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Citation for the original published paper (version of record):

Karlsson, J., Grauers, A. (2024). Agent-Based Investigation of Competing Charge Point Operators for Battery Electric Trucks. Energies, 17(12). http://dx.doi.org/10.3390/en17122901

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Article

Agent-Based Investigation of Competing Charge Point Operators for Battery Electric Trucks

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Abstract: This paper investigates the competition between two charge point operators at the same site for future battery electric long-haul trucks. The charge point operators are located along one of the busiest highways in Sweden. The investigation is carried out using an agent-based model where trucks select charge point operators based on charging prices and the length of any queues, while charge point operators adjust their prices and number of chargers to improve their profitability. The study aims to predict conditions for trucks and charge point operators in a future public fast-charging market. Our findings indicate the potential for a well-functioning future public fast-charging market with small queuing problems, high utilisation, and reasonable prices for public fast charging. Assuming a price for electricity of EUR 0.08/kWh and a minimum profit margin of EUR 0.001/kWh for charge point operators, the findings indicate that the price level outside rush hours will be low, approximately EUR 0.1/kWh. The prices during rush hours will likely be much higher, but it is harder to predict the value due to uncertainties of how charge point operators will act in the future market. Still, from the model result, the price during rush hours is suggested to be just above EUR 0.5/kWh, with an average charging price of around EUR 0.15/kWh. It also seems likely that it is profitable for charge point operators to build enough chargers so that charging queues are short.

Keywords: battery electric truck; battery electric vehicle; charger utilisation; charging station; charge point operator; CPO; long-haul truck; agent-based model; competing charge point operators; fast-charging market

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Citation: Karlsson, J.; Grauers, A. Agent-Based Investigation of Competing Charge Point Operators for Battery Electric Trucks. *Energies* **2024**, *17*, 2901. https://doi.org/10.3390/en17122901

Academic Editor: Giovanni Lutzemberger

Received: 22 March 2024
Revised: 28 May 2024
Accepted: 6 June 2024
Published: 13 June 2024

1. Introduction

Humans' dependency on and combustion of fossil fuels have severe disadvantages. Currently, the oil depletion time is less than 30 years [1], the Earth's climate system has likely been affected [2], and several adverse health impacts have emerged, as expressed in the literature [3]. Battery electric trucks seem to be a part of the solution since several studies have concluded that battery electric trucks could become a cost-efficient, fossil-free alternative to today's commercial diesel trucks [4–8]. The literature shows that the cost-effectiveness of battery electric trucks is sensitive to driving patterns [4], whereas relatively uniform driving patterns are most suitable for electrification [4,9]. Hydrogen trucks could also be a part of the solution; however, previous studies mostly favour battery electric trucks [10,11]. The feasibility of battery electric trucks will likely be good [12], but fuel cells might be better for heavy-duty trucks on extra-long journeys [13]. Thus, there is no unambiguous answer to which power train results in the lowest total cost of ownership since it will depend on how the vehicle is used [14]. The literature also highlights other essential factors for cost-effective battery electric vehicles, such as the battery price [15,16] and size [4,17]. Further, the price of public fast charging could strongly impact the cost-effectiveness, battery sizing and charging strategy [5]. Charger utilisation must be high enough for the installation of chargers to be worthwhile [18], and high utilisation is also a prerequisite for cheap public fast charging [5]. Some advantages of increased fees during rush hours were presented in a previous study [19], including a better meeting of demand, avoiding queues, and increasing profit. For long-haul trucks, fast charging is expected to be necessary [20], and a gratifying result from a previous study [21] is that it seems possible to achieve high charger utilisation and high charger availability of public fast chargers. In [21], the number of public fast chargers for a system of battery electric trucks was tuned manually. Also, ref. [21] raised the question of whether their utilisation would be that good on the free market: "If the system has all the chargers it needs, works well and is profitable, what is there to stop a new charge point operator from entering the market if there is money to be made? All the charge point operators might still profit, but the system has too many chargers". The present paper uses an agent-based model to investigate two competing charge point operators (CPOs). One of the aims is to fill the gap: Can the free market achieve the high utilisation of chargers while still having minor problems with queues? This paper also investigates the price of public fast charging and how prices are affected by the time variation in the charging demand. It is clear from the literature [4] that knowledge of the price level of public fast charging is inadequate and that the price of public fast charging is assumed to be constant over the day [5], which is questioned in the current paper. The authors of the current paper see the price for public fast charging as one of the key factors for cost-effective battery electric trucks and their charging strategy. In addition, possible variations in price over the day could be crucial for the haulage companies' route planning. Therefore, this study adds important knowledge and ideas to the existing research.

The method and conclusions are quite general, but only one charging demand is analysed. It is derived for a charging station in Ödeshög, midway between the Swedish cities Helsingborg and Stockholm, in a future scenario where all trucks are battery electric. The two cities are connected by the E4 highway shown on the map in Figure 1, and the distance between them is 553 km. Ödeshög was chosen since it likely will have a high demand for public fast charging of trucks. Also, the driving distance from both Helsingborg and Stockholm suits the mandatory break, and it already has large truck stops. In the present paper, the charging demand in Ödeshög is assumed to be reflected by the traffic flow. Thus, the charging need is derived from data from the Swedish Transport Administration [22].

In the present paper, there are two competing CPOs in Ödeshög. They are modelled as two agents, changing their price and number of chargers according to a set of rules, aiming to improve their profit. The trucks are also modelled as agents, selecting between the two CPOs to minimise their own costs, including a cost for queuing. An agent-based model is used because, from the author's view, it is more challenging to create a reliable macroscopic model than to find reasonable rules for the agents. The agent-based model provides an opportunity to obtain macroscopic results and to draw system conclusions by only designing rules on the microscopic level.

The main results of this paper are that the price for public fast charging will likely be low outside rush hours and significantly higher, but still reasonable, during rush hours. Also, the CPOs in the analysis seem profitable and able to meet the demand for charging with minor queuing problems, high utilisation of chargers, and reasonable prices for public fast charging. This indicates that the basic competition mechanisms seem to be able to provide an effective charging network.

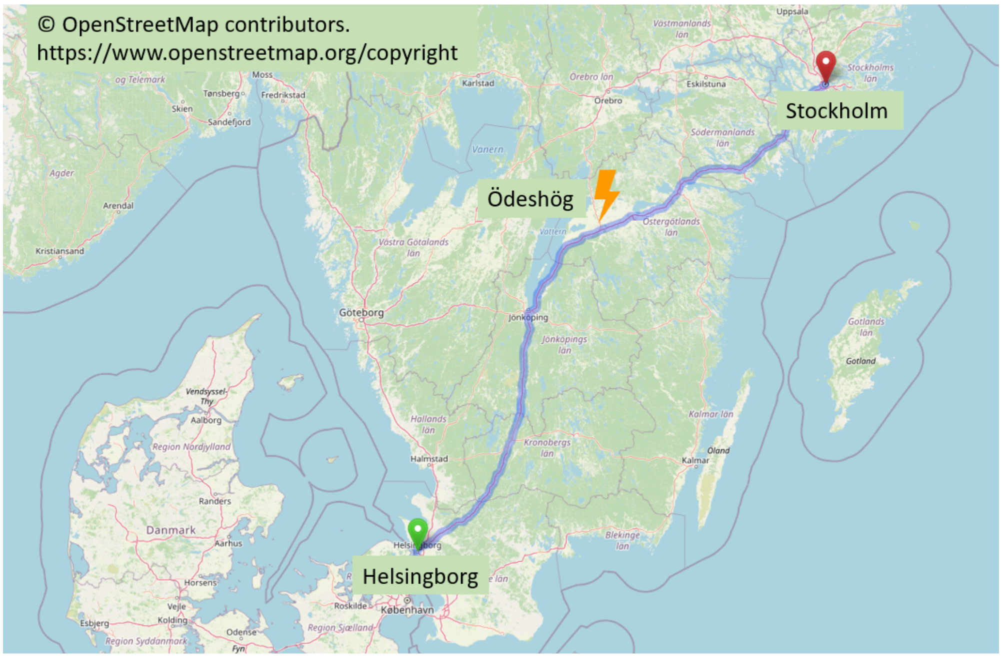


Figure 1. The municipality Ödeshög, strategically placed for en-route charging of battery electric long-haul trucks.

2. Charging Demand

This study analyses a case where all long-haul trucks are battery electric. The data show that the yearly daily average flow of trucks with trailers passing Ödeshög was $F_t = 3322$ trucks per day during the year 2022 [22]. Trucks without trailers were excluded because we believed that they would not drive long distances and, therefore, would not use public fast chargers. Further, Ödeshög is located in between Helsingborg and Stockholm. It takes a truck approximately 4 h to drive from Helsingborg to Ödeshög; therefore, it is a good place for the mandatory 45 min break and, thus, for charging. In this paper, all trucks that charged in Ödeshög were assumed to charge the following amount of energy: $E_b = 525$ kWh. Also, it was assumed that 499 of the 3322 passing trucks would charge at Ödeshög, corresponding to a share of $r_c = 15\%$. This resulted in a total daily charging demand of

$$E_c^{tot} = r_c \cdot E_b \cdot F_t = 260{,}000 \text{ kWh}. \quad (1)$$

Data for the hourly flow of trucks with trailers were available at Ödeshög for some days in 2022 [22]. By studying the data, it was found that the time variation for the different days was quite alike. Therefore, the time variation over the day used in this article was created from the time variation of the total flow from Thursday morning of 24 November to Friday morning of 25 November. The time variation was then scaled so that the total daily flow of trucks that wanted to charge equalled 499. The flow is presented in Figure 2 as the hourly flow of trucks, but the time they arrive at the charging stations is simulated with minute resolution. The flow over each hour is relatively even and was constructed so that no more than one truck arrives at the charging station per minute. Notice that the flow is the flow of *charging* trucks and not the total flow of trucks on the road passing Ödeshög. Since this paper investigates only the charge points, from now on, we call the flow of charging trucks the truck flow. The selected truck flow created in this paper attempts to represent charging demand on a typical day at Ödeshög in the case of full electrification. The truck flow with minute precision is presented in Appendix A.

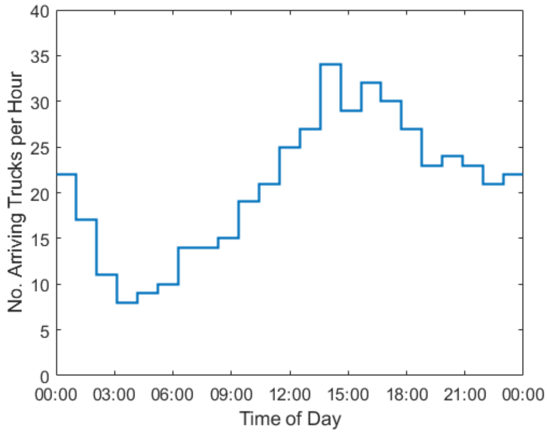


Figure 2. Total number of arriving trucks per hour that want to charge at one of the two stations as a function of time.

3. Model Description

The paper models the competition between two CPOs on one site, and the charging need for the typical day is described above. Each of the 499 trucks will charge 525 kWh at one of the two stations. The trucks will select the station associated with the lowest cost, considering both the charging price and the cost for the time spent queuing (described in a following subsection).

3.1. Calculating the Profit of the Charge Point Operator

The price for electricity that the CPO pays is assumed to be constant in this analysis, but the charging price paid by the trucks can vary each hour. In this paper, "each hour" corresponds to the time intervals 00:00–01:00, 01:00–02:00, and so on. The trucks that arrive at the stations charge at the price when they arrive, regardless of any price changes during charging and potential queuing. Thus, the profit for each CPO on the simulated day is then provided as follows:

$$I = \int_0^T \left(C_{epub}^{mean}(t) - C_e \right) \cdot P \cdot N(t)dt - C_{ch} \cdot r_p \cdot P \cdot N_{tot}, \tag{2}$$

where the parameters and variables in the above equation are defined in Table 1 except for the factor $r_p = \frac{9}{7}$, which is a factor that compensates for the fact that the charger does not run on full power all the time. The assumed value of $r_p = \frac{9}{7}$ corresponds to a charger of 900 kW, which is expected to deliver 700 kW on average during a charging session.

Table 1. Definition of parameters and variables.

Notation	Explanation
$[0, T]$	Time interval over the analysed typical day
$C_{epub}^{mean}(t)$	Mean price per kWh paid by the users at time t
$C_e = 0.08$ €/kWh	Purchase price for electricity from the grid (including any energy-based grid fee)
$P = 700$ kW	Average power of a charger when it is in use
$N(t)$	Number of chargers which are used at time t for a CPO
$C_{ch} = 0.32$ €/kW/day	Total cost per day for a charger, per kW of charger power (includes charger depreciation, interest, fixed grid fees, and maintenance)
N_{tot}	Total number of chargers of a CPO

To summarise the above equation, the integral term represents the daily income paid by the users minus the cost of the bought electricity, while the second term represents the daily cost for the chargers and grid connection.

The average charging power is chosen to match the trucks' need to charge the energy E_b in the required time during the mandatory driver break $T_c = 45$ min; thus,

$$P = \frac{E_b}{T_c} = 700 \text{ kW}. \tag{3}$$

3.2. Simulation of the Typical Day

To achieve good initial conditions for the simulation of the typical day, that day is simulated twice, starting with empty charging stations on the first day. Thus, the second day begins with trucks already using chargers. All the results presented are from the second day.

Charging during the day is simulated with a time step $\Delta t = 1$ min. In each time step, the following steps are carried out:

1. If a new truck arrives for charging, it decides if it shall charge at CPO 1 or 2. The new truck begins to charge or enters the queue if all chargers are occupied.
2. Each CPO delivers energy to the charging trucks according to the following equation:

$$E(t) = P \cdot N(t) \cdot \Delta t. \tag{4}$$

3. Each CPO receives income according to the following:

$$M(t) = P \cdot N(t) \cdot C_{epub}^{mean}(t) \cdot \Delta t. \tag{5}$$

   This income is used to calculate the income for the whole day using Equation (2).
4. All trucks that are finished charging leave their charger.

Each minute of the typical day is simulated as described above. After the whole day has been simulated, the profits for the two CPOs are calculated using Equation (2). The simulation procedure of the typical day is schematically visualised in the right-hand part of Figure 3. Notice that the investigated day is simulated many times during one simulation since the goal is to study prices, queues, utilisation, and more after a sufficiently long time of competition, which results in the market converging to an equilibrium. Since there is no guarantee that the market is stable, it may converge to a quasi-equilibrium, with small but repeated variations around a fairly stable state.

3.3. Repeated Simulations of the Typical Day

Each CPO can change its number of chargers and change its prices. The rules for how the CPO makes these changes are presented in the following subsection, while the details of the overall simulation are described in the following paragraph.

On a high level, the simulation procedure includes the following steps:

1. The initial conditions, i.e., the individual number of chargers for the CPOs, are set together with the individual prices of the CPOs.
2. The typical day is simulated, and the result is saved.
3. One of the CPOs updates its prices and its number of chargers (this procedure is explained in detail in a following subsection).
4. The typical day is once again simulated to evaluate if the updated prices and number of chargers are more profitable for the CPO that made the changes. If the profit is the same or higher than with the old prices and number of chargers, the CPO will change to the new setup. Otherwise, it retains the old one.
5. The typical day is simulated again, and the result is saved.
6. Steps 3 to 5 are repeated many times to give the market sufficient time to converge to an equilibrium. The number of times will be referred to as the "number of iterations". During these iterations, only one CPO attempts to change its prices and its number of chargers; in the next iteration, the other CPO makes its changes.

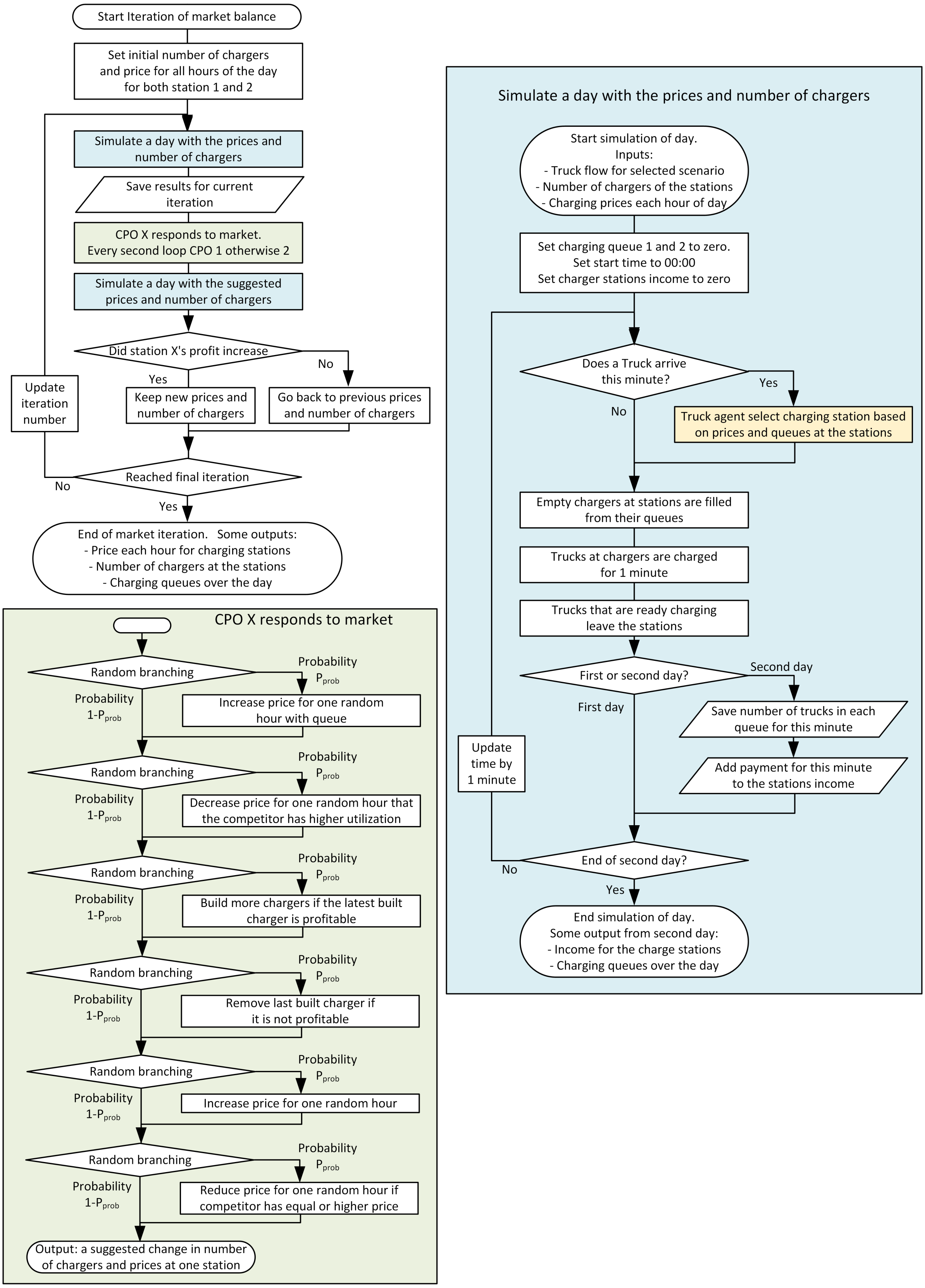


Figure 3. Upper left-hand part: flowchart of the main iterations to find market equilibrium. **Lower left-hand part:** flowchart of the subroutine in which CPOs update their number of chargers and prices. **Right-hand part:** flowchart of subroutine simulating the typical day.

Repeated simulations of the typical day are schematically visualized in the upper left-hand part of Figure 3. Repeating simulations of the same day is not intended to simulate several different days but rather to find the equilibrium state that the market forces will lead to. Exactly how that equilibrium is reached in the real world is not simulated. It is assumed that the market will find it sooner or later. In this paper, we have not looked into how the search for equilibrium is influenced by the agent's method of trying new prices and a new number of chargers. By doing so, a more stable equilibrium could probably be reached, and the convergence could be made faster by smarter search methods.

3.4. How the Truck Agent Selects a Charge Point Operator

In this subsection, the rules for the truck agents are explained. In summary, the trucks will aim to charge at the lowest cost when the cost for any queuing is included. Therefore, an estimated cost for queuing is derived as follows.

The total cost to operate a truck is estimated to be EUR 90/h [5], including the salary of the driver, vehicle depreciation, maintenance, insurance, and fuel costs. The extra cost for queuing per minute, $C_{q/t}$, is therefore set to

$$C_{q/t} = \text{ EUR } 90/\text{h} = \text{ EUR } 1.5/\text{min}. \tag{6}$$

This estimated cost includes energy consumption, which is not relevant for a truck standing still in a queue. However, this value is still used since queuing will result in a loss of income, which is typically close to the cost of operating a truck. It is assumed that the extra cost for selecting CPO 2 instead of CPO 1 is based on the extra queuing time given by the following:

$$C_q = T_{diff} \cdot C_{q/t}, \tag{7}$$

where T_{diff} is the difference in queuing time for the CPOs according to the following:

$$T_{diff} = T_2 - T_1, \tag{8}$$

where T_2 is the queuing time at CPO 2 and T_1 at CPO 1. Since the agents only have the information on the number of queuing trucks per charger and not exactly how long they will stay, T_{diff} is estimated to be as follows:

$$T_{diff} = r_q \cdot (q_2 - q_1) \cdot T_c, \tag{9}$$

where q_2 is the number of queuing trucks per charger at CPO 2 (including the one that makes the decision), and q_1 is the number of queuing trucks per charger at CPO 1 (including the one that makes the decision). Factor $r_q = \frac{1}{2}$ compensates for the fact that some charging trucks might have just started charging while others might just be about to end their charging, with others having any remaining charging time in between. One obtains the following equation:

$$C_q = r_q \cdot (q_2 - q_1) \cdot T_c \cdot C_{q/t}. \tag{10}$$

Further, the extra cost for selecting CPO 2 instead of CPO 1 due to the price difference is as follows:

$$C_p = (P_2 - P_1) \cdot E_b, \tag{11}$$

where P_2 is the price per kWh at CPO 2 and P_1 is the price per kWh at CPO 1. Thus, the total extra price for selecting CPO 2 instead of CPO 1 is as follows:

$$C_{tot} = C_q + C_p = r_q \cdot (q_2 - q_1) \cdot T_c \cdot C_{q/t} + (P_2 - P_1) \cdot E_b. \tag{12}$$

If $C_{tot} > 0$, the truck selects CPO 1; if $C_{tot} < 0$, the truck selects CPO 2. The first time a truck arrives and $C_{tot} = 0$, the truck selects CPO 1; the next time a truck arrives and $C_{tot} = 0$, that truck selects CPO 2 and so on.

It should be noted that it is assumed that the trucks have perfect information about the number of queuing trucks per charger at each CPO. In reality, this is not the case. CPOs are likely to announce whether there are free chargers via their charging app. However, they may not announce long queues. So, it will be possible for users to know if there are free chargers before they arrive. As the CPOs are on the same site, it is also possible for truck drivers to see the queues when they arrive. For market forces to exert pressure to reduce queues, it is not necessary to have perfect knowledge of queue length, as long as the station with a shorter or no queue benefits by getting more customers.

3.5. How CPO Agents Change Their Prices and Number of Chargers

The rules for how CPOs try to adjust their prices and the number of chargers will affect the outcome of the simulation. Of course, the behaviour of the trucks also affects the results. Later in this paper, the rules for the CPOs will be changed to investigate how sensitive the simulation results are to the rules. It is important to emphasise that not only could the model convergence be sensitive to the rules but also the actual outcome on a real charging market. With one type of behaviour, a specific price level could be successful, but it may not be successful under other circumstances. The selected rules for the CPOs are just one setup among infinitely many. They have been designed to be both realistic and concise, but most likely, future research will find better rules. It is assumed that CPOs cannot change the number of chargers or prices in large leaps, as that would probably lead to extremely fluctuating solutions. Despite this, the system does not run into a steady state but rather wiggles around a quasi-equilibrium.

The intentions of the CPOs are described in the bullet list below. To achieve these intentions, six rules are defined at the end of this subsection.

- CPOs try to adjust the number of chargers so that every charger is profitable.
- CPOs try to adjust prices so that the utilisation of their chargers is at least as good as the utilisation of the competitor's chargers.
- CPOs try to increase their prices when the demand exceeds the supply.
- CPOs test if other price changes, in addition to those previously mentioned, can increase profit.
- When a price increase is investigated, the price is set to just below the competitor's price or higher.
- When a price decrease is investigated, the price is set to the competitor's level or just below.
- CPOs always sell charging at a higher price than their cost for purchasing electricity, i.e., their income always covers the marginal cost.

Notice that the above intentions do not map the six rules for CPOs presented later in this subsection point by point.

CPOs can adjust their conditions in their charging station by changing their number of chargers by one and changing the price for some hours. Imagine that one of the chargers is only used when all the other chargers at the station are allocated; this charger is called the "last" charger. The decision to build or take away one charger depends on whether the last charger built is profitable or not. Let $C_{epub}(t)$ be the price for public fast charging for the arriving trucks. By assuming that $C_{epub}^{mean}(t) \approx C_{epub}(t)$ and slightly modifying Equation (2), one realises that the last charger for a CPO is probably *not* profitable if the following applies:

$$\int_0^T \sigma(t)\Big(C_{epub}(t) - C_e\Big) \cdot P dt - C_{ch} \cdot r_p \cdot P < 0, \tag{13}$$

where the integral estimates the net income per day from the "last" charger, the second term is the fixed cost per day for having one charger, and

$$\sigma(t) = \begin{cases} 1 & \text{if the charger is used} \\ 0 & \text{else.} \end{cases} \tag{14}$$

Since $P \neq 0$, one obtains

$$\int_0^T \sigma(t)\Big(C_{epub}(t) - C_e\Big)dt - C_{ch} \cdot r_p < 0. \quad (15)$$

This equation will be used as a condition for trying to change the number of chargers for the CPOs. The CPOs update their number of chargers and prices by the following rules, where each change for the individual operator occurs with a probability of $P_{prob} = \frac{1}{4}$ for each iteration. The reason that the probability is not 1 is that, if a CPO always tries to perform all changes, one misses the opportunity to make a change to one condition that may lead to a better profit, while two simultaneous changes may lead to a lower profit. For example, only increasing the price for one hour may lead to a better profit, but in combination with building an extra charger, it might lead to a decrease in profit. Sometimes, it could be the other way around, i.e., simultaneous changes increase profit, while one change alone does not. This method gives an opportunity to sometimes not make changes, sometimes make one, and sometimes make several.

1. The CPO removes one charger if

$$\int_0^T \sigma(t)\Big(C_{epub}(t) - C_e\Big)dt - C_{ch} \cdot r_p < 0. \quad (16)$$

   If the CPO only has one charger, it will not remove it. This reluctance to remove the last charger prevents the simulation from getting stuck in a monopoly situation.
2. The CPO adds one charger if

$$\int_0^T \sigma(t)\Big(C_{epub}(t) - C_e\Big)dt - C_{ch} \cdot r_p > 0. \quad (17)$$

3. If the competitor has a higher average utilization of the chargers for some hours. The CPO randomly picks one of these hours and sets its price ΔC_{epub} lower than that of its competitor's. One hour refers to, for example, the time between 4 a.m. and 5 a.m. or 2 p.m. and 3 p.m. However, the price cannot be lower than $C_e + P^i_{marg}$, where P^i_{marg} is the profit margin for CPO $i \in \{1, 2\}$.
4. If there are hours with queues, the CPO randomly pick one of these and increases the price by ΔC_{epub} for this hour. If that results in a higher price, the CPO increases the price to ΔC_{epub} less than that of its competitor's for this hour.
5. One hour of the day is selected randomly, where each hour has the same probability of being chosen. The price for that hour is increased by ΔC_{epub} or, if that results in a higher price, is altered to ΔC_{epub} less than the competitor's price for that hour.
6. If there exist hours when the price is higher than or equal to the competitor's, one of these hours is selected randomly, with equal probability. Then, the price is reduced to the competitor's level for this hour, with probability $\frac{1}{2}$. Otherwise, the price is reduced to ΔC_{epub} below the competitor's level for this hour. However, as stated earlier, the price cannot be lower than $C_e + P^i_{marg}$.

In this paper, parameter P^i_{marg} is called the profit margin and is set to EUR 0.001/kWh for all simulations. How the CPOs update the number of chargers and prices is schematically visualized in the lower left-hand part of Figure 3. The rules are designed to make the CPOs adjust their number of chargers and prices so they will improve their profit under competition. The rules do not perfectly reflect the actual market, but since the effect on the profit is always evaluated, the rules do not necessarily have to be perfect for the found quasi-equilibrium to reflect the market's response to the competitive situation in a good way.

4. Results

4.1. Low Sensitivity to Initial Conditions

The simulation results do not seem to be sensitive to the initial number of chargers and the initial prices at each station. For example, in Figures 4a and 5a, CPO 1 initially has one charger, and CPO 2 has two, while the initial price is EUR 0.15/kWh over the whole day for both CPOs. In Figures 4b and 5b, CPO 1 starts with 20 chargers and CPO 2 with 25, where the initial price is EUR 0.55/kWh over the whole day for both stations. Figure 4 shows the number of chargers as a function of the number of iterations, while Figure 5 shows the maximum and minimum price over the day and the mean price. The mean price (yellow curve) is defined as the total income for both CPOs divided by the total energy delivered by both stations. In these simulations, the parameter ΔC_{epub} was set to EUR 0.001/kWh. Even though the initial conditions were different, the price level and number of chargers were similar after a sufficiently number of iterations.

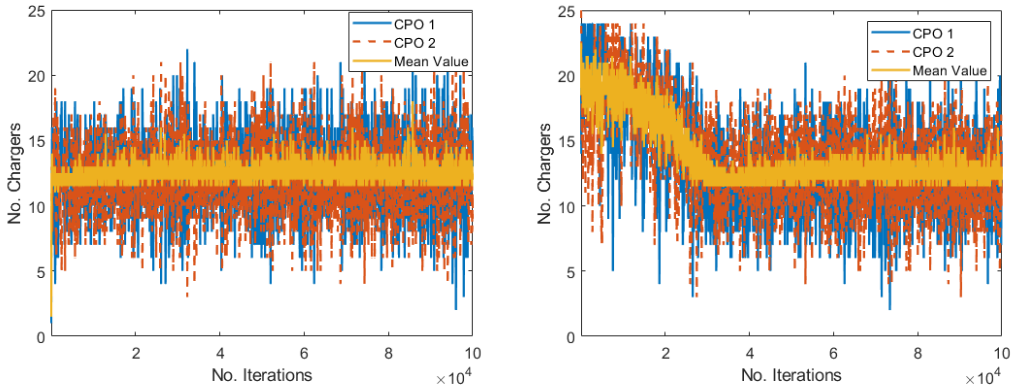


Figure 4. Number of chargers as a function of the number of iterations. (**a**) Initial number of chargers was set to one for CPO 1 and two for CPO 2. The initial price was was set to EUR0.15/kWh over the whole day for both CPOs. (**b**) Initial number of chargers was set to 20 for CPO 1 and 25 for CPO 2. The initial price was was set to EUR 0.55/kWh over the whole day for both CPOs.

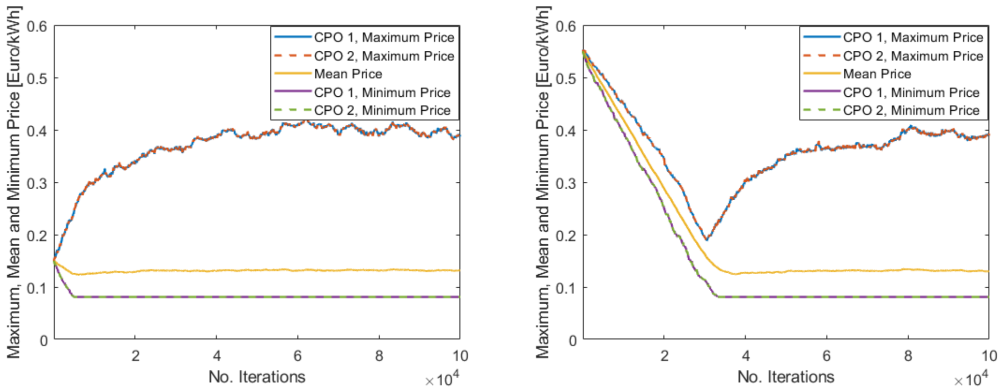


Figure 5. Price levels as a function of the number of iterations. (**a**) Initial number of chargers was set to one for CPO 1 and two for CPO 2. The initial price was was set to EUR 0.15/kWh over the whole day for both CPOs. (**b**) Initial number of chargers was set to 20 for CPO 1 and 25 for CPO 2. The initial price was was set to EUR 0.55/kWh over the whole day for both CPOs.

4.2. Market Convergence

Figures 4 and 5 show that the number of chargers and prices for CPO 1 and 2 are not converging to a fixed value after many iterations. Instead, the system wiggles around a steady state, which in this paper will be referred to as a quasi-steady state. This outcome seems reasonable since the CPOs try to adjust their strategies to improve their profit. The

CPOs then respond to each other's actions, and thus, the system fluctuates between the iterations. This is further discussed in Section 5. Due to the randomness of the changes in the number of chargers and prices for the CPOs, two simulations with the same initial conditions do not provide identical results. Still, the bigger picture is similar.

Now, it is investigated if the quasi-steady state is affected by the size of the parameter ΔC_{epub}. The initial number of chargers was set to 12 for both CPOs, and the initial price for fast charging was set to EUR 0.15/kWh over the whole day for both CPOs. The price levels can be seen in Figure 6 when the value on ΔC_{epub} is set according to the sub-captions in the figure. The number of iterations differs between the cases since a smaller value of ΔC_{epub} requires more iterations to reach the quasi-steady state. The figure shows that the maximum price level becomes more stable with decreasing ΔC_{epub}, while the lower price is unaffected. Also, one notices that the maximum price is significantly lower for $\Delta C_{epub} =$ EUR 0.01/kWh when compared with $\Delta C_{epub} =$ EUR 0.001/kWh and $C_{epub} = 10^{-4}$ EUR/kWh. One significant difference when comparing these three cases is that in the case with $\Delta C_{epub} =$ EUR 0.01/kWh, the price difference of ΔC_{epub} between the stations is high enough to make a truck prefer to queue instead of selecting the more expensive station, which puts a higher downward pressure on the prices. The conditions for this to happen are described in the following calculations.

Assume that CPO 1 has a price $\Delta C_{epub} =$ EUR 0.01/kWh higher than CPO 2; then, an arriving truck prefers to queue if the cost for queuing is less than the extra cost for charging, i.e., $C_{tot} < 0$ in Equation (12). Thus, the truck selects CPO 2 if

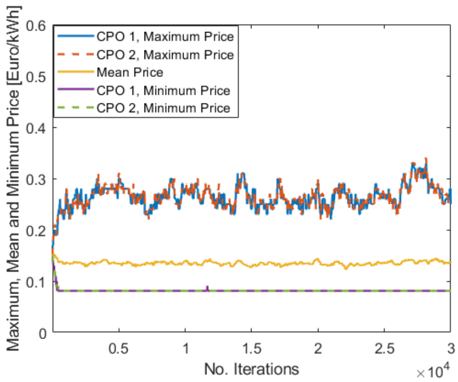
$$\begin{aligned} r_q \cdot (q_2 - q_1) \cdot T_c \cdot C_{q/t} + (P_2 - P_1) \cdot E_b < 0 &\iff q_2 - q_1 < \frac{(P_1 - P_2) \cdot E_b}{r_q \cdot T_C \cdot C_{q/t}} \\ &\iff q_2 - q_1 < \frac{\Delta C_{epub} \cdot E_b}{r_q \cdot T_C \cdot C_{q/t}}. \end{aligned} \tag{18}$$

Inserting $\Delta C_{epub} =$ EUR 0.01/kWh and the parameter values used in this paper, the queuing difference can be found. The trucks choose to queue if

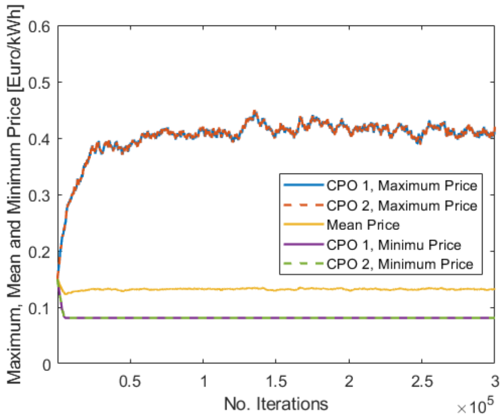
$$q_2 - q_1 < 0.16 \text{ queuing trucks per charger.} \tag{19}$$

Suppose there are free chargers at CPO 1, then $q_1 = 0$. If CPO 2 has 12 chargers or less (but more than 6), the above inequality means that one truck could select CPO 2 even if all its chargers are occupied. If CPO 2 has 13 chargers or more, it means that two trucks could select CPO 2 even if all its chargers are occupied. In the case when $\Delta C_{epub} =$ EUR 0.001/ kWh, the price difference of ΔC_{epub} for charging is too small to make trucks queue. Thus, the larger step size in prices will create a situation in which trucks prefer to queue even though they would not do that if they were given the option to pay just a little more to avoid queuing.

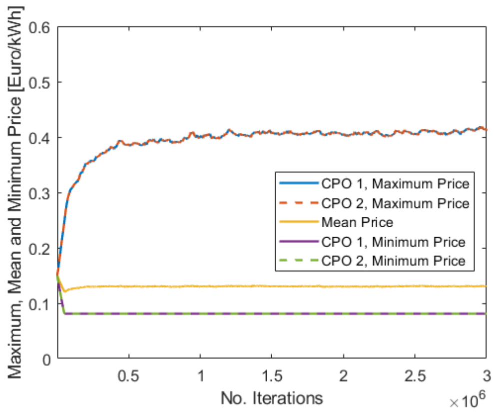
The way in which the size of ΔC_{epub} affects the number of chargers is not that clear. However, for the main results in this paper, the value of the parameter ΔC_{epub} is set to EUR 0.001/kWh since this is very similar to the resolution in the prices on the Swedish fast-charging market right now (SEK 0.01). A price difference of EUR 0.001/kWh leads to a total price difference of around EUR 0.5 when a truck charges 525 kWh.



(**a**) $\Delta C_{epub} = 0.01$ €/kWh.



(**b**) $\Delta C_{epub} = 0.001$ €/kWh.



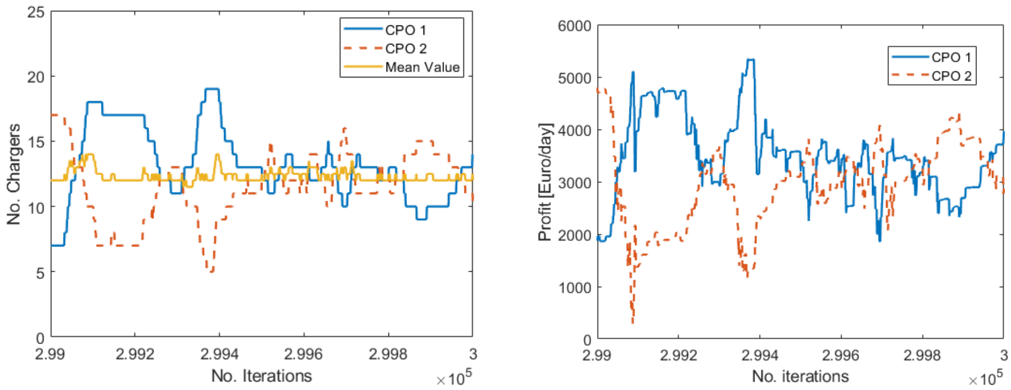
(**c**) $\Delta C_{epub} = 10^{-4}$ €/kWh.

Figure 6. Comparison between results for different values of ΔC_{epub}.

4.3. Main Results

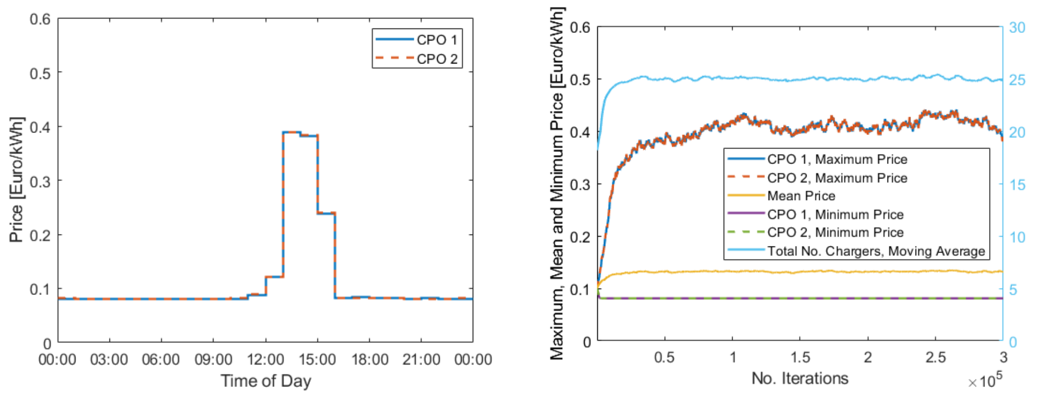
The model was then run again for $3 \cdot 10^5$ iterations. The initial number of chargers was set to 12 for both CPOs, and the initial price for fast charging was set to EUR 0.10/kWh over the whole day for both CPOs. The results are shown in Figures 7–10. By averaging over the last $2 \cdot 10^5$ iterations, one finds that the mean number of chargers for one CPO is 12.5, the mean profit per day for one station is EUR 3200, the mean value for the highest price at the two stations is EUR 0.413/kWh, the mean value for the price is EUR 0.132/kWh, the mean value of the longest queue during rush hours is 0.067 queuing trucks per charger (corresponding to an expected queuing time of 1.5 min), and the average charger time utilisation is 62.6%. The time utilisation of the chargers is defined as the share of time a charge is used per day. In this case, this is not the same as energy utilisation, which is the energy delivered by a charger divided by the highest possible energy the charger could have delivered. In this paper, utilisation refers to energy utilisation. Since it is assumed that 900 kW chargers, on average, deliver 700 kW, the energy utilisation of the chargers equals seven ninths of the time utilisation. The reason the time utilisation is shown in the figure is that it is easier to interpret. A charger time utilisation of 62.6% is a fantastic value, but unfortunately, it is only realistic when a single day is considered and not realistic if all weekdays and a whole year are considered. A more realistic value is presented in Section 5. Figure 10a shows the CPOs' hourly time utilisation over the day. The reason for the significantly higher time utilisation at midnight and just before rush hours for CPO 1 is the slightly lower price at this time of the day, which is barely visible in Figure 8a. The utilisation is higher after rush hours for CPO 2 due to it having fewer chargers than CPO 1, see Figure 7a.

In Figure 8b, one sees that the typical value for the peak price is around EUR 0.413/kWh and the mean price is around EUR 0.132/kWh. The lowest price over the day is stable and equals EUR 0.081/kWh, which is the lowest allowed price, i.e., the price for electricity plus the profit margin. Figure 8a shows the price over the whole day for the last iteration and is representative of all the iterations in the quasi-steady state. Comparing that price with the traffic flow in Figure 2, one sees that the price drops to a very low level throughout the day except during rush hours. This will be further analysed in Section 5. Figure 8a shows large variations in the price over the day, from very low throughout most of the day to much higher, but still reasonable, during rush hours. Interestingly, a reasonable price during rush hours is achieved with very short queues. Figure 9a shows the queue length that a truck arriving at different times of the day will experience for the last iteration. There is no queue almost all day, except for around 0.1 queuing trucks per charger during rush hours. This figure also shows one advantage of having more chargers than the competitor. Namely, if all chargers are allocated without a queue, the arriving truck prefers the station with the most chargers since it results in a queue with fewer queuing trucks per charger. Figure 9b shows that the *worst* queue over the whole day, considering both CPOs, is around 0.1 queuing trucks per charger or lower. A queue of 0.1 trucks per charger corresponds to an expected queuing time of around 2 min. In summary, the market reaches a state with reasonable prices and low queuing problems.



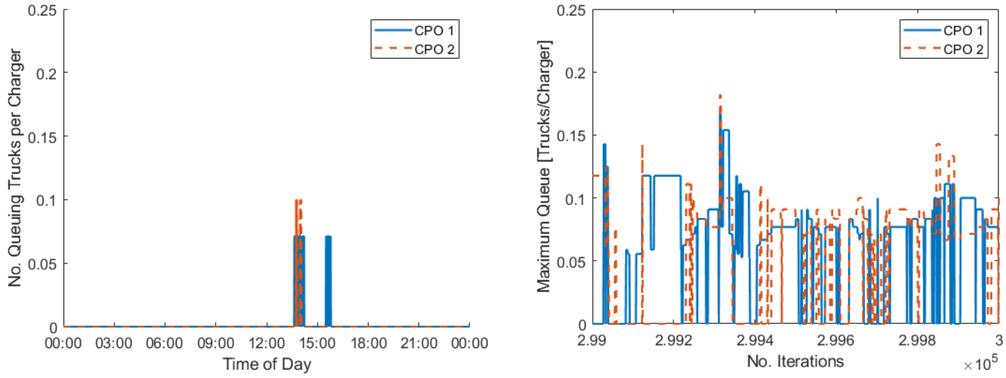
(**a**) (**b**)

Figure 7. (**a**) Number of chargers as a function of the number of iterations. (**b**) The CPOs profit as a function of the number of iterations.



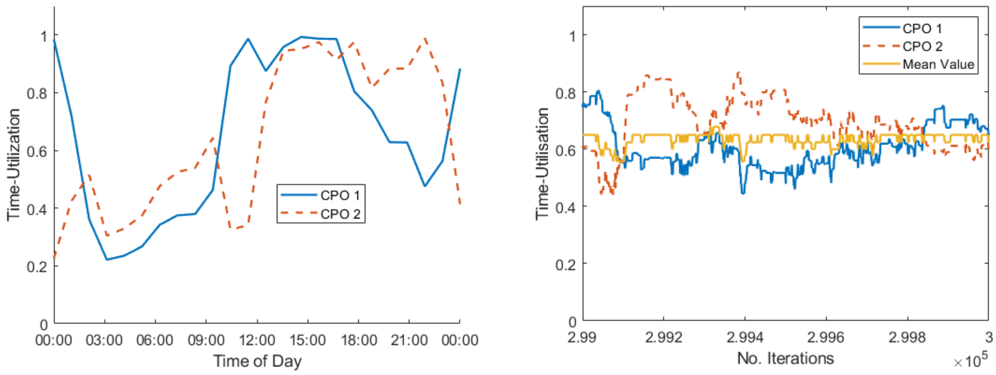
(**a**) (**b**)

Figure 8. (**a**) The price over the day for arriving trucks for the last iteration. (**b**) The maximum, mean, and lowest price as a function of the number of iterations shown on the left y-axis and moving average, over 10^4 iterations, of the total number of chargers in the system on the right y-axis.



(**a**) (**b**)

Figure 9. (**a**) The length of the queue that a truck arriving at different times of the day will experience for the last iteration. (**b**) The maximum queue over the day as a function of the number of iterations.



(**a**) (**b**)

Figure 10. (**a**) The time utilisation of the chargers over the day for the last iteration. (**b**) The time utilisation of the chargers for a full day as a function of the number of iterations.

5. Comparative Analytic Calculations: Analyses and Corrections

In this section, some analytic calculations are performed to support and explain the simulation results. Also, a more realistic average charge utilization for a whole year is estimated based on the results from the simulated day.

5.1. How Prices Reduce at Times with More or Less Charger Overcapacity

The model result shows prices at really low levels outside rush hours; see Figures 2 and 8a. Now, some calculations are performed to explain this result. First, start by assuming that the two CPOs have an equal number of chargers, N_{tot}. This is a reasonable assumption by symmetry since both CPOs have the same conditions to compete. During calm hours, the system has many more chargers than needed. Now, introducing the variable k, which is the ratio between charging demand and total charger power capacity,

$$k = \frac{\text{charging power demand}}{\text{available charger power capacity}}. \tag{20}$$

If k is below 0.5, the charging demand is so low that one CPO alone could supply the whole market. Then, the CPO that has the lowest price will sell charging to all trucks, and the other one will not sell any charging at all. This will likely lead to a price at the lowest level, which explains the low price during hours with really low demand. Now, consider the case when $k \in (0.5, 1)$ for a given time interval with length ΔT, meaning that there are more chargers than needed, but one CPO could not supply the whole market without increasing queues. The time ΔT is assumed to be long, so one can disregard the situation before and at the beginning of the time interval. Assume that the two CPOs have the same price, C_{epub}, which is over the minimum level. This leads to a charger utilisation for both CPOs of

$$\Gamma_{before} = k, \tag{21}$$

and the profit over the time interval becomes

$$\begin{aligned} I_{before} &= \Gamma_{before} \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) - \text{cost for chargers and grid} \\ &= k \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) - \text{cost for chargers and grid.} \end{aligned} \tag{22}$$

Then, one of the CPOs drops the price by ΔC_{epub}, leading to a charger utilization of

$$\Gamma_{after} = 1 \tag{23}$$

for that CPO since all trucks will prefer this station as long as there are free chargers at this station. This small price difference is, as seen before, not sufficient to make the trucks queue unless they have to. The new profit can now be obtained as follows:

$$\begin{aligned} I_{after} &= \Gamma_{after} \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - \Delta C_{epub} - C_e) - \text{cost for chargers and grid} \\ &= N_{tot} \cdot P \cdot \Delta t \cdot (C_{epub} - \Delta C_{epub} - C_e) - \text{cost for chargers and grid.} \end{aligned} \tag{24}$$

The difference in profit is given by the following:

$$\begin{aligned} \Delta I &= I_{after} - I_{before} \\ &= N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - \Delta C_{epub} - C_e) - k \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) \\ &= N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e)(1-k) - N_{tot} \cdot P \cdot \Delta T \cdot \Delta C_{epub}. \end{aligned} \tag{25}$$

Thus, the CPO will lower the price if the following is true:

$$\Delta I \geq 0 \iff \Delta C_{epub} \leq (C_{epub} - C_e)(1-k). \tag{26}$$

Notice that a lower value for ΔC_{epub} is necessary if either C_{epub} is low or k is large. If ΔC_{epub} can be set arbitrarily small, the CPO will always improve the profit by dropping the price just below the competitor. In response, the competitor can lower its price, increase its profit, and so on. Thus, the price will likely be at the lowest level after a sufficient number of iterations regardless of k. In reality, ΔC_{epub} cannot tend to zero; in our case, the size of ΔC_{epub} is set to EUR 0.001/kWh. The above inequality means that CPOs will lower their prices if the following is true:

$$\frac{\Delta C_{epub}}{1-k} + C_e \leq C_{epub}. \tag{27}$$

The case with equality will be an upper price limit, and its dependence on k is shown as the blue curve in Figure 11 for ΔC_{epub} = EUR 0.001/kWh and C_e = EUR 0.08/kWh. From the figure, one may, for example, see that $k = 2/3$, $k = 0.75$, and $k = 0.90$ lead to a maximum price of EUR 0.083/kWh, EUR 0.084/kWh, and EUR 0.090/kWh, respectively. To clarify, if both CPOs have the same price, above this limit, one of the CPOs will increase their profit by lowering the price with the step ΔC_{epub}.

Now, the opposite case is investigated, i.e., when two CPOs have the same price and one of them considers increasing the price. The profit for the CPOs before the increase is given by the following:

$$\begin{aligned} I_{before} &= \Gamma_{before} \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) - \text{cost for chargers and grid} \\ &= k \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) - \text{cost for chargers and grid.} \end{aligned} \tag{28}$$

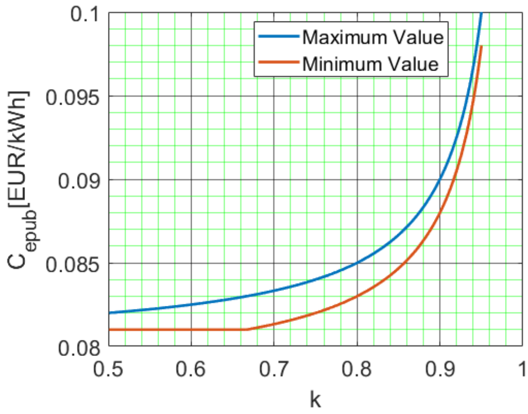


Figure 11. The maximum and minimum price for a long time period when the ratio of the demand of charging power to the available charging power equals k and both CPOs have the same number of chargers.

After the increase, the CPO with the higher price will have a utilization of

$$\Gamma_{after} = 2k - 1 \tag{29}$$

since $2k$ is the sum of the average charger utilisation. After the increase, the CPO with the lower price will have charger utilisation 1, and the CPO with the higher price will only get the trucks which could not find a charger at the low-price station. The profit for the CPO with the higher price after the increase is given as follows:

$$\begin{aligned} I_{after} &= \Gamma_{after} \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} + \Delta C_{epub} - C_e) - \text{cost for chargers and grid} \\ &= (2k-1) \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} + \Delta C_{epub} - C_e) - \text{cost for chargers and grid.} \end{aligned} \tag{30}$$

The difference in profit is now obtained as follows:

$$\begin{aligned} \Delta I &= I_{after} - I_{before} \\ &= (2k-1) \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} + \Delta C_{epub} - C_e) - k \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) \\ &= k \cdot N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) - N_{tot} \cdot P \cdot \Delta T \cdot (C_{epub} - C_e) + (2k-1) \cdot N_{tot} \cdot P \cdot \Delta T \cdot \Delta C_{epub} \\ &= N_{tot} \cdot P \cdot \Delta T((C_{epub} - C_e)(k-1) + (2k-1)\Delta C_{epub}). \end{aligned} \tag{31}$$

The price increase is profitable if the following is true:

$$\begin{aligned} \Delta I \geq 0 \iff & (C_{epub} - C_e)(k-1) + (2k-1)\Delta C_{epub} \geq 0 \\ \iff & C_{epub} \leq \frac{2k-1}{1-k} \cdot \Delta C_{epub} + C_e, \end{aligned} \tag{32}$$

where the last form of the inequality is reached by the fact that $k - 1 < 0$ and $2k - 1 > 0$. Since the price for public fast charging is never smaller than the sum of the price for electricity and the profit margin, which in this paper is the same for both CPOs, one knows that $C_{epub} \geq C_e + p^i_{marg}$. In this paper, $p^i_{marg} = \Delta C_{epub} =$ EUR 0.001/kWh, and according to inequality (32), the price does not increase from the lowest level if the following applies:

$$\frac{2k-1}{1-k} \leq 1 \iff k \leq \frac{2}{3}. \tag{33}$$

This, together with inequality (32), determines the lower limit of the price, shown as the red curve in Figure 11. Thus, if both CPOs have the same price, below this limit, one of the CPOs will increase their profit by increasing the price with the step ΔC_{epub}. It might be interesting to notice that the gap between the two curves in the figure for $k \geq \frac{2}{3}$ is given as follows:

$$\frac{\Delta C_{epub}}{1-k} + C_e - (\frac{2k-1}{1-k} \cdot \Delta C_{epub} + C_e) = \frac{2-2k}{1-k} \cdot \Delta C_{epub} = 2 \cdot \Delta C_{epub}. \quad (34)$$

If the price for both CPOs is between the curves in Figure 11, none of the CPOs will increase their profit by either increasing or decreasing their price for fast charging. Even though the calculations in this subsection are performed under simplified conditions, they show quite a strong force acting for low prices even for relatively low overcapacity of chargers in the system. It also shows that for medium to large overcapacity, it is even harder not to have prices at the lowest level. Furthermore, the results of these calculations, shown in Figure 11, strongly suggest that for a given number of chargers, it is favourable to change the prices with varying demand. This is an argument that a CPO that uses time-varying prices will compete better than a CPO that uses a fixed price over the whole day.

5.2. Price during Rush Hours

The previous subsection investigated the situation when there is more charger capacity than demand. Now, the opposite situation is considered. Assume that there is a period when k is slightly smaller than one followed by a period of length T_h when there is a greater charging demand than available charger power, visualised in Figure 12. Since the price difference of ΔC_{epub} is too small to make a truck queue instead of selecting more expensive charging, a CPO can, without losing many users, increase the price by this small step and thereby increase its profit. It is even possible that the CPO that makes the increase does not lose any users at all since, with equal conditions on prices and queues, a truck has to make a decision, and one station will be rejected, with or without a higher price. After the increase, the other station can increase its price and so on. So, when there is a time when the demand is equal to or greater than the supply, the prices will likely increase. This will continue, but at some point, the price is sufficiently high to build more chargers, and when more chargers are built, the system no longer has a greater demand than supply, so the price increase stops. The fluctuations in both chargers and price at rush hours in the simulations, observed in, for example, Figure 8b, indicate that the system does go back to a condition with more chargers than necessary, which makes the prices fall again until the extra chargers are removed and so on. It is likely that the fluctuating behaviour in the system is increased because the number of chargers only changes in steps of one, which is a rather big step relative to the average 12.5 chargers that the stations have in the analysed case.

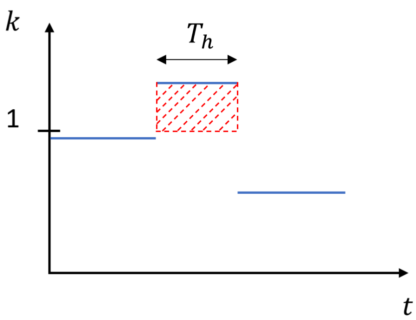
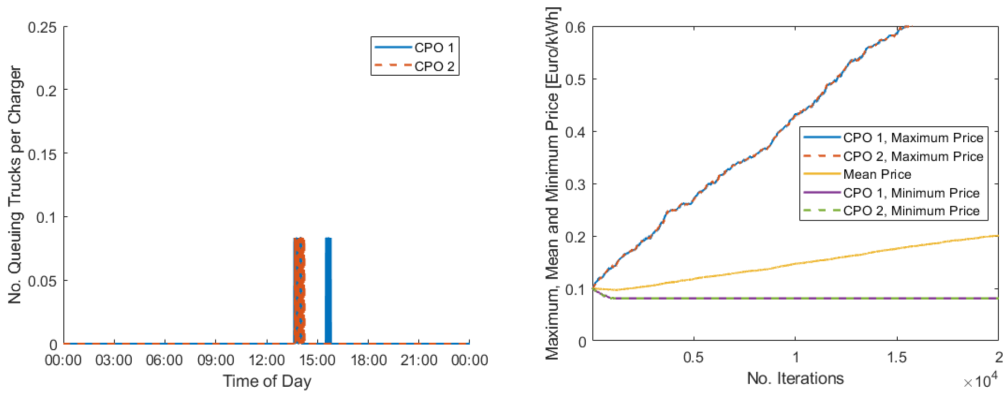


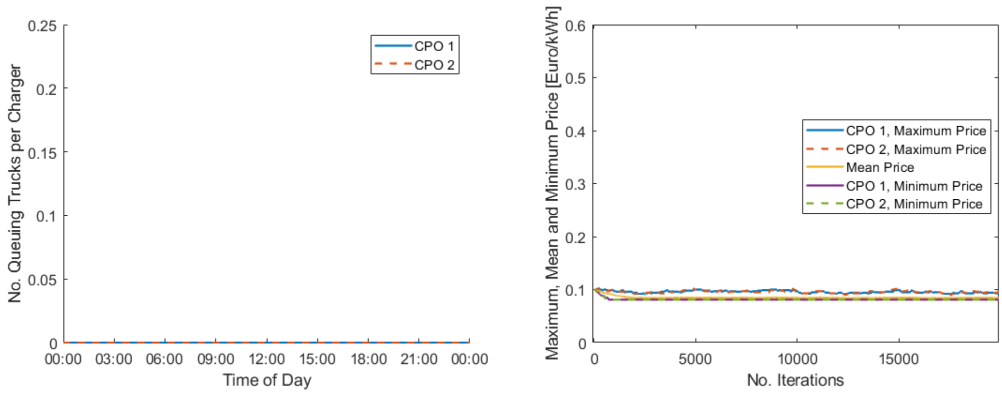
Figure 12. A schematic figure of k as a function of the time during rush hours when there is a greater demand than supply in the system.

To check the model, the simulation is rerun two times for $2 \cdot 10^4$ iterations. The starting price is set to EUR 0.1/kWh over the whole day for both CPOs but with the same fixed number of chargers for both CPOs over all iterations. First, the number of chargers for each CPO is set to 12, see Figure 13, and then the number of chargers for each CPO is set to 13, see Figure 14. As seen from the figures, the model follows the predictions. In Figure 13a, one notices that there are times with queues and, therefore, also times when there is no queue but all chargers are allocated. As seen from Figure 13b, this leads to increasing prices during rush hours. There are only queues at CPO 1 in the late afternoon because of the slightly higher price offered by CPO 2. From Figure 14a, one notices that the queue is gone when the number of chargers is increased to 13 for both CPOs, resulting in a greater supply than demand and low prices. Still, the prices in rush hours are a bit higher than the prices at other times and are around EUR 0.095/kWh, which, according to Figure 11, corresponds to a value of k close to one in the simplified analytic calculation.



(**a**) (**b**)

Figure 13. Simulation results when both CPOs have 12 chargers each, which cannot be changed. (**a**) The queuing situation for the last iteration. (**b**) Price levels as a function of the number of iterations.



(**a**) (**b**)

Figure 14. Simulation results when both CPOs have 13 chargers each, which cannot be changed. (**a**) The queuing situation for the last iteration. (**b**) Price levels as a function of the number of iterations.

Finally, finding a rule of thumb for when new chargers are built would be desirable. Assume that the number of chargers is a continuous variable and consider Figure 12. With the same price for public fast charging, C_{epub}, and the same number of chargers, the two CPOs will split the charging demand that the system cannot supply at time T_h. The red striped area in the figure corresponds to this unfulfilled charging demand if it is multiplied by the total charging power in the system. Thus, a CPO that builds chargers for this peak demand will increase its income corresponding to half this energy, i.e., the extra income for building chargers for the peak demand is given as follows:

$$\text{extra income} = \frac{(k-1)\cdot T_h \cdot P_{tot}}{2} \cdot (C_{epub} - C_e), \tag{35}$$

where P_{tot} is the total power in the system before any extra chargers were built. To meet the demand, the extra chargers have to be able to charge the energy $(k-1)\cdot T_h \cdot P_{tot}$ in the time T_h, which gives the extra needed power as follows:

$$\text{extra power} = \frac{(k-1)\cdot T_h \cdot P_{tot}}{T_h} = (k-1)\cdot P_{tot}. \quad (36)$$

This will increase the cost according to the following:

$$\text{extra cost} = (k-1)\cdot P_{tot}\cdot T\cdot r_p\cdot C_{ch}, \quad (37)$$

where we recall that T is one day, C_{ch} is the cost for the charger and grid per kW and day, and r_p is the factor compensating for the charger's average power being lower than their maximum power. So, new chargers will increase the profit if the extra income is greater than the extra cost, i.e.,

$$\frac{(k-1)\cdot T_h \cdot P_{tot}}{2}\cdot(C_{epub} - C_e) > (k-1)\cdot P_{tot}\cdot T\cdot r_p\cdot C_{ch}. \quad (38)$$

Since it was assumed that $k > 1$, this can be simplified as follows:

$$C_{epub} > \frac{2T\cdot r_p\cdot C_{ch}}{T_h} + C_e. \quad (39)$$

By roughly studying Figure 13a, one may say that k is about one or larger for approximately 2 to 3 h. This corresponds well to Figure 8a, where two hours (1 p.m.–3 p.m.) have high prices and one hour (3 p.m.–4 p.m.) has relatively high prices. Thus, we insert $T_h = 2.5$ h in the above inequality among with $T = 1$ day, $r_p = \frac{9}{7}$, $C_{ch} =$ EUR 0.32/kW/day and $C_e =$ EUR 0.08/kWh and obtain the approximate limit for when new chargers are built for the example used in our simulations:

$$C_{epub} > 0.409\ €/\text{kWh}, \quad (40)$$

which agrees with the result. See, for example, Figure 8b. Clearly, this limit and the results would not have been that alike if T_h had been set to 2 or 3 h instead of 2.5. Still, the limit agrees fairly well and is used as a plausibility check of the agent-based model.

5.3. Discussion of Fluctuations around a Quasi-Steady State

Previously, it was discussed that the simulation fluctuations are caused by a variation in the number of chargers in the system, as too few chargers favours high prices and too many chargers favours low prices. This simulation seems to keep the system fluctuating around a quasi-steady state. The prices increase until more chargers are built, and prices drop until chargers are removed. Still, the system fluctuates and does not run into a true steady state. This subsection will analyse these fluctuations by studying some examples of prices and the number of chargers.

The model is rerun for 10^5 iterations, and the prices and number of chargers for the last iteration are used as the starting point for this subsection. The price at CPO 2 between 1 p.m. and 2 p.m. for this iteration is EUR 0.001/kWh higher than for CPO 1. The number of chargers is 13 for both CPOs. Since the number of chargers is enough to supply the trucks without queues (according to previous investigations), one would expect the profit to increase for CPO 2 if the price this hour is set to EUR 0.001/kWh below the price at CPO 1. When the typical day is run with this price change, CPO 2 increases its profit. But, if CPO 2 instead increases its price during this hour by EUR 0.001/kWh, it is likely that the income would also increase since the price difference of EUR 0.002/kWh still does not make trucks queue at CPO 1. Thus, CPO 2 does not lose any users but increases the price, leading to an increase in profit. This is confirmed by increasing the price and running the typical day once again. Situations like this are likely to be common during a simulation. If the price is lowered, CPO 1 might successfully respond with prices below CPO 2, and the price falls. If CPO 2 instead increases the price, CPO 1 could increases its price by EUR 0.001/kWh and increase its profit, leading to increasing prices. In summary, so far, there are situations where both a decrease and an increase in price for an hour lead to an increase in profit for a

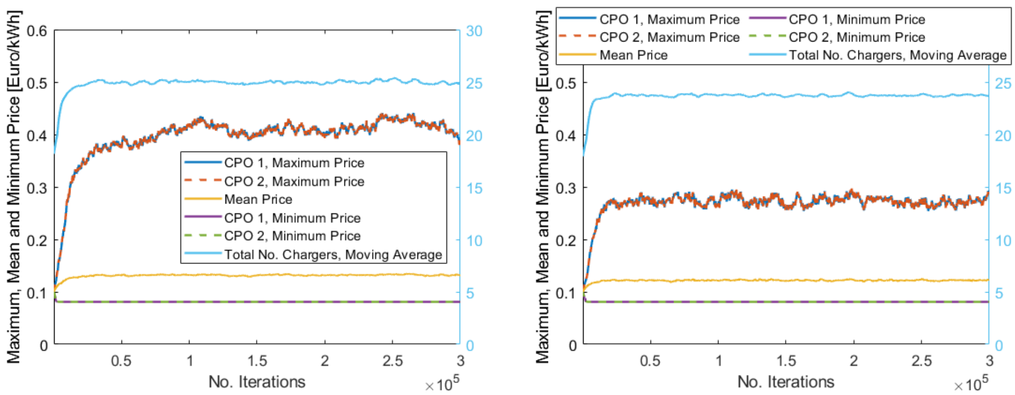
CPO. This means there is no unambiguous direction for the price to change and this is one possible explanation for the fluctuating behaviour of the system.

One may ask if an optimal setup of prices and number of chargers exists. This means that if a CPO has this setup, no other setup generates a higher profit against this setup. If so, an idea for finding this setup could be to run two different setups and save the one with the highest profit. Then, one tests other setups using some optimisation methods and if one finds a setup that makes a higher profit than the previous one, one saves this setup and continues searching for a setup that beats the new setup and so on until one finds an optimal setup. Then, one ends up in a stable, steady state where all possible changes decrease the profit. However, this seems not to be the case since examples can be found that contradict this, like in the game "Rock, Paper, Scissors", where none of the items wins over both the others. As an example, three different setups will now be considered. Firstly, setup "rock", with prices for CPO 1 being the same as in the above simulation but with 14 chargers. Secondly, setup "scissors", with prices being the same as for CPO 2 with 13 chargers. Thirdly, setup "paper", with prices the same as for CPO 1 with 12 chargers. Just as in the game, simulations of the typical day show that rock beats scissors, scissors beats paper, and paper beats rock. These three setups were found manually, without much effort, which is a reason to believe that this property is common during a simulation. This finding indicates that an optimal setup does not exist, but rather, whether a setup is successful depends on the competitor's setup. This can be likened to natural evolution, where there is no optimal species. Whether a species is successful or not depends on the environment and its competitors. These findings explain the fluctuating behaviour of the simulation. It is a topic of future research to develop methods to find the quasi-steady state.

5.4. Sensitivity to the Rules for the CPOs

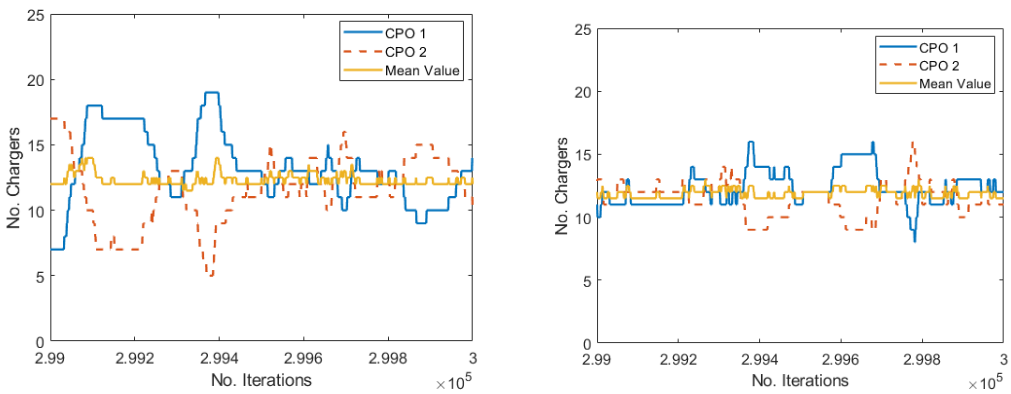
One may ask if this model is sensitive to changes in how the agents act. The trucks trying to minimise their cost for each individual charging decision seems reasonable but, of course, the model for that might be conducted in other ways. The CPOs aim to increase their profit, but in which way? In this paper, they follow six different rules. These rules could be designed in many ways, still with good arguments. Would small changes in the rules change the results to a great extent? In many cases, the answer seems to be no. For example, changing the rules so that one and only one update to the prices or number of chargers is carried out in every iteration, with equal probability, the result remains very similar to the results presented in Section 4.3. But, as seen from the work carried out in this paper, a change of ΔC_{epub} from EUR 0.001/kWh to EUR 0.01/kWh decreased the price during rush hours from around EUR 0.40/kWh to a little less than EUR 0.30/kWh. Previously, it was shown that there are situations where a CPO can increase its profit both by increasing or decreasing the price just a little bit. Thus, one may guess that the price level depends on how likely it is that the CPOs try to increase their prices compared to how likely they try to decrease their prices. As seen previously, there are no queues when there are 26 chargers in the system. Therefore, one will suspect that the number of chargers for each CPO should be around 12 to 13. Still, there are situations when a CPO successfully continues building chargers far above these values (consider Figure 7, where CPO 1 has many chargers and high profit for many iterations). In a similar simulation, the authors observed that the price during rush hour was slightly lower for the CPO, which increased the number of chargers. Since the price was lower, all the chargers of the CPO with more chargers were selected first, which in rush hours means that the chargers have full utilisation even if there are many. The CPO with fewer chargers but a higher price still did not utilise their chargers well, resulting in the removal chargers. But, if a CPO has fewer chargers than the competitor, would that CPO not have the opportunity to offer fast charging at a lower price due to a lower cost for the chargers? So, a seventh rule was implemented for the CPOs, which occurred with probability $P_{prob} = 0.25$. The rule says that if the competitor has more chargers, the CPO test to put the price during rush hours (1 p.m. to 4 p.m.) a step ΔC_{epub} below the competitors for these three hours. The result is seen in Figure 15b and can be compared with the result without this rule in Figure 15a and with the new rule added one notices that the price during rush hours is lower, down to a little less than EUR 0.30/kWh. Thus, a change in the rules for the CPOs can affect the price level during rush hours. Notice that the total number of chargers, in the same way, decreased with more than one charger on average, likely because the lower price level in the peak was insufficient to fully meet the demand for charging. Also, comparing the left and right-hand panels of Figure 16 shows that the magnitude of the fluctuations in the number of chargers for the individual CPOs decreased with the extra rule.

By averaging the last $2 \cdot 10^5$ iterations, one finds that the maximum queue each day in the system is 0.125 queuing trucks per charger to be compared with 0.067 queuing trucks per charger for the original simulations. These queues correspond to an expected queuing time of 2.8 and 1.5 min, respectively. So, lower prices generated a little worse queues. Still, a price difference of EUR 0.1/kWh corresponds to an extra cost of EUR 52.5 for a full charge, and a queuing difference of 1.3 queuing trucks per charger corresponds to an extra queuing cost of only EUR 2.0, so this new setup seems to be more cost-effective overall.



(**a**) (**b**)

Figure 15. The maximum, mean, and lowest price as a function of the number of iterations shown on the left y-axis and the moving average of the total number of chargers in the system on the right y-axis. For local means, 10^4 iterations were used. (**a**) The original rules for the CPOs. (**b**) Including the extra rule that a CPO with fewer chargers strives to have slightly lower prices than the competitor during rush hours.

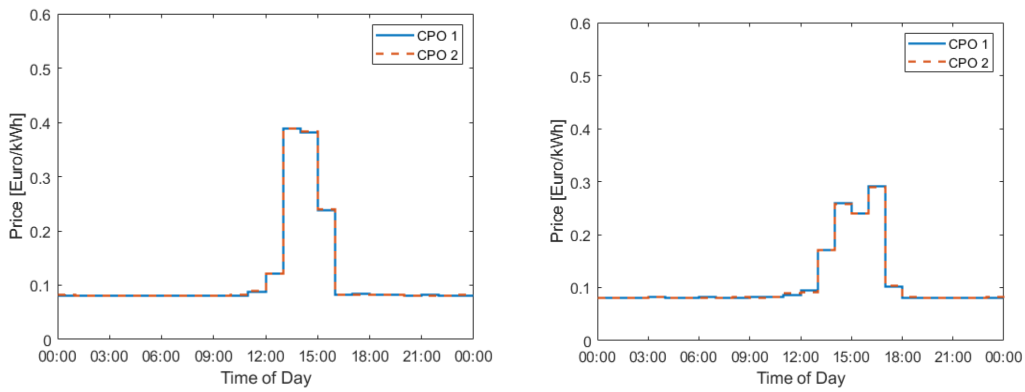


(**a**) (**b**)

Figure 16. The number of chargers as a function of the iterations. (**a**) The original rules for the CPOs. (**b**) Including the extra rule that a CPO with fewer chargers strives to have slightly lower prices than the competitor during rush hours.

Outside rush hours, the overall price picture was quite similar when comparing the original rules with the extra rule added, see Figure 17. One notices that the peak in price is higher and a bit thinner in the original case (left-hand panel) compared to when the extra rule is added (right-hand panel). The thinner price peak does not fully compensate for the additional height, which can be seen by comparing the mean price in Figure 15, where the left-hand side is about EUR 0.13/kWh and the right-hand side is about EUR 0.12/kWh. This subsection shows that the price during rush hours can be sensitive to the actions of CPOs, while the price at other times seems far more stable. Still, the simulations show prices at rush hours of similar magnitude and far higher than those during other times. The mean prices are quite similar when the rules of the CPOs are changed, and the queuing conditions seem pretty good in both cases. Thus, the investigations indicate that the rules of CPOs can affect prices during rush hours and, to some extent, queuing times for trucks. Thus, no exact answer for the future price during rush hours can be given, but this method could be a good way of estimating a likely value. In this paper, the prices are assumed to be time-dependent, with arguments that this will outcompete a fixed price over the day. Still, there might be other ways of varying the prices, such as a function of charger utilisation.

As shown in this section, there are situations when a CPO can increase its profit either by decreasing or, just as well, increasing the price at a particular hour. This was presented as a part of the explanation for the fluctuating behaviour of the solution in the quasi-steady state. A suggestion to address this ambiguity could be to investigate which of the actions gives rise to the highest profit and select that one. However, that has not been done in this paper.



(**a**) (**b**)

Figure 17. The price over the day for arriving trucks for the last iteration. (**a**) The original rules for the CPOs. (**b**) Including the extra rule that a CPO with fewer chargers strives to have slightly lower prices than the competitor during rush hours.

5.5. Adjusting Charger Utilisation for Non-Modelled Variations in Charging Demand

In Section 4.3, the time utilisation of the chargers was found to be 62.6%. This agrees well with results from a previous study [21] in which the number of chargers was manually tuned under the co-condition that the queuing problems should be minor instead of decided by market mechanisms. The previous study observed the utilisation of fast chargers along the road between Helsingborg and Stockholm (see Figure 1) to be 59% before compensating for variations in traffic flow, such as unexpected peaks in traffic flow, weekends, and the factor $r_p = \frac{9}{7}$. After these compensations, the previous study ended up with a utilisation factor as high as 30% and minor queues. That paper concluded that the result was very good but asked, "If the system has all the chargers it needs, works well and is profitable, what is there to stop a new CPO from entering the market if there is money to be made? All the charge point operators might still profit, but the system has too many chargers". However, the result from this paper indicates that the free market will manage to keep the utilisation high and queues short, just as well as the manual selection in the previous study. In addition, this study also found that this is achievable with low prices for much of the day and high prices only during rush hours. In [21], the required number of chargers for the system was increased by 33% to resist unmodelled variations in traffic flows, such as unexpected peaks or increased traffic volume on certain days. Further, the utilisation was multiplied by $\frac{7}{9}$ to go from time utilisation to energy utilisation. Finally, the utilisation was multiplied by a factor of $\frac{6}{7}$ since it was assumed that the trucks were on the road on average six days per week, while the typical day models a weekday. By applying the same compensation in the present study, one obtains a charger utilisation as high as 31%. In addition, since the price is predicted to have significant variations, such that it will be much cheaper to charge at off-peak hours, some haulage companies might reschedule their trips. That will lead to even better charger utilisation and likely lower the average price on public fast charging.

5.6. Adjusting the Price to Reflect Non-Modelled Flow Variations

In this subsection, the price level will be adjusted in a similar way as the utilisation factor was adjusted in the previous section. Here, we assume that the extra cost for increasing the number of chargers by 33% in the system and the reduced income due to the total charging demand being reduced by a factor of $\frac{6}{7}$ is compensated by increasing the price for public fast charging. Section 4.3 shows that the typical total number of chargers for one CPO is 12.5; thus, the typical number of chargers in the system is 25. The mean price, i.e., total charging cost for all trucks divided by the total amount of energy delivered by both CPOs, was found to be EUR 0.132/kWh and the peak price to be EUR 0.413/kWh. Consider Equation (2). The total number of chargers in the system is increased by 33%, which corresponds to eight additional chargers. This results in an increased cost for the chargers (the last term of the right-hand side) according to the following equation:

$$\text{cost for extra chargers} = \text{ EUR } 0.32/\text{kW}/\text{day} \cdot \frac{9}{7} \cdot 700 \text{ kW} \cdot 8 = \text{ EUR } 2300/\text{day}. \tag{41}$$

The difference between the mean charging price and the electricity price is approximately EUR 0.05/kWh. Since the traffic flow is decreased by a factor of $\frac{6}{7}$ due to weekends, the CPOs will lose income according to one-seventh of the charging need multiplied by EUR 0.05/kWh, resulting in the following:

$$\begin{aligned} \text{reduce income due to weekends} = \frac{1}{7} \cdot 260{,}000 \text{ kWh}/\text{day} \cdot \text{EUR } 0.05/\text{kWh} \\ = \text{EUR } 1900/\text{day}. \end{aligned} \tag{42}$$

Using Equations (41) and (42), one obtain the following:

$$\text{extra cost after adjustment} = \text{ EUR } 2300/\text{day} + \text{ EUR } 1900/\text{day} = \text{ EUR } 4200/\text{day}. \tag{43}$$

It is assumed that COPs can compensate this by implementing higher prices. Thus, the price adjustment is as follows (remember that the charging need is reduced by a factor of $\frac{6}{7}$):

$$\text{price adjustment} = \frac{\text{EUR } 4200/\text{day}}{\frac{6}{7} \cdot 260{,}000 \text{ kWh}/\text{day}} = \text{ EUR } 0.019/\text{kWh}. \tag{44}$$

Thus, the adjusted mean price is as follows:

$$\text{typical mean price} = \text{EUR } 0.132/\text{kWh} + \text{EUR } 0.019/\text{kWh} \approx \text{ EUR } 0.15/\text{kWh}. \tag{45}$$

The results in this paper indicate that it is hard to increase the prices for non-rush hours. Thus, this extra cost is assumed to spread over the hours with already high prices, i.e., 1 p.m.–4 p.m., see Figure 8a. According to Figure 2, approximately 100 of the almost 500 trucks per day arrive during these hours. Since the typical value of the peak price was found to be EUR 0.413/kWh, the new, adjusted, typical price during rush hours is estimated to be as follows:

$$\begin{aligned} &\text{typical price during rush hours} \\ &= \text{EUR } 0.413/\text{kWh} + \text{ EUR } 0.019/\text{kWh} \cdot \frac{500 \text{ trucks}}{100 \text{ trucks}} \approx \text{ EUR } 0.5/\text{kWh}. \end{aligned} \tag{46}$$

Since the extra cost is assumed only to be distributed over rush hours, the lower price level remains the same:

$$\text{typical price outside rush hours} = \text{EUR } 0.081/\text{kWh} \lessapprox \text{ EUR } 0.10/\text{kWh}. \tag{47}$$

5.7. Profitability of CPOs

The mean total profit for one CPO can be found in Section 4.3 to be EUR 3200/day, with the typical value of 12.5 chargers per CPO. Thus, for the entire system, the profit is EUR 6400/day with a typical value of 25 chargers. The daily profit is the income minus all daily costs minus fixed costs like the payback of investments. Of course, one may ask, is this profitable enough? As previously mentioned in [4,5], chargers are assumed to be used for seven years before they are replaced, and the cost of the charger and grid connection, including depreciation, is estimated to be C_{ch} = EUR 0.32/kW/day. The fixed costs for twenty-five 900 kW chargers and the corresponding grid connection over seven years becomes

$$\begin{aligned} &\text{cost for twenty-five 900 kW charger over 7 years} \\ &= 25 \cdot \text{ EUR } 0.32/\text{kW}/\text{day} \cdot 900 \text{ kW} \cdot 7 \text{ years} \cdot 365 \text{ days}/\text{year} = \text{EUR } 18{,}400{,}000 \end{aligned} \tag{48}$$

and the corresponding profit becomes

$$\begin{aligned} &\text{profit for twenty-five 900 kW charger over 7 years} \\ &= \text{ EUR } 6400/\text{day} \cdot 7 \text{ years} \cdot 365 \text{ days}/\text{year} = \text{EUR } 16{,}350{,}000\ . \end{aligned} \tag{49}$$

Thus, the ratio of the profit to the expenditures over seven years can be calculated as follows:

$$\frac{\text{profit}}{\text{expenditures}} = \frac{16{,}350{,}000 \text{ EUR}}{18{,}400{,}000 \text{ EUR}} = 88.87\%. \tag{50}$$

Indeed, this seems to be a very profitable business for CPOs. This indicates that the fairly low prices and short queues are not achieved at the expense of the profitability of the CPOs. Instead, one may ask, if there is hard competition between CPOs, would the profit not be lower than this? Naturally, it is possible that the CPOs in this paper do not compete that strongly, and further improvement of the agent rules may lower the prices and, thus, the profit. Such analysis has not been made in this paper, but it is an interesting topic for further research. A reason for this high profit could be that the CPOs try to adjust the number of chargers so that every charger is profitable. So, if the least used charger is profitable, all the others are even more profitable, which makes good business for the CPOs. Notice that the profit is *not* adjusted for less charging on weekends and overcapacity due to variations in the daily traffic flow since we, in this paper, assume that CPOs can adjust the price to compensate for this, as presented in the previous subsection.

6. Discussion and Conclusions

6.1. Limitations of the Study and Further Developments

This paper studied the market interaction between charging trucks and two competing CPOs on the same site, with a reasonably simple spot market model with inflexible charging demand and no competing charging stations elsewhere. Therefore, the results and conclusions mainly describe a few fundamental market forces in a market with spot prices and are not predictions for the overall market. The simulation uses traffic flow from real data, but only one variation over the day has been analysed, even though the same method can be used to include variations from day to day if one simulates, for example, a typical year instead of a typical day. Of course, one may add more details to the model, but there is no guarantee that a more complicated model will provide more accurate results or provide a better understanding of the system.

The cost-minimizing rules for the trucks are reasonable, but the choices for real trucks are probably more complex. Likely, they act partly on habit, so they are more prone to charging where they used to charge, even if the price is slightly higher. Most likely, there are other things than the charging price that are also relevant, such as good food. Still, it is argued that for commercial vehicles, there will always be a strong component of selecting chargers based on low prices and short queues, even if other factors will add to the decision.

The rules for the CPOs were designed with the aim of increasing profit under competition. There are many sets of rules that, through the market iterations, can increase the profit, and the ones used in this analysis have been selected to be easy to understand and include some random changes to avoid getting stuck in a sub-optimum. Even though the rules seem to work well and feel intuitive, it has been shown that the design of these rules can impact the results. As a further development of this study, it will be interesting to investigate competing CPOs that follow different rules to see which behaviours can out-compete others. Could competing CPOs that follow different rules compete equally well? Further, it will be interesting to investigate a system with more than two CPOs and charging stations spread out geographically. Two charging stations far from one another are not directly competing since trucks cannot choose between those two stations when they need to charge. But, between them, there might be several charging stations, each competing with its closest neighbours. Therefore, one may suspect that the price at a station is affected by the price at another station that is far away due to the chain of stations in between.

6.2. Conclusions

The interactions in the fast-charging market are rather complex, and this paper demonstrates two ways of investigating the conditions and some basic market mechanisms in the future fast-charging market. On the one hand, analytic calculations on limited parts of the market mechanisms increase the understanding of the system with a high degree of control but fail to find the bigger picture. On the other hand, an agent-based model allows one to investigate a more complicated and realistic system, but one loses some of that control since it acts partly as a black box. The agent-based model provides an opportunity to obtain macroscopic results and draw system conclusions by only designing rules on the microscopic level, which is a strength. Combined with simplified analytic calculations, the authors consider agent-based models as a powerful tool to investigate the complexity of the system of battery electric trucks and CPOs. Thus, it will be a key to a better understanding of how a system with public chargers will work from a market perspective. So, despite having to rely on rules for the agents and some other assumptions presented in this paper, this investigation has produced some interesting conclusions:

1. For the analysed location and a charging demand reflecting the current traffic flow, the study indicates potential for really low prices, around EUR 0.1/kWh over a large part of the day. The price will likely be much higher during rush hours, about EUR 0.5/kWh. The price during rush hours was found to be sensitive to changes in how the CPOs act. The mean price was found to be EUR 0.15/kWh. These prices can be achieved with profitable CPOs.
2. Under the assumption that truck owners are willing to pay the price, the results indicate low problems with queues, even during rush hours. This may make charger booking systems less important or even redundant.
3. The system charger utilisation factor was estimated to be 31%, which is very high, especially considering that it is achievable with such minor queuing problems. This utilization is derived for one long-haul truck flow in Sweden and a strategically located charging station along a busy road. The utilization will be different for different types of charging stations with different time variation in charging demand. Stations with

lower utilization will likely lead to higher average charging prices than found in this study.
4. The calculations and simulations performed in this paper indicate that a CPO in competition will adjust its prices in line with demand and supply. Thus, this study makes it likely that a CPO that uses time-varying prices will out-compete a CPO with a fixed price for charging over the day.
5. Even though the market simulation converges, there seems to be no stable equilibrium in which a CPO can just keep its price and number of chargers fixed. Instead, a CPO needs to constantly adjust to what the competing CPO does, much like the game "Rock, Paper, Scissors", in which there is no move that always wins.
6. The simulations indicate that the free market can provide a system of chargers with high utilisation, profitable CPOs, low queuing problems, and reasonable prices on public fast charging only due to competition and profit interests.

This paper suggests rules for how trucks select CPOs and how competing CPOs set prices and decide the number of chargers at a station. These rules (presented in Section 3) seem to work quite well, and similar rules might be used in future models where one may add, for example, geographically spread charging stations.

Many things could be changed in the rules and the iteration method in the agent-based model to study the sensitivity of the results. Thus, more and deeper investigations on this subject would be good to either confirm or question the above conclusions.

Author Contributions: Conceptualisation, J.K. and A.G.; methodology, J.K.; software, J.K.; formal analysis, J.K.; investigation, J.K.; writing—original draft preparation, J.K.; writing—review and editing, J.K. and A.G.; supervision, A.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Swedish Transport Administration, TripleF, grant number 2020.3.2.32.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data used can be found at https://vtf.trafikverket.se/SeTrafikinformation (accessed on 14 September 2023).

Acknowledgments: Financial support from the Swedish Transport Administration has been gratefully received.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Nomenclature

C_{tot}	Extra cost for selecting CPO 2 (EUR)
C_{ch}	Combined price for charger and grid (EUR/kW/day)
C_e	Price for electricity for the CPO (EUR/kWh)
$C_{epub}(t)$	Price for public fast charging for arriving trucks at time t (EUR/kWh)
$C_{epub}^{mean}(t)$	Mean price for the users at a CPO at time t (EUR/kWh)
C_p	Extra cost for price difference (EUR)
C_q	Extra queuing cost (EUR)
$C_{q/t}$	Cost for operating a truck (EUR/min)
ΔC_{epub}	Discretisation step of the price for charging (EUR/kWh)
ΔI	Difference in income after a change in price (EUR)
ΔT	Length of a time interval with a given demand and supply (hour)
Δt	Time step (min)

$E(t)$	Delivered energy from a CPO during a time step (kWh)
E_b	Charging need for each truck (kWh)
E_c^{tot}	Total daily charging need at Ödeshög (kWh)
F_t	Average flow of trucks with trailer passing Ödeshög (trucks per day)
Γ_{after}	Utilisation after change in price (-)
Γ_{before}	Utilisation before change in price (-)
I	Profit for a CPO (EUR/day)
k	Ratio of power demand to power supply (-)
$M(t)$	Earning during a time step (EUR)
$N(t)$	Number of charging trucks at a charging station at time t (-)
N_{tot}	Number of chargers at a CPO (-)
P	Average power for the chargers (kW)
P_1	Charging price at CPO 1 (EUR/kWh)
P_2	Charging price at CPO 2 (EUR/kWh)
P^i_{marg}	Profit margin for CPO i (EUR/kWh)
P_{prob}	Probability for the different changes of N.o. chargers and prices (-)
q_1	Queuing trucks at CPO 1 (trucks/charger)
q_2	Queuing trucks at CPO 2 (trucks/charger)
r_c	Share of charging trucks passing Ödeshög (-)
r_p	Factor compensating power decrease with state of charge (-)
r_q	Factor for uncertainty in queuing
$\sigma(t)$	Defined by Equation (14) (-)
T	Length of the typical day (day)
T_h	Length of time interval with high power demand (hour)
T_1	Queuing time at CPO 1 (min)
T_2	Queuing time at CPO 2 (min)
T_{diff}	Different in queuing time between the CPOs (min)
T_c	Time for charging (min)

Abbreviations

CPO	Charge Point Operator

Appendix A

This appendix presents the truck arrival time used in the simulations. The truck flow is described for each hour, where hour 1 corresponds to the time interval 00:00–01:00, hour 2 corresponds to the time interval 01:00–02:00 and so on. Minute 1 of a given hour corresponds to the first minute of that hour, while minute 33, for example, corresponds to the 33rd minute of that hour. The truck flow is given in Table A1.

Table A1. Arrival times of the trucks used in the simulations.

Hour	One Truck Arrives Minute
1	1, 4, 7, . . . , 58 and 2, 59
2	4, 7, 10, . . . , 55 with exception of 25
3	1, 7, 13, . . . , 55 and 2
4	7, 13, 19, . . . , 55 with exception 25
5	7, 13, 19, . . . , 55
6	1, 7, 13, . . . , 55
7	1, 7, 13, . . . , 55 and 2, 14, 36, 52
8	1, 7, 13, . . . , 55 and 2, 14, 36, 52
9	1, 7, 13, . . . , 55 and 2, 14, 36, 48, 52
10	1, 4, 7, . . . , 58 with exception of 4
11	1, 4, 7, . . . , 58 and 5
12	1, 4, 7, . . . , 58 and 5, 23, 33, 42, 57

Table A1. *Cont.*

Hour	One Truck Arrives Minute
13	1, 3, 5, . . . , 57 with exception of 5, 31
14	1, 3, 5, . . . , 59 and 4, 30, 38, 58
15	1, 3, 5, . . . , 59 with exception of 3
16	1, 3, 5, . . . , 59 and 4, 30
17	1, 3, 5, . . . , 59
18	1, 3, 5, . . . , 59 with exception of 3, 31, 47
19	1, 4, 7, . . . , 58 and 3, 32, 47
20	1, 4, 7, . . . , 58 and 3, 32, 38, 47
21	1, 4, 7, . . . , 58 and 3, 32, 47
22	1, 4, 7, . . . , 58 and 3
23	1, 4, 7, . . . , 58 and 3, 32
24	1, 4, 7, . . . , 58 and 3, 32

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