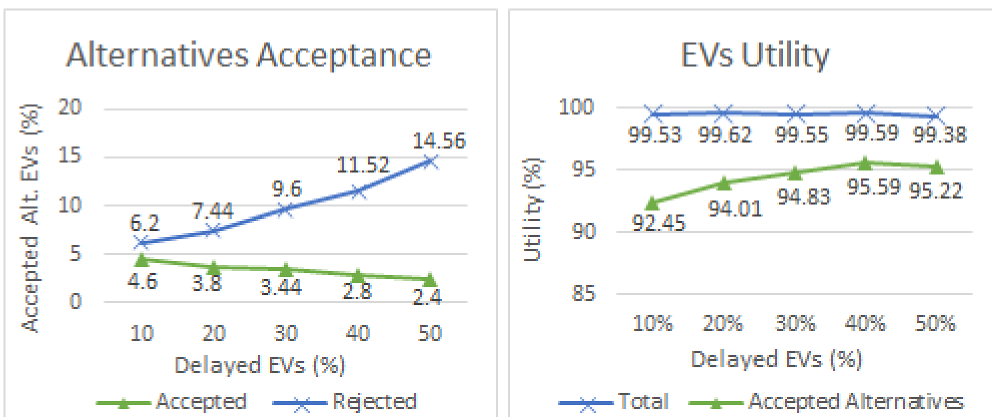

Figure 6: Single Station - Delays: Alt. Proposals Acceptance & EVs Utility

proposals decreases while the rejections are increased. This is due to the fact that when the number of delays increases more EVs request charging in future slots thus congestion emerges. This means that the station has to calculate more alternative proposals as it does not have the required availability. The alternative proposals, however, are far from the EVs' preferences, again, because of limited availability.

6.3. Two Stations Simulation

After the single station simulation in the previous sections, we now add a second station into the system. The second station is identical to the first one, meaning that it has the same number of chargers. The stations may behave differently concerning the proposal of alternative offers. First, we begin with no alternative proposals from any of the stations. We then modify the behavior of one station to suggest alternative proposal and finally we run a simulation in which both stations make alternative proposals. Along with these simulations the results of the Offline Mode simulation are also presented. Table 1 presents these simulations in a more clear manner and sets a name for each one. The number of chargers in each station is 50 and the number of EVs in the system is set to 500.

Table 1: Two Stations - Simulations Setup

	Offline	**Online**		
		Alternatives		
Station 1		No	No	Yes
Station 2		No	Yes	Yes
Sim. Name	*Sim1*	*Sim2*	*Sim3*	*Sim4*

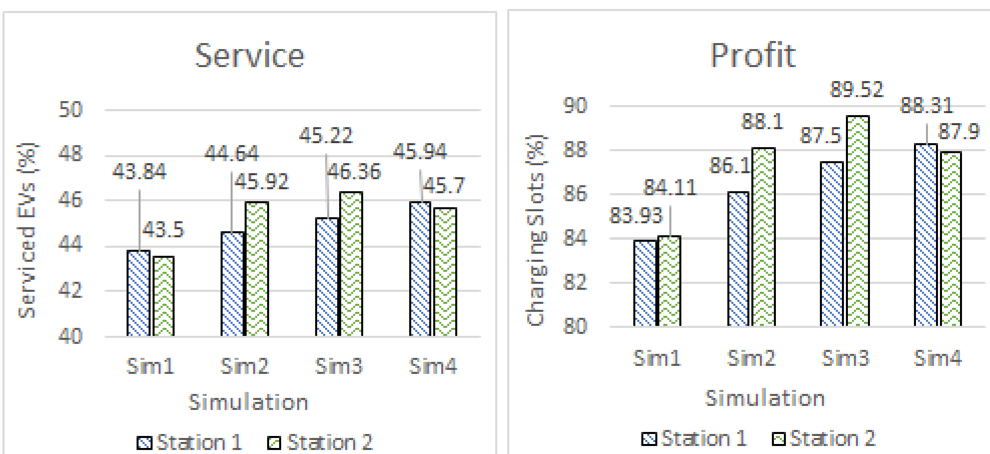

Figure 7: Two Stations - Service & Profit

When the stations compete in the Offline Mode their basic metrics (service, profit) are very close to each other (Figure 7). Both stations make optimal use of their resources and charge as many EVs as possible. The small difference between them results from the random choices of the EVs about which station they will choose. Comparing the Online Mode in *Sim2* to *Sim1* we notice that the service and profit have increased (Figure 7). In the Offline Mode the stations compute their schedule only once so when EVs reject them they don't have the chance to fill the charging slots that left empty. However, in the Online Mode the station has the chance to fill that kind of slots as new EVs will request in future time points.

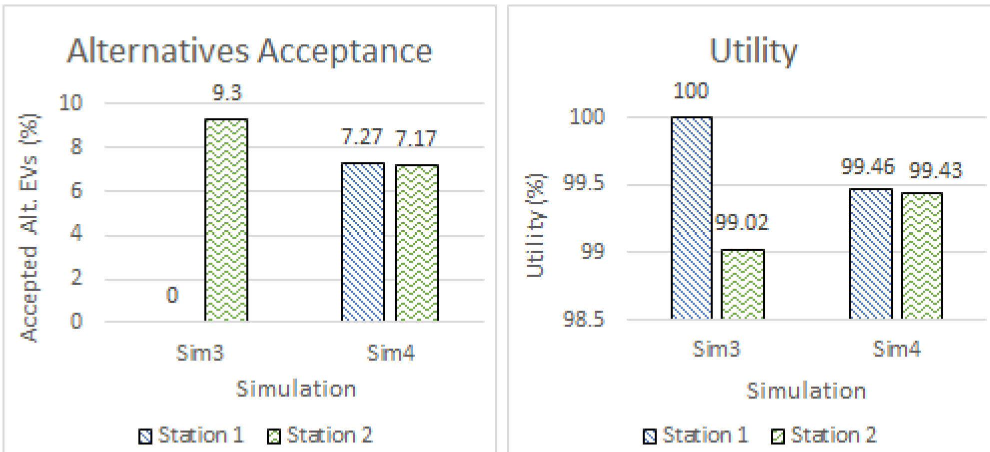

Figure 8: Two Stations - Alt. Proposals Acceptance & EVs Utility

In the variations of the Online Mode both stations are pretty close in terms of services. However, there is noticeable difference in their profits. This relies on the fact that one station concentrates EVs with more energy demands so as a result more charging slots are used. In *Sim3*, when one of the two stations suggests alternative proposals, the collective service of the two stations as well as the average profit is increased. Specifically, the collective service in *Sim3* is 91.58%, 1% more than that of *Sim2* and the average profit in *Sim3* is 88.51%, 1.41% more than that of *Sim2* (Figure 7). This happens because the one station attracts more EVs and thus it increases its metrics and this way more space emerges in the other station to service more EVs. The EVs that accepted an alternative proposal are the 9.3% of the total EVs that charged in that station and their utility is at 99.46%. In *Sim4* the two stations manifest very similar metrics. Collective service is similar to that of the other three setups and the average profit remains high at 88.1%. The number of EVs that accepted an alternative in both stations are very close and their average utility is 99.45% (Figure 8).

6.4. Four Stations Simulation

In this section, we add two more stations in the system and increase the number of the EVs to 1000. First, the results of the Offline Mode are given and then two more experiments follow up where in the one none of the stations applies alternative proposals and in the second one all of the stations do. As in the previous sections, the results for service and profit are displayed. In the Online Mode 30% of the EVs are set to declare a delay in case they accept to charge in a station.

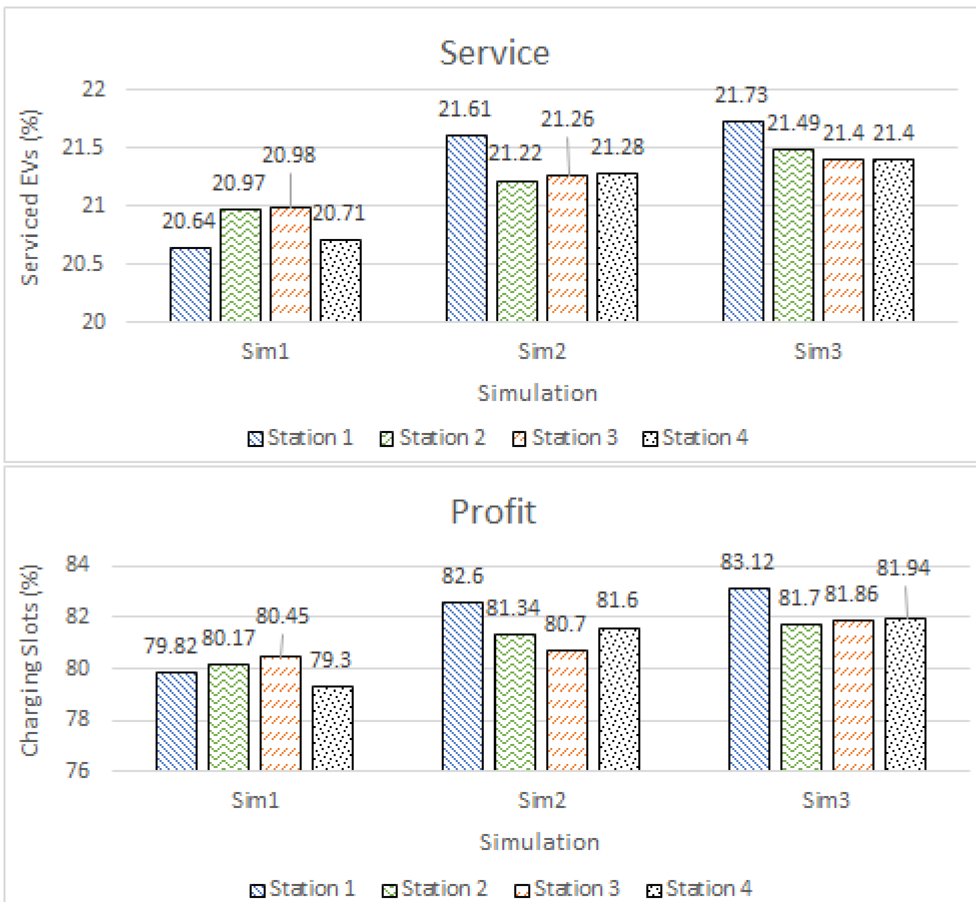

Figure 9: Four Stations - Service & Profit

Similarly with the two stations simulation the stations showcase lower values in service and profit for the reason mentioned in the previous section. In the Offline Mode the average service is very close to the one of the Online

Mode. On the other hand, the average profit increases by 1.62% in the Online Mode without alternative proposals and by 2.21% when alternative proposals are applied. Even though the total profit increases, the number of the EVs that accepted an alternative proposal is below 1% but still offers a small boost, because unused charging slots are being exploited. In contrast, the number of the EVs that rejected equals to 44.2% (for all stations). This means that the stations try to service EVs by calculating new offers for them, however, the EVs have a large pool of choices for their charging so they are likely to select a station which offers to charge them at their initial preference. This discourages the use of alternative proposals when the number of the stations is large. Finally, as in the previous experiments it is noticed that the EVs tend to be equally distributed among the stations.

6.5. Simulation Time

Finally, we present a comparison on the execution times of our proposed algorithms. We run tests for the three modes of this paper (Offline, Online, Online with Alternatives) for different number of EVs. The time is measured at the level of one station, which means that it is the average value of the time that each station needs to compute its final charging schedule. The parameters of the simulations are the same as those in the previous section, but the number of EVs varies.

As we notice (Figure 10), both versions of the online algorithms are much faster than the offline one. In more detail, at 1000 EVs the online algorithms have a mean value of 2.16 seconds, while the offline has a value of 14.95 seconds. This happens because when there is a large number of EVs in the system, in the Offline Mode, each station has to solve a much more complicated problem than the online solutions as it tries to find the optimal schedule for all these EVs at once. However, time is not a major problem in the Offline Mode as there is no need for immediate response from the station. In contrast, the Online Mode simulations solve sub-problems of the main problem at each time point and thus they are much faster. This, however, is not observed when the number of EVs is very small, in our case below 300. In that case, the stations have more charging slots than needed so there are less collisions between the EVs and the schedule is computed much faster. Comparing the two online modes, it is noticed that they are very close but the one with the alternative proposals gets slower as the number of the EVs increases. Having less availability than demand a station has to compute

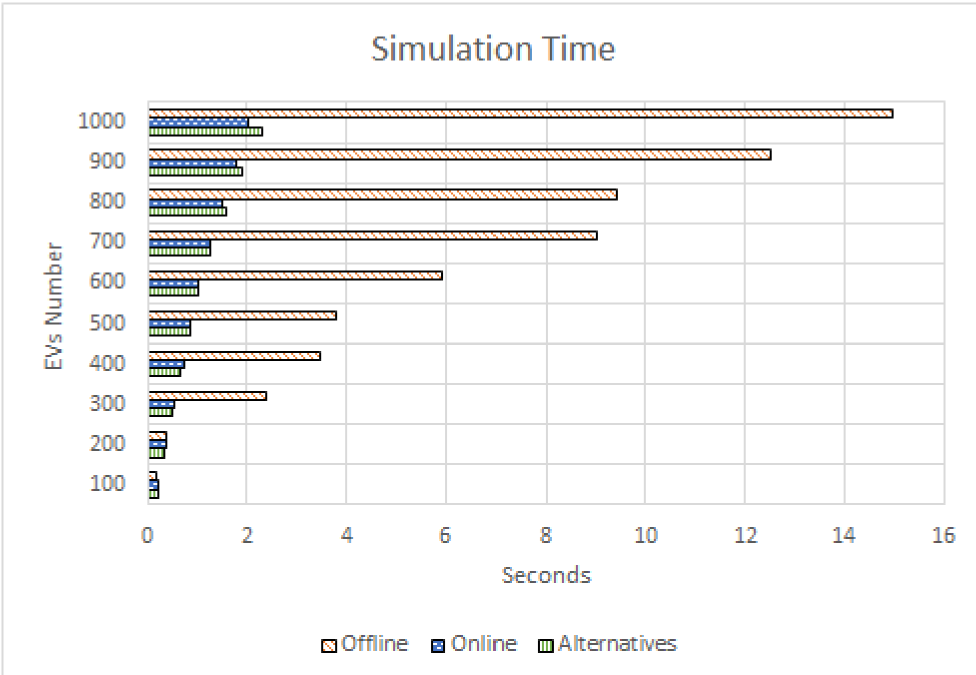

Figure 10: Simulation Time

more alternative proposals and this adds more time to the simulation. However, at 1000 EVs, the difference between the two online simulations is just 0.28 seconds.

6.6. Evaluation Discussion

In this section, we presented various simulations based on the problem definition given in Section 3. We first showcased how the different scenarios we proposed work for a single station, then we moved on by presenting a two-station and a four-station environment and how the number of the stations affect aspects of the simulations such as the suggestion of alternative proposals.

In our single-station simulation we showed that the Offline Mode is the optimal one and that the Online ones are pretty close to it. However, the Online Mode with alternative proposals is even closer to the optimal, in both terms of service and profit. Additionally, it was explained that alternative proposals do not increase the metrics by an absolute number, but they contribute in improving the final result. In addition, the usage of the charging slots was commented. Moving on, we showed how the proposed Online algorithms react when the EVs declare delay. The service and profit decreased as the number of delays increased, but the use of alternative proposals alleviated this decrease. In the two-stations and four-stations simulation we showed how the EVs are distributed in the stations and how the application of alternative proposals affect the overall service and profit. Finally, we compared the time that the simulations need to be completed, showing that the Offline Mode takes longer time and that the alternative proposals cost little time.

7. Conclusions and Future Work

In this paper, we proposed a multiagent methodology for the problem of scheduling EV charging at multiple charging stations. In more detail, we present an agent-based simulation scheme which consists of an Offline Mode where an optimal charging schedule is computed, and an online one, which incrementally calls the Offline Mode's scheduling algorithm, when EVs send requests at the stations. Moreover, we use agent-based negotiation techniques between the charging stations and the EV-agents. Finally, we inserted the possibility of an EV delaying its arrival and shifting it to a later time point. Through an empirical evaluation, we show that the use of alternative proposals improves the metrics of a single station and brings them closer to those of the optimal scenario. It is also observed that when more stations are added in the system the negotiations have less contribution and the Online scenarios manifest better results than the Offline one. Moreover, delays proved to have negative impact on the metrics of a station, however, alternative proposals soothe this problem. When there are more than one stations in the system, alternative proposals tend to increase the collective metrics of the stations. Finally, based on the execution times, we observe that the use of Offline Mode is not encouraged in systems with a large number of EVs as it will not increase significantly the metrics of a station, while it adds extra computation time. On the other hand, the Online Mode manifests better results and takes far less time.

Future work will look at applying learning techniques so as EVs' profiles to be modeled [37]. In this way, personalized alternative proposals can be made from the station to the EVs during the negotiation procedure in order to increase the probability of an EV accepting an offer, as well as stations will be able to predict the amount of energy demanded by the EVs. In this vein, the ability of EVs to store energy when being parked, within a vehicle-to-Grid scheme [38], will be considered in order to increase the storage capacity of the stations. In addition, a more efficient mechanism to participate in electricity markets using electronic auctions and mechanism design will be considered. Mechanism design techniques can also be applied so as to force EVs to always report their preferences truthfully. Additionally, the location of the stations on the map will be considered [39] as well as sophisticated load balancing techniques will be investigated so as the integration of the charging stations and the EVs to the smart grid to take place in the most efficient manner. Finally, an important matter is the integration of our simulation scheme into EVLibSim [26] as well as the redesign of our system in accordance to some generic framework for agent-based simulation of electricity markets such as the one proposed by [35].

8. Acknowledgment

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