energies

Article

Electric Vehicle Charging Schedules in Workplace Parking Lots Based on Evolutionary Optimization Algorithm

Stavros Poniris and Anastasios I. Dounis *

Department of Biomedical Engineering, University of West Attica, Egaleo Park Campus, Ag. Spyridonos Str., Egaleo, 12243 Athens, Greece
* Correspondence: aidounis@uniwa.gr

Abstract: The electrification of vehicles is considered to be the means of reducing the greenhouse gas (GHG) emissions of the transport sector, but "range anxiety" makes most people reluctant to adopt electric vehicles (EVs) as their main method of transportation. Workplace charging has been proven to counter range anxiety and workplace charging is becoming quite common. A workplace parking lot can house hundreds of EVs. In this paper, a program has been developed in MATLAB that uses the well-known evolutionary optimization algorithm, the genetic algorithm (GA), to optimize the charging schedule of fifty EVs that aims at achieving three goals: (a) keeping the electricity demand low, (b) reducing the cost of charging and (c) applying load shifting. Three schedules were developed for three scenarios. The results demonstrate that each schedule was successful in achieving its goal, which means that scheduling the charging of a fleet of EVs can be used as a method of demand-side management (DSM) in workplace parking lots and at the same time reduce the energy cost of charging. In the scenarios examined in this paper, cost was reduced by approximately 2%.

Keywords: electric vehicle; genetic algorithm; charging schedule; workplace charging; evolutionary optimization; demand-side management

check for updates

Citation: Poniris, S.; Dounis, A.I. Electric Vehicle Charging Schedules in Workplace Parking Lots Based on Evolutionary Optimization Algorithm. *Energies* **2023**, *16*, 221. https://doi.org/10.3390/en16010221

Academic Editor: Hugo Morais

Received: 5 November 2022
Revised: 13 December 2022
Accepted: 22 December 2022
Published: 25 December 2022

1. Introduction

Climate change has unfortunately evolved into a climate crisis [1]. The main reason is that greenhouse gas emissions have increased dramatically as a result of the prolonged use of fossil fuels by major sectors such as the energy sector and the transportation sector.

The necessity for reducing greenhouse gas emissions has led to renewable energy sources becoming more common. Therefore, the share of renewable energy sources in electricity generation in the EU27 increased from 15.87% in 2004 to 37.48% in 2020 [2]. The advent of lithium batteries made utility-scale battery energy storage systems feasible and several countries are adopting energy storage system policies to further reduce their carbon footprint [3]. However, fossil fuels still dominate the transportation sector, with the related emissions not showing any signs of reduction [4].

Lithium batteries also made EVs become a commercial alternative solution to conventional vehicles. Although the EU aims for the proliferation of the use of EVs, the public still has qualms about adopting EVs as the main means of transportation. The primary reason is the fear that the energy stored in the vehicle's batteries will not last long enough for the car to reach a charging station. This was made apparent during the test use of the first modern electric vehicle General Motor's EV1, when the term "range anxiety" was coined [5]. It is of great importance to counter the range anxiety for EVs to become alternative conventional vehicles and researchers examine various ways to tackle this issue. A hybrid electric vehicle that utilizes renewable energy by incorporating PV cells, a wind generator, a fuel cell and a superconductor is proposed in [6]. The battery swapping method as an alternative to charging stations is examined in detail in [7]. Among the ways that have been successful in reducing the range anxiety, with currently available means and technology, is access to charging stations at the place of employment. An employee with access to a workplace charging station is 6-fold more likely than the average worker to drive an EV [8]. Therefore, workplace charging is an appealing idea and, in a recent survey, it was revealed that approximately 15–20% of charging events occur at the workplace [9].

Along with the advantages that EVs bring, some challenges also follow that were never an issue with conventional engines. Among these challenges is introducing vast numbers of EVs at a grid level. In [10], Ahmad et al. discuss a cost-efficient method of integrating EV charging in a microgrid by using the India power market as a case study. Nevertheless, similar challenges can exist at a lower level too. Among these cases is charging a large number of EVs in a workplace parking lot, where EVs arrive at the same time and are expected to be sufficiently charged in a finite amount of time. When all the EVs start charging, the electricity demand will reach a peak and, as the EVs become charged, one by one the demand will drop until it is very low or zero. If the electrical infrastructure is sized to handle the peak demand, it will become expensive, especially since the peak does not last long. Using a schedule for EV charging can mitigate this hindrance and additionally provide further advantages.

There is active interest in scheduling the charging of EVs to achieve specific goals and related subjects. Therefore, the existing literature on the subject is extensive, especially since the variety of circumstances and objectives provide a broad topic for research. In [11], a tool for the short-term forecast of loads was developed using the Lion Algorithm with Niche Immunity. A paper examined the maximization of the benefit of charging EVs in a workplace parking lot using the electric grid and a PV system developed Dynamic Charging Scheduling Scheme using Model Predictive Control [12]. In [13], a workplace that integrates EVs is treated as a microgrid by using G2V and V2G power transfer and a Multi-Agent System was developed to minimize the energy cost of charging. A mixed-integer linear programing-based optimization was used to maximize the profits of an EV charging station based on solar energy and EV arrival forecast [14]. Similar research that aimed at the maximization of the profits of a commercial parking lot that also employed a PV system used the Grey Wolf Optimizer and the Improved Grey Wolf Optimizer [15]. Another paper used a day-ahead solar energy forecast aimed at minimizing the cost of charging through scheduling [16]. The need to flatten the curve of daily power consumption in residential areas by peak shaving—valley filling using Grid-to-Vehicle and Vehicle-to-Grid technology—has also led researchers to use the GA for scheduling the charging and discharging of EVs with successful results [17]. Another case of peak shaving—valley filling using Grid-to-Vehicle and Vehicle-to-Grid technology to minimize the load variance in power grids using the GA was examined in [18]. In [19], a mixed-integer non-linear programing-based optimization was used to minimize the cost of a charging station with a limited number of chargers and a forecast in power demand. A significant effort that aims at managing the power in a municipal parking lot has used three different algorithms to draw conclusions, the Estimation of Distribution Algorithm (EDA), the Particle Swarm Optimization (PSO) and the Interior point method [20]. One notable work uses a stochastic algorithm, Particle Swarm Optimization, to integrate plug-in hybrid EVs in smart buildings with RES [21]. CAPSO (Coordinated Aggregated Particle Swarm Optimization) was used in order to achieve maximum customer satisfaction and improve grid performance [22]. The Improved Marine Predator Algorithm (IMPA) was used to achieve minimum energy cost by taking advantage of variable energy prices and Vehicle-to-Grid technology [23]. In [24], a fuzzy logic optimization was used to schedule the charging of EVs aiming at avoiding overloading the distribution transformers.

In comparison with related previous works, the main contributions lie in the case of charging a large number of EVs in a workplace parking lot, where the goal is not profit, as is the case with commercial parking lots. The idea is to achieve optimal charging scheduling based on a stochastic approach. We discuss the advantages an optimal scheduled charging cycle can provide by setting three goals. These goals are:

- The handling of the peak in power demand at the beginning of the charging cycle.

- The decrease in the charging cost by taking advantage of lower energy prices during non-peak hours.
- The development of a flexible program that can apply load shifting to avoid charging EVs during time periods when the available power is lower than normal.

The first schedule aimed to meet the first goal. The second schedule aimed to meet both the first and second goals. The third schedule aimed to meet all three goals. Finally, the results of all three schedules were compared to each other to present the advantages and disadvantages of using optimized schedules in workplace parking lots when trying to meet the aforementioned goals.

The optimization problem of the charge scheduling can be tackled by evolutionary algorithms. In this paper, the optimization strategy is based on the popular evolutionary algorithm of the GAs; to create the schedules, a program was developed in Matlab that uses the GA for the calculations. The stochastic properties of the GA cannot assure that the schedules will reach the global optimum; however, the GA is a well-established optimizing method and guarantees results.

2. Materials and Methods

2.1. Problem Formulation

Optimizing the schedule of EV charging aiming at minimum power consumption or minimum cost with:

1. An upper limit of total power consumption;
2. A lower limit of individual SoC

Poses a constrained optimization problem that generally can be expressed in the form of:

$$\min f(\mathbf{x}), \mathbf{x} = (x_1,\ x_{2,} \ldots,\ x_n)^T \in \mathbb{R}^n \text{ with problem constraints}$$
$$\begin{gathered} a_{11} \cdot x_1 + a_{12} \cdot x_2 + \ldots + a_{1\mathrm{n}} \cdot x_\mathrm{n} \ \leq\ b_1 \\ a_{21}\ \cdot x_1 + a_{22} \cdot x_2 + \ldots + a_{2\mathrm{n}}\ \cdot x_\mathrm{n} \ \leq\ b_2 \\ \ldots \\ a_{\mathrm{m}1} \cdot x_1 + a_{\mathrm{m}2}\ \cdot x_2 + \ldots + a_{\mathrm{mn}}\ \cdot x_\mathrm{n} \ \leq b_\mathrm{m} \end{gathered}$$

where a_{mn} is either a power or an energy parameter and b_m is either a power or an energy boundary. It can also be expressed as $\mathbf{A} \cdot \mathbf{x} \leq\ \mathbf{b}$. **A** is a matrix containing all the parameters and **b** is a vector containing all the boundaries.

For this problem, **x** is the complete charging schedule. It comprises bits to signify which vehicle charges at which time and which do not. Since the GA is used to solve this problem, x is the chromosome, namely an individual of population, that is to say a candidate solution, used in the evolving procedure of the GA to achieve the minimum of the objective Equations (1) and (2).

A is a matrix that contains the parameters of the constraints. As mentioned earlier, there are two distinctive criteria. The first criterion is the upper limits for the power consumption of each power segment and the second criterion is the lower limits of energy transfer to each EV. For this second part, in order to stay true to the formula $\mathbf{A} \cdot \mathbf{x} \leq\ \mathbf{b}$, all parameters associated with this part of the **A** matrix are multiplied by -1.

Finally, **b** is a vector that contains the boundaries for the constraints. As with the **A** matrix, it comprises two parts. In the first part are the boundaries on power consumption for each time segment. These represent the available power for charging during each time segment and are dependent on the problem environment. The second part of the vector is the boundaries regarding the energy of each EV. These boundaries correspond to an arbitrary state of charge (SoC) that signifies sufficient charging or a SoC that is depended on the problem environment. The lower of these two SoC is chosen for each EV. Additionally, as mentioned in the second part of **A**, all these boundaries are multiplied by -1.

2.2. Scenario Description

All the scenarios are about a hypothetical parking lot for the employees of a company. The parking lot will also serve as workplace charging for these employees. The working hours are considered to start at 08:00 and end at 16:00. All charging will occur during that time.

The fleet of vehicles are comprised of fifty EVs from twenty different models. For simplicity reasons, all charging is considered to occur with 100% efficiency. Each EV is connected to a typical 3-phase charger capable of providing up to 7.4 kW of power. There are more powerful chargers available but, in the spirit of keeping expenses low in order to make workplace charging more affordable, they were excluded.

The chargers will receive signals every five minutes. These five minutes are considered as one time segment. There are eight hours available for charging, which means a total of ninety six time segments. The starting time segment is number 1 at 08:00 and the ending segment is number 96 at 15:55.

The SoC of each EV's battery when they arrive at the workplace parking lot cannot be predicted since real-world data do not exist. For this reason, a random SoC for each EV was selected using the rand() function in Excel. The lowest SoC allowable is 20% and the highest is 75%.

The scheduling program will also be implemented to achieve two DSM goals:

- A reduction in energy costs when the electric utility uses Electricity Time Bands, which means that the price of each kWh of electrical energy is dependent upon the time it is consumed. Endesa's Tempo 3 Periodos pricing, a Spanish electric utility company, is used in order to provide realistic energy costs. The Electricity Time Bands between 08:00 and 16:00 are:
    1. 08:00–10:00, 0.267070 EUR/kWh;
    2. 10:00–14:00, 0.325836 EUR/kWh;
    3. 14:00–16:00, 0.267070 EUR/kWh [25].
- A reduction in power used for charging in certain time periods when the available power is lower than usual, through load shifting. In essence, the schedule will avoid charging EVs over a limit at specific time segments. Specifically,
    1. 09:30–10:30, available power up to 60 kW;
    2. 12:00–12:30, available power up to 80 kW;
    3. 15:00–15:15, available power up to 15 kW.

These values are set arbitrarily, aiming at demonstrating how the schedule will differentiate when severe boundaries are set, during peak and non-peak hours.

Three scenarios are examined:

- In Scenario 1, the program is scheduling EVs to charge using the minimum average power;
- In Scenario 2, the program is scheduling EVs to charge with the minimum average cost;
- In Scenario 3, the program is scheduling EVs to charge with the minimum average cost while load shifting.

The EVs and starting SoC are presented in Table A1.

2.3. Objective Function

The first scenario aims at minimizing the average power used for charging. The objective function is:

$$f_1(\mathbf{x}) = \frac{\left(\sum_{\mathrm{j}=1}^{\mathrm{Nev}} \sum_{\mathrm{i}=0}^{\mathrm{Ts}-1} \mathrm{x}_{\mathrm{j}+(\mathrm{Ts}-1)\cdot \mathrm{i}} \cdot \mathrm{P}_{\mathrm{i}}\right)}{\mathrm{T_s}} \tag{1}$$

The second and third scenarios aim at minimizing the average cost of charging. The objective function is:

$$f_2(\mathbf{x}) = \frac{\left(\sum_{j=1}^{Nev} \sum_{i=0}^{Ts-1} x_{j+(Ts-1)\cdot i} \cdot Q_i\right)}{T_s} \quad (2)$$

N_{ev} is the number of EVs—in this case, N_{ev} = 50. T_s is the number of time segments—in this case, T_s = 5 min or 300 s. P in (1) is the power consumption, and Q in (2) is the cost multiplied by a penalty factor. The penalty factor is 5 during peak hours and 0.5 for the rest of the time.

A case without any scheduling will also be calculated to demonstrate the differences between scheduled and unscheduled charging. This case is referred as the baseline.

2.4. Constraints

As mentioned in Section 2.1., there are two different types of constraints. The first type of constraint is an upper limit of total power consumption and the second type is a lower limit of the SoC of each EV.

The first type ensures that the total electrical power used for charging does not exceed a limit. That limit is set based upon the electrical infrastructure's materials own limitations, and by time-dependent circumstances that require a different limit for a specific time periods. The second type ensures that each EV will meet a minimum SoC requirement to be considered as sufficiently charged.

These two constraints work against each other. On the one hand, the constraint for minimum SoC pushes the total power used for charging up; on the other hand, the total power limit forces it within the specified limits.

2.5. Total Power Boundaries

The total power boundary sets a ceiling of 200 kW in power consumption in all three scenarios. This value is chosen arbitrarily and it symbolizes the limit set by the electrical infrastructure that cannot be exceeded at all times. A lower value of the total power constraint is used in the time periods that load shifting is applied.

The SoC boundaries are chosen between two options. The first option is an arbitrary SoC that at which EVs are considered sufficiently charged. The second option is the SoC that corresponds to the maximum energy that can be transferred during the available time. The reasoning behind this is that it is no use trying to schedule the charging of an EV to achieve a final SoC that exceeds what is physically possible during the available time. From these two options, the lower value is selected to create the boundary for each EV.

For the first option, an EV is considered to be sufficiently charged when it reaches a SoC of 80%. For the second option, an EV is considered to be sufficiently charged when it receives energy during all the available time segments. The available segments are ninety six minus spare time segments. These spare time segments are used to prevent a few EVs with a large battery capacity and a low starting SoC to monopolize all ninety six time segments. They are more crucial to the schedule when load shifting is applied and a few time segments have severely reduced power available for charge implementation.

The following flowchart in Figure 1 describes the way the scheduling program works:

The program was developed in MATLAB and the GA included in the software package was used for calculating the schedules. The default settings were used in all the options with the exception of the population size. Therefore, the selection function was set to "selectionstochunif", the elitism factor was 0.05, the crossover factor was 0.8, the mutation function was set to "mutationgaussian", the crossover function was set to "crossoverscattered" and finally the population size was set to 400. The multicore option was used for faster results.

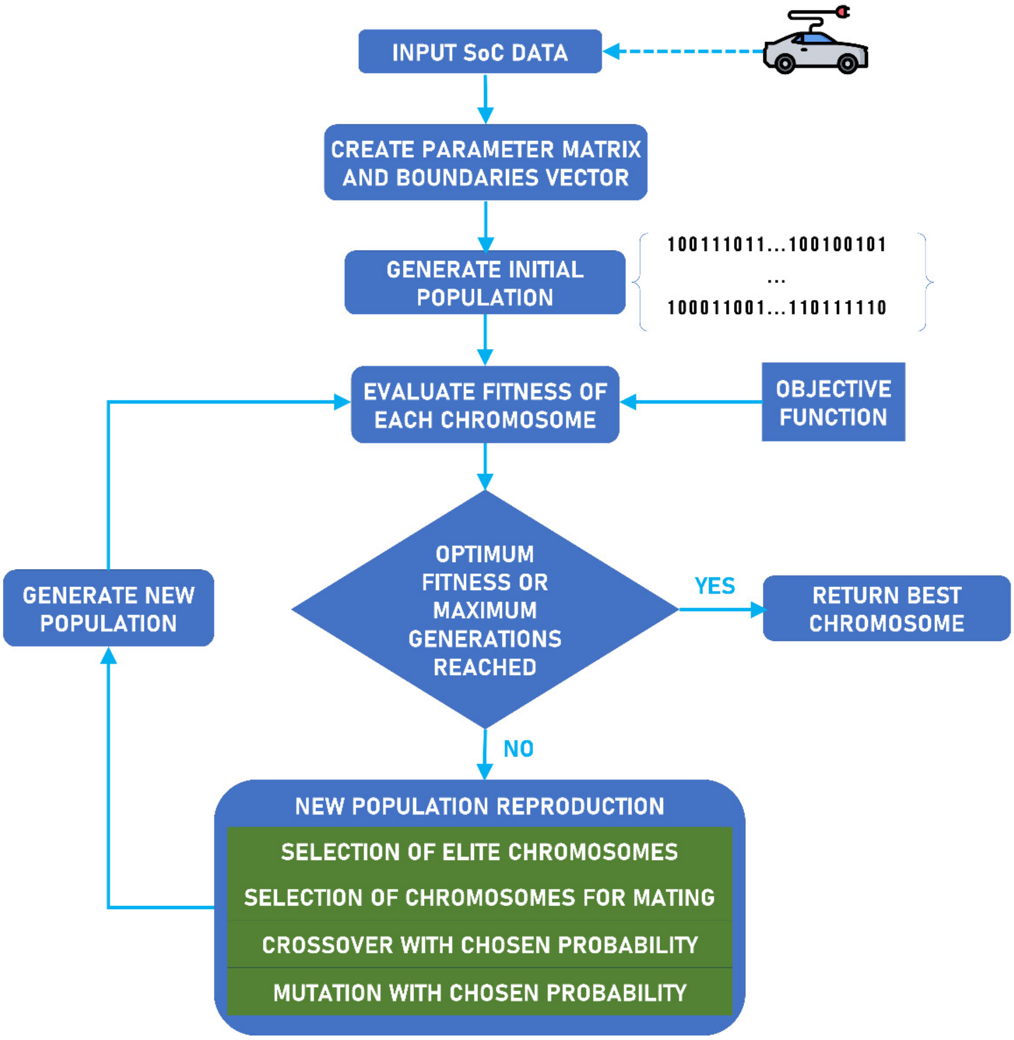

Figure 1. Flowchart of the program's operation.

The process of the optimization using the GA in MATLAB can be visualized with the penalty value to generations diagram. The penalty value is what the GA actually minimizes. When the chromosomes in a generation represent only infeasible solutions, the penalty value of each chromosome is calculated as the sum of all constraint violations. This way, it saves computing power by not calculating each objective function's value. When at least one chromosome in a generation represents a feasible solution, the algorithm calculates the penalty values differently. The penalty value in this case is calculated as:

- The objective function value for every chromosome that represents a feasible solution.
- The sum of the constraints violations plus the worst objective value in the generation for every chromosome that represents an infeasible solution [26,27].

In Scenario 1, the initial generations produce infeasible solutions. After approximately 100 generations, the first feasible solutions are found with a penalty value of over 100. In the first scenario, there is no penalty factor in the objective function so the penalty value from for feasible solutions from this point on also represents the average power. As shown in Figure 2, the process ends at the 424th generation, with the best solution having a penalty value of 84.1625.

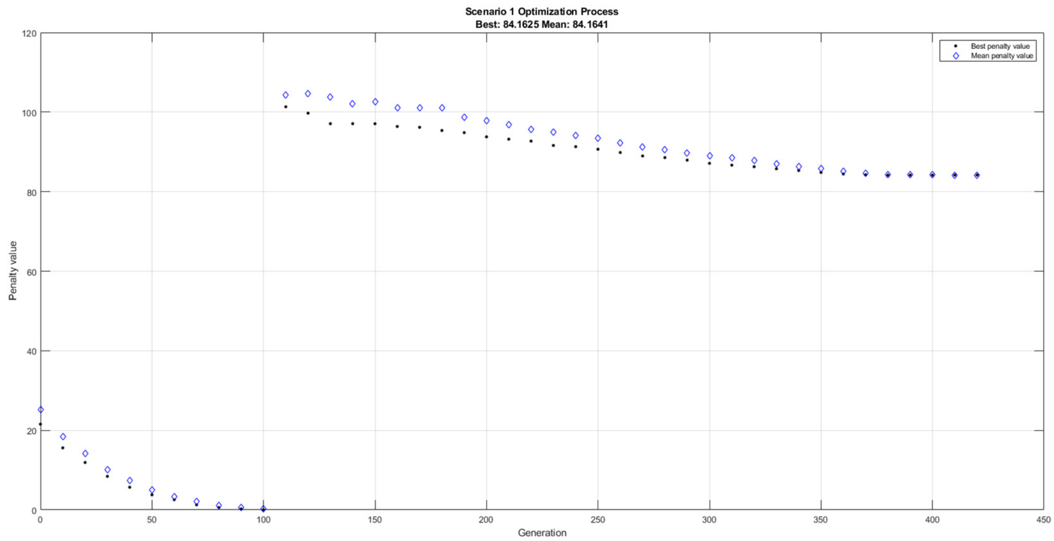

Figure 2. Scenario 1 optimization process.

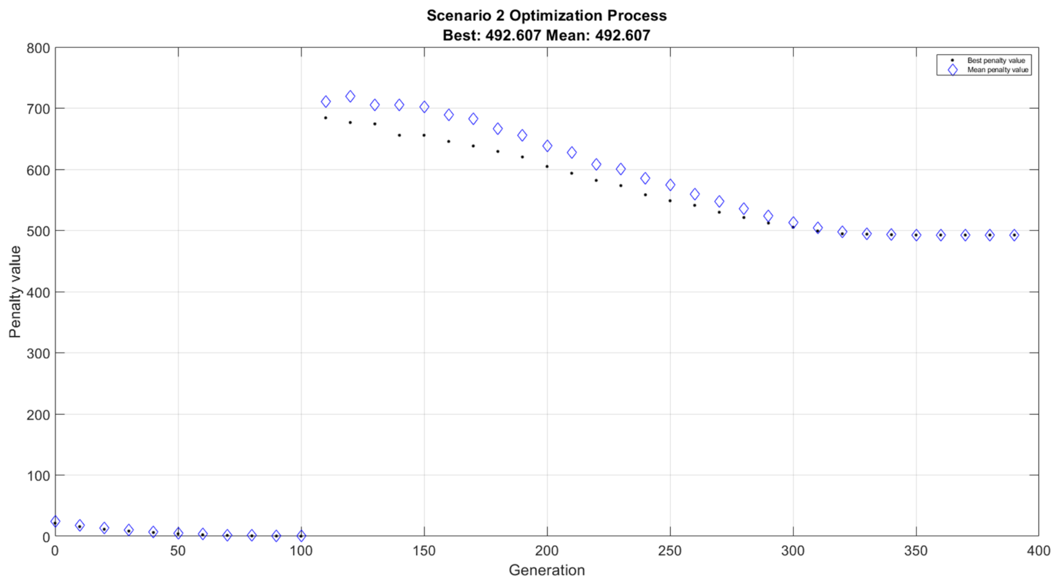

Figure 3. Scenario 2 optimization process.

In Scenario 2, the initial generations also produce infeasible solutions. After approximately 100 generations, the first feasible solutions are found with a penalty value of approximately 700. In the second scenario, a penalty factor is applied in the objective function, so the penalty value for feasible solutions from this point on also represents the average cost of charging after applying the penalty factors. As shown in Figure 3, the process ends at the 398th generation, with the best solution having a penalty value of 492.607.

In Scenario 3, the initial generations also produce infeasible solutions. After more than 100 generations, the first feasible solutions are found with a penalty value of approximately 500. In the third scenario, a penalty factor is applied in the objective function, so the penalty value for feasible solutions from this point on also represents the average cost of charging after applying the penalty factors. As shown in Figure 4, the process ends at the 395th generation with the best solution having a penalty value of 382.

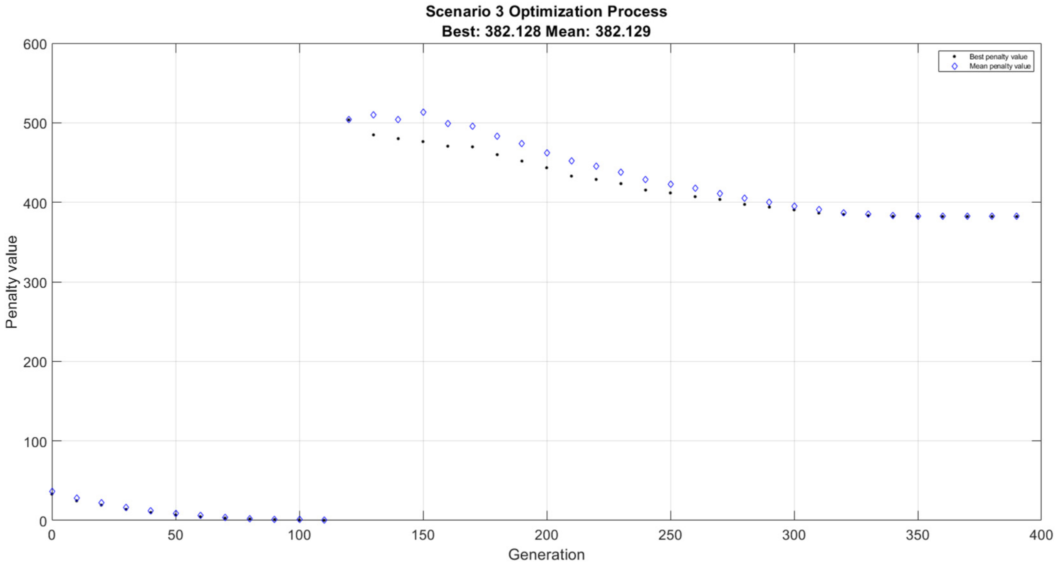

Figure 4. Scenario 3 optimization process.

3. Results

In this section, starting with the baseline and following with the three scenarios, the results of the charging schedule are presented.

3.1. Baseline

The results of an unscheduled charging of the EVs in Table A1 are presented in Figure 5:

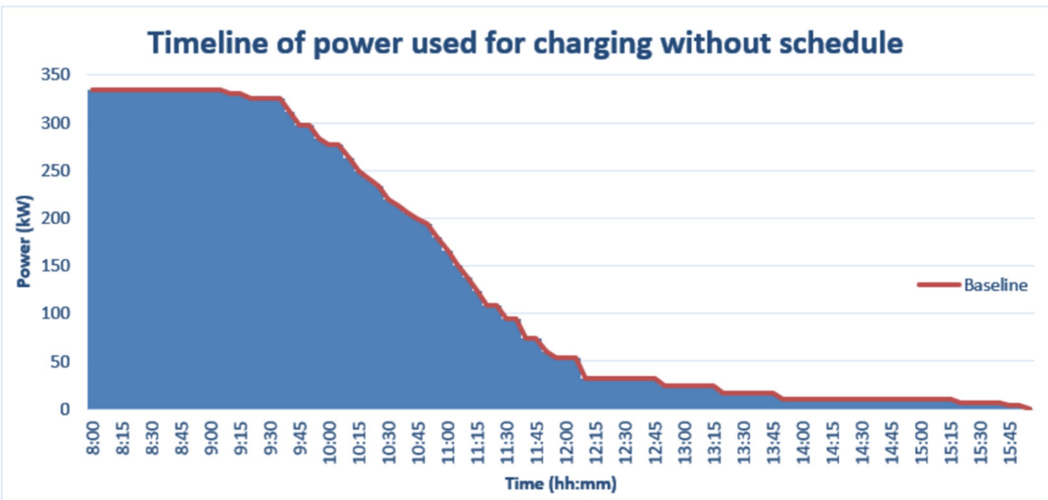

Figure 5. Baseline.

As expected at 08:00, and for a while, the EVs draw power all at the same time, forming a peak in demand. The sum of the power reaches 330 kW. After the first hour, the EVs begin to be fully charged and consequently the power used for charging begins to drop. After 14:00, only 10.8 kW are used for charging and it keeps dropping until 15:55, when all vehicles become fully charged. In this case, the total energy consumed for charging is 1058.45 kWh and the cost is EUR 305.41.

3.2. Scenario 1: Peak Shaving and Valley Filling

The goal of the first scenario is to schedule the charging of EVs in a way that avoids overloading the electrical infrastructure.

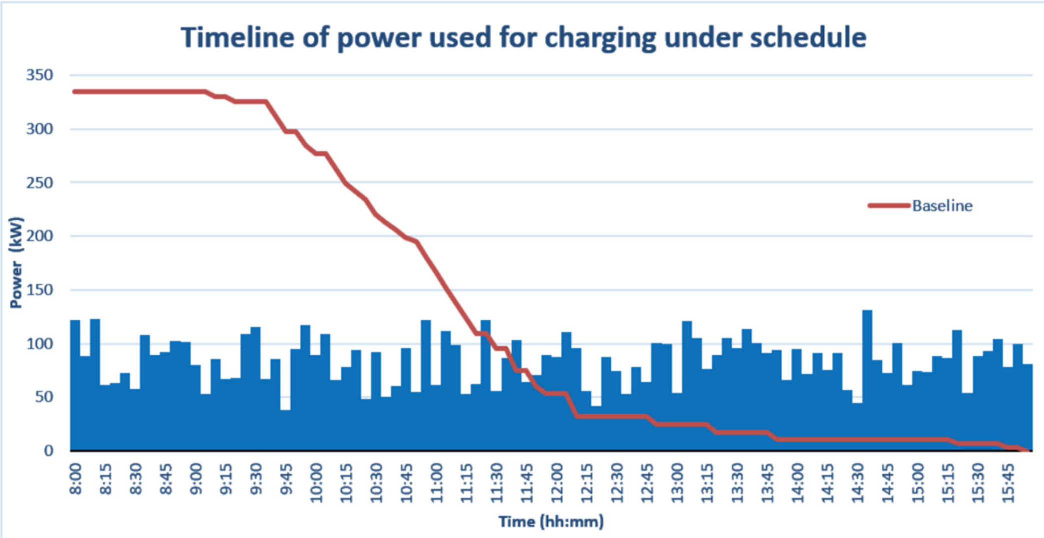

Figure 6. Scenario 1 results.

As shown in Figure 6, the peak and valley have disappeared when the EVs charge under schedule, and the power used for charging is more uniform from start to end. The upper limit of 200 kW was kept at times. The average power used for charging is 84.16 kW, with a peak of only 131.20 kW.

The total energy consumed for charging is 673.30 kWh and the cost is EUR 199.44. Although this scenario did not intent to minimize the costs of charging, by aiming at charging EVs at 80%, the energy used for charging was reduced by 385.15 kWh and therefore the cost dropped by EUR 105.97, 34.70% decrease.

3.3. Scenario 2: Reduction in Energy Cost

In the second scenario, the program will aim at scheduling the charging of the EVs in such a way as to avoid as much as possible the time period between 10:00 and 14:00 that has a higher energy cost. The price of energy during the costlier Electricity Time Band is multiplied by 5, and during the rest of the time, it is multiplied by 0.50, as their penalty factor.

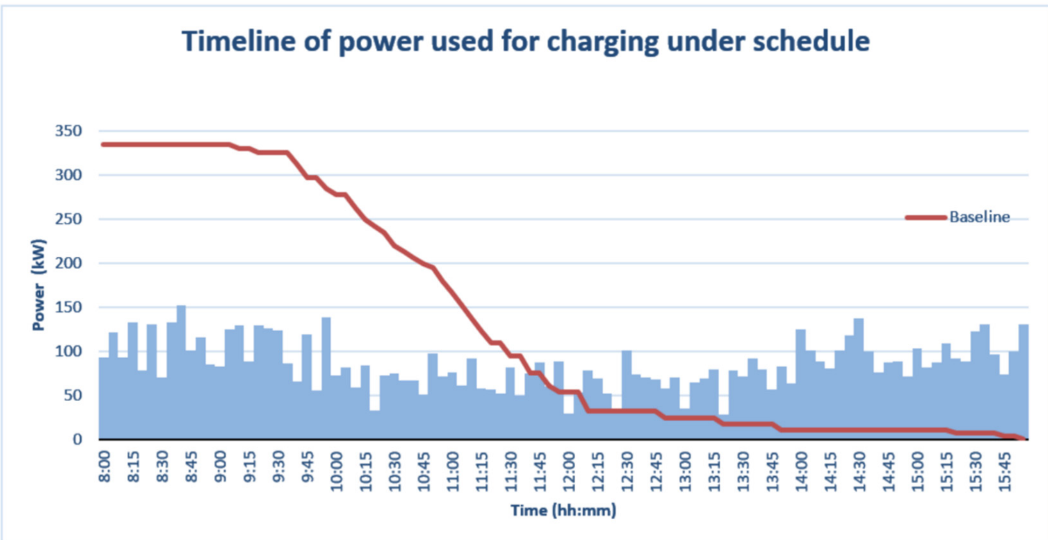

Figure 7. Scenario 2 results.

As shown in Figure 7, the schedule has avoided charging all EVs at once and utilized all the available time and has allocated more EVs to charge from 08:00 to 10:00 and 14:00 to 16:00, when the energy is less expensive. The average power used for charging is 85.21 kW, with a peak of 151.20 kW.

The total energy consumed for charging is 681.67 kWh and the cost is EUR 197.83. This scenario aimed at minimizing costs by avoiding charging EVs during peak hours, when the tariff is higher. This means that, in this scenario, there are two factors that reduce costs, a DSM strategy and the 80% SoC target for every EV. These led to a reduction of 376.78 kWh in energy and EUR 107.58 in costs, a 35.22% decrease.

3.4. Scenario 3: Load Shifting

In the third scenario, the schedule will try to minimize energy costs similar to in Scenario 2, with the added parameters of reduced available power during specific time segments. Unlike in the previous scenarios, where there is a blanket limit throughout the working hours, in this case, the danger of overloading the electrical infrastructure can occur during the time periods specified in Section 2.

The spare time segments in this scenario are increased because the total available time segments to the EVs are decreased and some EVs would be unable to reach the charged status, as considered by the scheduling program, with the previous setting.

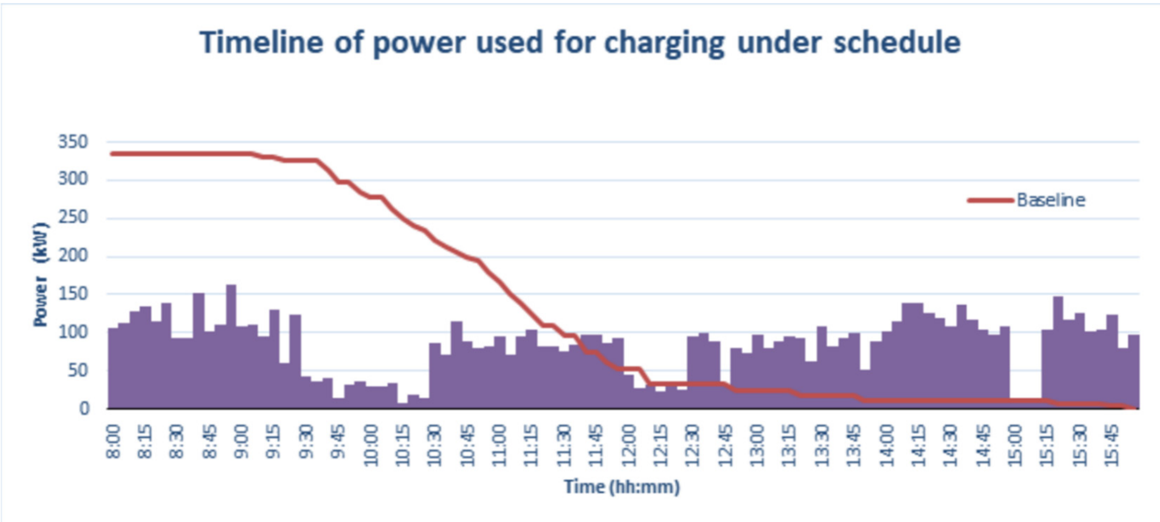

Figure 8. Scenario 3 results.

Figure 8 shows that the schedule has successfully restricted the power used for charging for the specified time periods and has shifted their load to the rest available time. Additionally, the schedule preferred the time segments between 08:00 and 10:00, and 14:00 and 16:00, to assign more EVs to charge because the energy costs less at these periods. Even during 15:00 to 15:15, the available power was extremely low. The average power used for charging is 84.59 kW, with a peak of 163.80 kW.

The total energy consumed for charging is 676.72 kWh and the cost is EUR 197.39. This scenario had two DSM at work, avoiding charging during peak hours and charging EVs up to a certain power during three time periods. Along with the aim of 80% SoC for every EV, this resulted in a reduction of 381.73 kWh in energy and EUR 108.52 in costs, a 35.37% decrease.

4. Discussion

In Section 3, the results of the three scenarios were presented and were compared with the baseline in order to assess the effects of scheduling the charging of EVs against no charging at all. Here, the results of the three scenarios are compared to each other, examining the power use and the cost of charging.

4.1. Electricity Demand

In order to better examine the differences between each scenario, the power of each time segment of every scenario is subtracted from the corresponding power from the rest of the scenarios and presented as a graph. Typically, two more timelines are produced for every scenario: Scenario 1 minus Scenario 2, Scenario 1 minus Scenario 3, Scenario 2 minus Scenario 1, Scenario 2 minus Scenario 3, Scenario 3 minus Scenario 1 and Scenario 3 minus Scenario 2. Since, i.e., Scenario 1 minus Scenario produces the reverse graph of Scenario 2 minus Scenario; only Scenario 1 minus Scenario 2, Scenario 1 minus Scenario 3 and Scenario 2 minus Scenario 3 are needed to draw conclusions.

These timelines and their graphs will help to better understand how each scenario distributes power over time, essentially electrical energy, in comparison with each other.

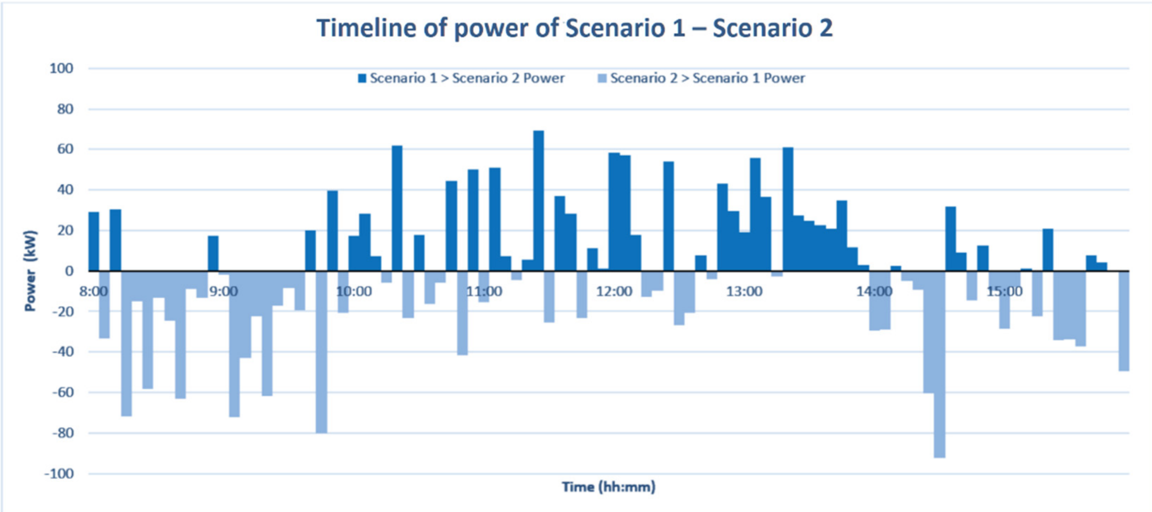

Figure 9. Scenario 1 vs. Scenario 2.

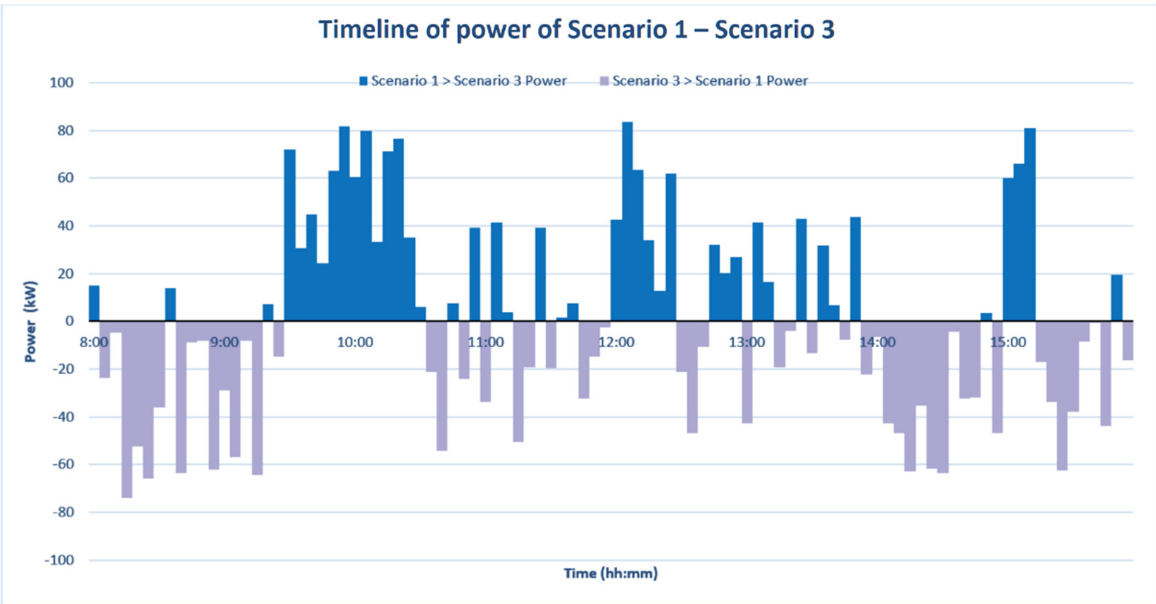

Figure 10. Scenario 1 vs. Scenario 3.

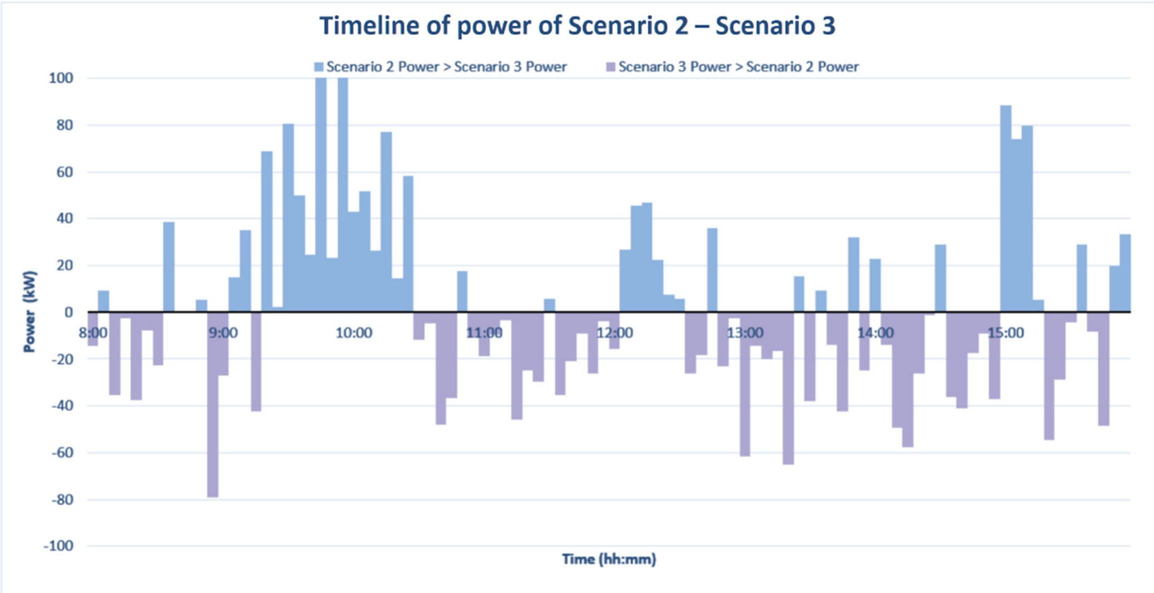

Figure 11. Scenario 2 vs. Scenario 3.

4.1.1. Scenario 1 vs. Scenario 2

The first scenario was chosen as a basic option, one that tries to keep the average power as low as possible to make the infrastructure used for charging less expensive. Scenario 1 does not take into account any time-dependent factors to its schedule. The second scenario aims at keeping the cost of charging as low as possible by avoiding charging EVs during the peak hours. This DSM strategy forces the scheduling program to try and allocate more power during off-peak hours.

In the Scenario 1 minus Scenario 2 graph as shown in Figure 9, between 08:00 and 10:00 and 14:00 and 16:00, the area of power over time is mostly on the negative side. Therefore, Scenario 2 charges more EVs than Scenario 1 during that time. The exact opposite occurs between 10:00 and 14:00, when Scenario 2 tries to charge fewer EVs. The area of power over time is mostly positive, which means that Scenario 1 charges more EVs during that period than Scenario 2.

The above observations show that the scheduling program in Scenario 2 has adapted to the demand-side strategy and managed to avoid charging during peak hours as much as possible. The schedule for Scenario 1, being totally indifferent to such strategies, demonstrates that the success of the scheduling program in adapting its schedule to implement the demand-side strategy is not coincidental.

4.1.2. Scenario 1 vs. Scenario 3

This case is more complicated than the previous comparison. We can see in the timeline of power of Scenario 1 minus Scenario 3, as shown in Figure 10, that from 08:00 to 09:30, Scenario 3 transfers more energy to EVs; from 09:30 to 10:30, it is Scenario 1 that transfers more energy; between 10:30 and 12:00, it is Scenario 3 that transfers slightly more energy; between 12:00 and 12:30, it is Scenario 1 that transfers more energy; between 12:30 and 14:00, the two scenarios transfer approximately the same amount of energy to EVs; from 14:00 to 15:00, it is Scenario 3 that transfers more energy; from 15:00 to 15:15, it is Scenario 1 that transfer more energy; and from 15:15 to 16:00, it is Scenario 3 that transfers more energy to EVs.

These time periods are not unexpected. Scenario 3 has the same aim as Scenario 2 but has another demand-side strategy to adapt to, load shifting. The periods between 09:30 and 10:30, 12:00 and 12:30 and 15:00 and 15:15 are periods when the scheduling program has low available power, which leaves most of the charging to occur during the rest of the time.

The scheduling program in Scenario 3 has successfully shifted loads away from the aforementioned time periods with low available power and still aimed to minimize the cost of charging. Nevertheless, its allocation of power during peak hours, with the exception of the time period between 12:00 and 12:30, is more or less the same as that of Scenario 1. This means that load shifting reduces the flexibility of the scheduling program to allocate time segments as it needs to avoid costs. Yet, a decrease in the cost of charging can be achieved. This depends on how extensive the load shifting is.

4.1.3. Scenario 2 vs. Scenario 3

This case is more apprehensible. Both scenarios aim at minimizing the cost of charging, but Scenario 3's load shifting strategy is clearly intervening in its attempt, in comparison with Scenario 2, which does not have such restrictions. As shown in Figure 11, Scenario 2 transfers more energy to EVs almost exclusively during the load-shifting periods of Scenario 3 (the periods of time between 09:30 and 10:30, 12:00 and 12:30 and 15:00 and 15:15). Even during the period of 10:00 to 14:00, when both scenarios try to avoid charging EVs, the handicap of load shifting for Scenario 3 forces the schedule program to allocate a lot more EVs then.

If we focus on the period between 12:00 and 12:30, it shows that only when the load shifting coincides with the period of time that the schedule program tries to avoid charging it is favorable for Scenario 3 in avoiding charging EVs during peak hours. In general, the required power and time for load shifting play critical roles in such comparisons, and each case is unique and should be examined individually.

4.2. Cost of Charging

In order to evaluate the cost of charging in each scenario, the stochastic quality of the GA must be taken into account. The cost of charging is dependent upon the total energy transferred to all the vehicles. Even if the starting SoC and the target SoC of each EV are the same in every scenario, the randomness inherent in the GA makes the final SoC of each EV a bit random. The scheduling program aims at a final SoC of at least 80%, or the highest it can achieve if 80% is not possible, not exactly 80%. The GA could be configured to aim at exactly 80% final SoC in every EV but that would reduce the possible solutions immensely, require more computing power and, in the end, the GA may never find one such solution. However, as mentioned before, minor variances between the total energy transferred to EVs will occur.

This complicates things because one run of the scheduling program of one scenario may transfer more energy than another run of the scheduling program of another scenario. For this reason, the average cost of 100 kWh in every scenario is used to evaluate which scheduling program calculated the least expensive schedule, as shown in Table 1.

Table 1. Comparison of the costs of charging in each scenario.

Scenario	Total Energy Transferred (kWh)	Average Energy Transferred (kWh/EV)	Average SoC (%)	Cost (EUR)	Cost per 100 kWh (EUR/100 kWh)
1	673.30	13.47	80.80	199.44	29.62
2	681.67	13.63	81.15	197.83	29.02
3	676.72	13.53	80.91	197.39	29.17

Even when Scenario 2 transferred more energy to the EVs, the DSM strategy of reducing costs by avoiding charging EVs during peak hours worked and it is the least expensive. Scenario 3 aimed to reduce costs similar to Scenario 2 but with an extra DSM strategy, load shifting, and did not do as well for the reasons discussed in the previous paragraphs. Nevertheless, Scenario 3 managed to be less expensive than Scenario 1. In conclusion, the cost of charging in Scenarios 2 and 3 was reduced by approximately 2%, when compared to that of Scenario 1.

5. Conclusions

The results demonstrate that the evolutionary optimization method used in this paper was successful in achieving its objectives. Scenarios 2 and 3 show how the scheduling program is affected by DSM strategies in comparison with a plain scheduling program that aims to avoid forming peaks and valleys in electricity demand. If there is no absolute need to avoid great fluctuations in power use, then there is no disadvantage in applying demand-side strategies for charging a high number of EVs. Comparing Scenario 2 with Scenario 3 confirms that load shifting plays a critical role in how the scheduling program allocates the charging of EVs. When the load-shifting periods coincide with the peak hours, then these two demand-side strategies are compatible, but when the load-shifting periods do not coincide with the peak hours, then they are incompatible. A case-by-case analysis should be performed to decide which strategy better fits the specific needs of that case.

The comparison of costs demonstrates that the proposed scheduling method was successful in adapting to the DSM strategies regarding reducing the cost of charging. Although the variance in costs is not substantial, it may be higher in other circumstances. The higher the difference in tariffs between off-peak and peak hours, the higher the gains. The same is valid for the number of EVs. This suggests that if avoiding great fluctuations in electrical power for charging is not of the utmost importance, there are benefits in adapting the scheduling program to avoid charging when the tariff is higher. When applying load shifting though, these benefits diminish. Consequently, the profits from a demand-side strategy that aims to reduce the cost of charging must be compared with the costs of mitigating the need for load shifting, and a decision should be made for each case regarding which demand-side strategy is more advantageous.

Author Contributions: Conceptualization, S.P. and A.I.D.; methodology, S.P.; software, S.P.; validation, S.P., formal analysis, A.I.D.; investigation, S.P.; resources, S.P.; data curation, S.P.; writing—original draft preparation, S.P.; writing—review and editing, A.I.D.; visualization, S.P.; supervision, A.I.D.; project administration, A.I.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. EV details and starting SoC [28].

EV	Maker	Model	Charging Power (kW)	Battery Capacity (kWh)	Starting SoC (%)
1	Nissan	Leaf	3.60	40.00	30
2	Nissan	Leaf e+	6.60	59.00	53
3	Smart	EQ forfour	4.60	16.70	63
4	Renault	Megan E-tech 130 hp	7.40	40.00	53
5	Volkswagen	e-Up	7.20	32.30	61
6	Dacia	Spring Electric	6.60	26.80	39
7	Mazda	MX-30	6.60	30.00	58
8	Subaru	Soltera AWD	6.60	71.40	72
9	Honda	e Advance	6.60	28.50	62
10	Hyundai	Ioniq	7.20	38.30	28
11	Hyundai	Kona Electric	7.20	39.20	43
12	Kia	e-Niro	7.20	39.20	53
13	Kia	e-Soul	7.20	39.20	39
14	Opel	Mokka e	7.40	45.00	51

Table A1. *Cont.*

EV	Maker	Model	Charging Power (kW)	Battery Capacity (kWh)	Starting SoC (%)
15	Opel	Combo-e Life	7.40	45.00	21
16	Opel	Corsa-e	7.40	45.00	72
17	Audi	Q4 e-tron 35	7.20	52.00	26
18	Citroen	e-C4	7.40	45.00	64
19	Citroen	e-Jumpy Combi M	7.40	45.00	49
20	Cupra	Born 110 KW	7.20	45.00	57
21	Nissan	Leaf	3.60	40.00	34
22	Nissan	Leaf e+	6.60	59.00	59
23	Smart	EQ forfour	4.60	16.70	69
24	Renault	Megan E-tech 130 hp	7.40	40.00	60
25	Volkswagen	e-Up	7.20	32.30	30
26	Dacia	Spring Electric	6.60	26.80	50
27	Mazda	MX-30	6.60	30.00	29
28	Subaru	Soltera AWD	6.60	71.40	66
29	Honda	e-Advance	6.60	28.50	56
30	Hyundai	Ioniq	7.20	38.30	27
31	Hyundai	Kona Electric	7.20	39.20	32
32	Kia	e-Niro	7.20	39.20	47
33	Kia	e-Soul	7.20	39.20	24
34	Opel	Mokka e	7.40	45.00	31
35	Opel	Combo-e Life	7.40	45.00	33
36	Opel	Corsa-e	7.40	45.00	52
37	Audi	Q4 e-tron 35	7.20	52.00	47
38	Citroen	e-C4	7.40	45.00	71
39	Citroen	e-Jumpy Combi M	7.40	45.00	43
40	Cupra	Born 110 KW	7.20	45.00	62
41	Nissan	Leaf	3.60	40.00	29
42	Nissan	Leaf e+	6.60	59.00	69
43	Smart	EQ forfour	4.60	16.70	22
44	Renault	Megan E-tech 130 hp	7.40	40.00	57
45	Volkswagen	e-Up	7.20	32.30	49
46	Dacia	Spring Electric	6.60	26.80	23
47	Mazda	MX-30	6.60	30.00	23
48	Subaru	Soltera AWD	6.60	71.40	46
49	Honda	e-Advance	6.60	28.50	47
50	Hyundai	Ioniq	7.20	38.30	38

References

1. Guterres, A. United Nations. 2019. Available online: https://www.un.org/sg/en/content/sg/speeches/2019-09-23/remarks-2019-climate-action-summit (accessed on 2 November 2021).
2. Eurostat. Energy from Renewable Sources. 2022. Available online: http://ec.europa.eu/eurostat/web/energy/data/shares (accessed on 1 July 2022).
3. Prakash, K.; Ali, M.; Siddique, M.N.I.; Chand, A.A.; Kumar, N.M.; Dong, D.; Pota, H.R. A review of battery energy storage systems for ancillary services in distribution grids: Current status, challenges and future directions. *Front. Energy Res.* **2022**, *10*, 971704. [CrossRef]

4. European Environmental Agency. CO_2 Emissions from Cars: Facts and Figures (Infographics). 2022. Available online: https://www.europarl.europa.eu/news/en/headlines/society/20190313STO31218/co2-emissions-from-cars-facts-and-figures-infographics (accessed on 1 July 2022).
5. Eberle, U.; Helmolt, R.V. Sustainable transportation based on electric vehicle concepts: A brief overview. *Energy Environ. Sci.* **2010**, *3*, 689–699. [CrossRef]
6. Mamun, K.A.; Islam, F.R.; Haque, R.; Chand, A.A.; Prasad, K.A.; Goundar, K.K.; Prakash, K.; Maharaj, S. Systematic Modeling and Analysis of On-Board Vehicle Integrated Novel Hybrid Renewable Energy System with Storage for Electric Vehicles. *Sustainability* **2022**, *14*, 2538. [CrossRef]
7. Ahmad, F.; Alam, M.S.; Shariff, S.M. A Cost-Efficient Energy Management System for Battery Swapping Station. *IEEE Syst. J.* **2019**, *13*, 4355–4364. [CrossRef]
8. U.S. Department of Energy. Workplace Charging Challenge Progress Update 2016: A New Sustainable Commute. January 2017. Available online: https://www.afdc.energy.gov/uploads/publication/wpc_2016_progress_report.pdf (accessed on 27 June 2018).
9. Lee, J.H.; Chakraborty, D.; Hardman, S.J.; Tal, G. Exploring electric vehicle charging patterns: Mixed usage of charging infrastructure. *Transp. Res. Part D Transp. Environ.* **2020**, *79*, 102249. [CrossRef]
10. Ahmad, F.; Alam, M.S.; Shariff, S.M.; Krishnamurthy, M. A Cost-Efficient Approach to EV Charging Station Integrated Community Microgrid: A Case Study of Indian Power Market. *IEEE Trans. Transp. Electrif.* **2019**, *5*, 200–214. [CrossRef]
11. Li, Y.; Huang, Y.; Zhang, M. Short-Term Load Forecasting for Electric Vehicle Charging Station Based on Niche Immunity Lion Algorithm and Convolutional Neural Network. *Energies* **2018**, *11*, 1253. [CrossRef]
12. Zhang, Y.; Cai, L. Dynamic Charging Scheduling for EV Parking Lots with Photovoltaic Power System. *IEEE Access* **2018**, *6*, 56995–57005. [CrossRef]
13. Lakshminarayanan, V.; Pramanick, S.K. Real-Time Optimal Energy Management Controller for Electric Vehicle Integration in Workplace Microgrid. *IEEE Trans. Transp. Electrif.* **2019**, *5*, 174–185. [CrossRef]
14. Dukpa, A.; Butrylo, B. MILP-Based Profit Maximization of Electric Vehicle Charging Station Based on Solar and EV Arrival Forecasts. *Energies* **2022**, *15*, 5760. [CrossRef]
15. Jiang, W.; Zhen, Y. A Real-Time EV Charging Scheduling for Parking Lots With PV System and Energy Store System. *IEEE Access* **2019**, *7*, 86184–86193. [CrossRef]
16. Mohammed, S.S.; Titus, F.; Thanikanti, S.B.; Sulaiman, S.M.; Deb, S.; Kumar, N.M. Charge Scheduling Optimization of Plug-In Electric Vehicle in a PV Powered Grid-Connected Charging Station Based on Day-Ahead Solar Energy Forecasting in Australia. *Sustainability* **2022**, *14*, 3498. [CrossRef]
17. Alonso, M.; Amaris, H.; Germain, J.G.; Galan, J.M. Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms. *Energies* **2014**, *7*, 2449–2475. [CrossRef]
18. Tan, K.M.; Ramachandaramurthy, V.K.; Yong, J.Y.; Padmanaban, S.; Mihet-Popa, L.; Blaabjerg, F. Minimization of Load Variance in Power Grids—Investigation on Optimal Vehicle-to-Grid Scheduling. *Energies* **2017**, *10*, 1880. [CrossRef]
19. Liu, J.; Lin, G.; Rehtanz, C.; Huang, S.; Zhou, Y.; Li, Y. Data-driven intelligent EV charging operating with limited chargers considering the charging demand forecasting. *Int. J. Electr. Power Energy Syst.* **2022**, *141*, 108218. [CrossRef]
20. Su, W.; Chow, M.-Y. Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck. *Appl. Energy* **2012**, *96*, 171–182. [CrossRef]
21. Wang, Z.; Wang, L.; Dounis, A.I. Integration of Plug-in Hybrid Electric Vehicles into Building Energy Management System. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011; pp. 260–266.
22. Hajforoosh, S.; Masoum, M.A.; Islam, S.M. Online optimal variable charge-rate coordination of plug-in electric vehicles to maximize customer satisfaction and improve grid performance. *Electr. Power Syst. Res.* **2016**, *141*, 407–420. [CrossRef]
23. Ravichandran, S.; Sankaranarayanan, V. Optimal vehicle-to-grid and grid-to-vehicle scheduling strategy with uncertainty management using improved marine predator algorithm. *Comput. Electr. Eng.* **2022**, *100*, 107949.
24. Kurniawan, T.; Baguley, C.A.; Madawala, U.K.; Suwarno; Hariyanto, N.; Adianto, Y. An Electric Vehicle Charge Scheduling Approach Suited to Local and Supplying Distribution Transformers. *Energies* **2020**, *13*, 3486. [CrossRef]
25. Endesa. Tempo Rate. 2022. Available online: https://www.endesa.com/en/companies/electricity/Tempo-rate (accessed on 4 May 2022).
26. MATHWORKS. Nonlinear Constraint Solver Algorithms. Available online: https://uk.mathworks.com/help/gads/description-of-the-nonlinear-constraint-solver.html (accessed on 31 October 2022).
27. Deb, K. An efficient constraint handling method for genetic algorithms. *Comput. Methods Appl. Mech. Eng.* **2000**, *186*, 311–338. [CrossRef]
28. Electric Vehicle Database. 2022. Available online: https://ev-database.org (accessed on 3 May 2022).