energies

MDPI

Article

Electromobility and Flexibility Management on a Non-Interconnected Island

Enea Mele, Anastasios Natsis, Aphrodite Ktena *, Christos Manasis and Nicholas Assimakis

Energy Systems Laboratory, General Department, National & Kapodistrian University of Athens, 34400 Psachna, Greece; dimitrismele@uoa.gr (E.M.); anatsis@teiste.gr (A.N.); cmana@uoa.gr (C.M.); nasimakis@uoa.gr (N.A.)

* Correspondence: apktena@uoa.gr

Abstract: The increasing penetration of electrical vehicles (EVs), on the way to decarbonizing the transportation sector, presents several challenges and opportunities for the end users, the distribution grid, and the electricity markets. Uncontrollable EV charging may increase peak demand and impact the grid stability and reliability, especially in the case of non-interconnected microgrids such as the distribution grids of small islands. On the other hand, if EVs are considered as flexible loads and distributed storage, they may offer Vehicle to Grid (V2G) services and contribute to demand-side management through smart charging and discharging. In this work, we present a study on the penetration of EVs and the flexibility they may offer for services to the grid, using a genetic algorithm for optimum valley filling and peak shaving for the case of a non-interconnected island where the electricity demand is several times higher during the summer due to the influx of tourists. Test cases have been developed for various charging/discharging strategies and mobility patterns. Their results are discussed with respect to the current generating capacity of the island as well as the future case where part of the electricity demand will have to be met by renewable energy sources, such as photovoltaic plants, in order to minimize the island's carbon footprint. Higher EV penetration, in the range of 20–25%, is enabled through smart charging strategies and V2G services, especially for load profiles with a large difference between the peak and low demands. However, the EV penetration and available flexibility is subject to the mobility needs and limited by the population and the size of the road network of the island itself rather than the grid needs and constraints. Limitations and challenges concerning efficient V2G services on a non-interconnected microgrid are identified. The results will be used in the design of a smart charging controller linked to the microgrid's energy management system.

Keywords: electric vehicles; genetic algorithm; V2G services; valley filling; peak shaving; flexibility

Citation: Mele, E.; Natsis, A.; Ktena, A.; Manasis, C.; Assimakis, N. Electromobility and Flexibility Management on a Non-Interconnected Island. *Energies* **2021**, *14*, 1337. https://doi.org/10.3390/en14051337

Academic Editor: Amela Ajanovic

Received: 6 February 2021
Accepted: 22 February 2021
Published: 1 March 2021

1. Introduction

Electric vehicles (EVs) have an important role in the transition towards a low-carbon economy and, more specifically, in the decarbonization of the transportation sector, which is responsible for 22% of total EU-28 greenhouse gas emissions, excluding international aviation and maritime emissions [1]. The increasing penetration of electric vehicles (EVs) reflects the technological advances in electromobility as well as the impact of the policies implemented at the EU and national levels. As a result, the market of electromobility has been growing at an accelerating pace: in 2018, the global electric vehicle fleet exceeded 5.1 million, up two million from the previous year, with the number of new electric vehicle registrations almost doubling [2].

The increasing penetration of EVs presents several challenges to and opportunities for the operation of the power grid and the electricity markets as well as to the end users. The additional electricity needed for charging the EVs could mitigate the environmental benefits if the power generation mix is fossil fuel-oriented [3]. If, however, this additional electricity demand is met by increasing the share of renewables (e.g., solar and wind power), it has been shown that increased penetration levels of EVs lead to a lower carbon footprint than conventional vehicles [3,4].

Uncontrolled charging, based solely on the needs of the EV user, may lead to higher peaks in electricity demand stressing the capacity limits of the distribution grid [5–7], especially in small, isolated grids such as those of small non-interconnected islands which are also popular tourist destinations, as is the case of Greek islands.

The distribution grids of these islands rely on diesel autonomous power stations (APSs) which are progressively complemented by renewable energy sources (RESs), mainly photovoltaic (PV) plants and wind turbine (WT) parks. Due to the lack of interconnections with other electrical systems or the country's transmission system, non-interconnected islands have an increased cost of electricity generation, while they are more affected by load disturbances resulting in a greater risk for power quality problems, such as voltage and frequency stability, black-outs, and load rejection [8]. In addition, due to high fluctuations of demand on a daily and monthly basis and the seasonal peak demand due to the touristic period, there is the need for each electrical system to operate with an excessive power capacity in order to meet peak demands [9]. Note that the influx of tourists during the high season is several times that of the population. The integration of RESs in a small standalone system decreases the cost of electricity generation and the carbon footprint of the island, but the intermittent nature or solar or wind power may prove challenging for the stability of the microgrid. Electrical storage is one way to increase RES penetration, optimize the generation of the thermoelectric power plant, and address stability and power quality issues [10].

The transition towards "green" islands requires that the electricity demand is met mainly by RESs and that mobility relies mostly on EVs. This means that the power system of the island must meet the additional energy required by the island's EV fleet and any demand-side management strategies and policies must take into account the EV charging rate, stations' distribution, mobility patterns, etc. [11]. To achieve that, smart EV charging, adaptable both to the operation of the power grid and the EV users' preferences, is required. In contrast to uncontrolled charging, smart charging allows a certain level of control over the charging process [12]. A simple approach is that end users alter their charging behavior and shift the charging of their EVs from peak hours to off-peak hours (load shifting) in response to price signals or incentives [13].

A more advanced approach is a direct control mechanism, via an intermediate market entity such as an aggregator, that optimizes EV charging schedules in real time based on the needs of the power grid, the signals from the electricity market, and the preferences of the end users [12]. Scheduling EV charging so that the aggregated power demand from EVs fills the overnight valley reduces the daily cycling of the thermoelectric power plant and the operational cost of utilities [14].

On the other hand, EVs, acting as controllable and distributed storage, may be used to offer Vehicle to Grid (V2G) services and actively contribute to demand-side management. Cars, including EVs, spend the majority of their lifetime (95% on average) parked. In these periods of inactivity, EVs could charge their batteries when demand is low (valley-filling) and send power back to the grid (discharge) when demand is high (peak shaving) [15], thus becoming part of the solution and curtailing the need for costly infrastructure upgrades. V2G services may include also ancillary services (spinning reserve), active power support, and reactive power compensation [16]. In grid-connected EVs, available energy can be used as additional generation capacity in order to support the power grid in case of generation outages (spinning reserve). Furthermore, the capability of EVs to channel reactive power to the grid can be beneficial to the grid operation [17]. It has been shown that smart charging improves the saturation of grid transformers for the same number of EVs and can decrease reverse power flows from distributed generation to the transformer [12]. An overall smart and flexible management of a fleet of EVs has the potential to shave peak demand, flatten the load profile, and allow higher shares of renewable energy while accommodating more EVs to the power grid [12].

In this paper, we study the effect of EV penetration on the electricity demand of a non-interconnected island powered by a diesel-fueled autonomous power station (APS) and the flexibility offered by their storage. We use a genetic algorithm (GA) to calculate the optimum EV penetration level for the valley filling and peak shaving of electricity demand curves during both the low and high seasons. Four test cases of charging strategies are studied, taking into consideration random and specific mobility patterns, in order to evaluate the impact of the level of EV penetration on the APS generation levels and to examine the potential of EVs for flexibility services. Furthermore, according to the National Plan for Energy and Climate in accordance with the UN Agenda 2030, "for islands that are not expected to be interconnected, a significant reduction in the use of diesel for power generation is also being promoted, with the setup of state-of-the-art RES plants combined with storage technologies" [18]. To address this, we repeat the calculations for the case where the APS is complemented by a PV plant.

The structure of the paper is as follows: Section 2 gives a summary review of the relevant literature while Section 3 focuses on the formulation of the optimization problem. The GA developed to solve the problem is presented and discussed in Section 4. Section 5 is dedicated to the simulation experiments and their results, which are discussed in Section 6. Section 7 summarizes the main conclusions.

2. Literature Review

The aim of this literature review is to establish a knowledge base concerning the factors that affect EV penetration on autonomous microgrids, such as the distribution grids of small, non-interconnected islands and the charging strategies to be considered in a smart charging controller embedded or linked to the energy management system of the microgrid.

Research on the topic has focused mainly on interconnected power systems with the capacity to host large numbers of EVs. Results such as those in [19] show that a large deployment of EVs could result in violation of supply/demand matching and statutory voltage limits as well as power quality problems and voltage imbalance under certain operating conditions. It is, therefore, necessary to design charging strategies and apply charging schedules as EV penetration increases. The flexibility offered to the grid by the energy management of EV batteries is enhanced when discharging to the grid is also allowed.

Several approaches have been proposed for optimum charging and discharging strategies and schedules. The optimal charging scheduling of electric vehicles proposed in [20] employs a genetic algorithm-based optimization routine, where thermal line limits, the load on transformers, voltage limits and parking availability patterns were considered to establish an optimal load pattern for EV charging-based reliability. The results showed that a smart charging schedule for EVs led to a flattening of the load profile, to peak load shaving and to the prevention of the aging of power systems' elements. A similar approach has been adopted in [21] where an adaptive discharging and smart charging management scheme for peak shaving and load leveling in a residential distribution grid is introduced. A reference operating point is considered to flatten the load curve on a 24-hour basis by using the EV mobility characteristics and the non-EV base load. A particle swarm optimization algorithm was developed in [15] for the smart, centralized scheduling of optimum EV charging/discharging of plug-in electric vehicles in order to achieve peak shaving and valley filling of the grid load profile. Smart charging compared to uncontrolled charging is superior in terms of voltage drop and maximum loading. On the other hand, optimizing the charging cycles of an electric car in [22] using demand-side management achieves financial savings, increased demand on renewable energy, reduced demand on thermal generation plants and reduced peak load demand.

A distributed iterative algorithm for the management of the charging/discharging set-points of an EV fleet is proposed in [23], which is designed to optimize the profits of the aggregator based on the day-ahead energy forecast. The optimization problem is formulated as a mixed-integer quadratic problem. A cost-effective and an eco-friendly scheme for the centralized management of plug-in hybrid electric vehicles (PHEVs) are compared in [24]. Representative hourly driving patterns and electricity data from eight North American Electric Reliability Corporation (NERC) regions were leveraged to examine the results of the proposed schemes. The findings indicate that the management schemes proposed result in very different charging schedules: optimal cost-effective charging should take place very early in the morning and optimal eco-friendly charging later in the afternoon. As the number of PHEVs increases, charging control becomes more cost-effective and environmentally friendly. The variation in charging patterns among plug-in electric vehicle (PEV) owners as a function of charging location and charging level is studied in [25]. The results showed that the use of home, work and public charging infrastructures is interconnected, highlighting the importance of having an integrated infrastructure investment plan for different locational charging patterns among PEV owners. A study on the existing and potential charging infrastructure for PEVs in the USA [26] showed that the potential for future residential infrastructure is limited by the availability of dedicated parking locations where chargers could be installed, acting as a barrier to mainstream EV penetration. An algorithmic framework was presented in [27] for the joint optimization of the routes and charging schedules of a fleet of self-driving EVs providing on-demand mobility, taking into account the battery energy level of each vehicle and the power grid needs and constraints. The results verified the near optimality of this method, while suggesting that through vehicle to grid (V2G) operation, a 100% penetration of renewable energy could be enabled and still provide high quality mobility services.

For charging schedules and services procurement to be efficient, coordination is needed between the EV Aggregator and the System Operator [28]. Results have shown that when coordination over the charging schedule of EVs is performed, the system can accommodate a higher share of EVs without any infrastructure upgrade. The results reported concern mainly valley-filling services.

Formulations of the less-studied problem of discharging through the grid are offered, but the results refer to large, interconnected power grids with the capacity to host large EV fleets, and coordination is necessary to avoid stability and power quality problems.

Problems related to EV penetration, energy management, charging scheduling or routing also refer mainly to distribution grids connected to transmission grids. Limited results exist for EV penetration on non-interconnected grids, such as those of islands or other isolated RES microgrids. EVs are studied as a means to reduce CO_2 emissions and lower energy costs in isolated regions, as in Sao Miguel, Azores [29], where three scenarios of EV penetration have been studied. It was concluded that if at least 15% of the fleet is replaced by EVs, significant reductions in fossil fuel use and energy can be expected. However, smart charging and V2G services have not been considered. Furthermore, 15% of the fleet is very small compared to the target of the nearly 100% electrification of the transportation sector on "green islands".

According to a recent study on the potential of islands to serve as testbeds for innovative solutions [30], it is stressed that in order to enable higher penetration levels while minimizing the impact on an autonomous microgrid, an EV control system with smart charging, metering and billing functionalities must be embedded in the energy management system linked to the island's distribution grid. Such a system would aggregate the response and interface with the EVs and the grid to manage the aggregated flexibility, send messages and price signals to the EV users and offer services to the grid. It is also stressed that it is necessary to study the impact of the scaling of several existing pilot implementations which currently concern only a small number of EVs.

The main contributions of this work consist in studying the impact of EV penetration, controlled charging and V2G services on the electricity demand of a non-interconnected island, where the high-season demand is several times that of the low-season demand, and the contribution of electromobility towards the decarbonization of the island through gradually phasing out thermoelectric generators and replacing them with RESs. The results will be used in the design of a smart charging controller interconnected with or embedded in the island's energy management system. Limitations and challenges concerning efficient V2G services on a non-interconnected microgrid are identified.

3. The Optimization Problem

The optimization problem solved in order to study the effect of a fleet of N EVs on the load demand of a non-interconnected microgrid is the optimum energy available for valley filling and peak shaving for various charging schemes and EV penetration levels.

The assumptions concerning the mobility patterns and demand profiles are based on actual data from a Greek island which is normally populated by a few hundred people but in the summertime receives an influx of several thousands of tourists. As a result, the electricity demand during the summer months is several times higher than during the rest of the year (Figure 1). The peak demand in the summertime approaches 1.0 MW with the base load around 0.5 MW in the high season. On the other hand, the consumption for the rest of year is in the range of 0.2 to 0.5 MW. The load data have been provided by the Hellenic Distribution Network Operator (HEDNO) Islands Directorate.

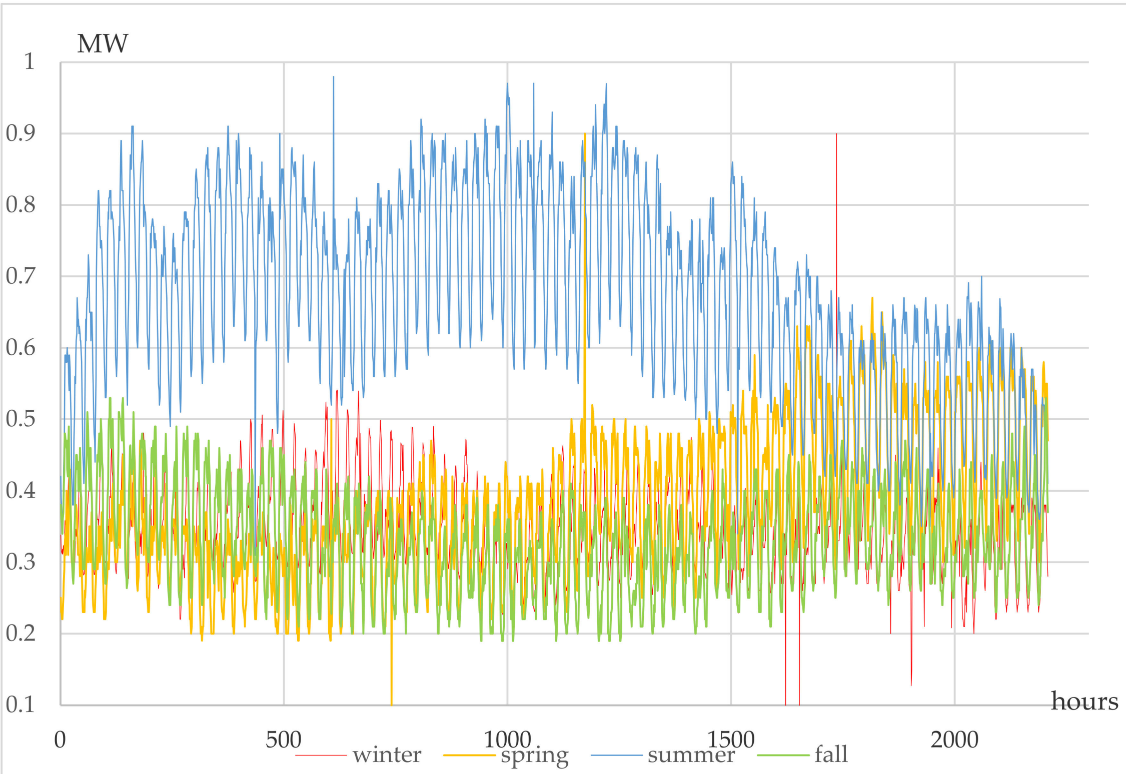

Figure 1. Hourly electricity demand for the winter, spring, summer and fall months for 2018.

The island is powered by diesel generators of approximately 1.5 MW total installed capacity [31]. The region does not have a considerable wind potential, so any RESs for electricity generation would have to rely on solar power [32]. According to a recent decision of the Greek Regulatory Authority for Energy, which, taking into account grid stability issues, redefined the renewables penetration margins in non-interconnected islands, the maximum power output from an installed PV plant on the given island has been set to 150.0 kW. Respecting this limit, a 140.0 kWp PV plant has been considered for the output curve (Figure 2) obtained for one typical winter day and one typical summer day, using PVGIS [32].

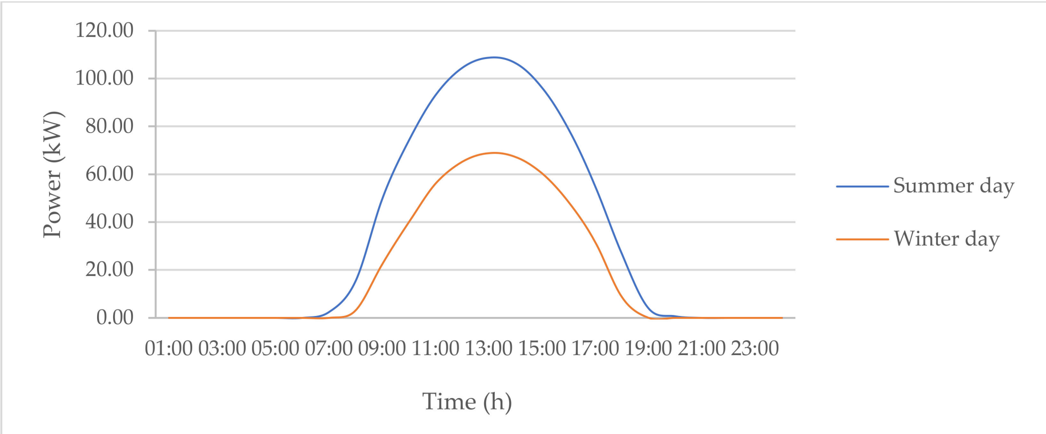

Figure 2. Output power curve of a 140.0 kWp photovoltaic (PV) plant for a typical summer and winter day.

In order to study the EV fleet impact on the electricity demand and APS output required, with and without PV generation, taking into account valley filling and peak shaving, the following assumptions are made.

The EV fleet consists of N vehicles, of which kN cars are for private use, charged at home or at public parking lots, and mN are rental cars used mostly during the tourist season, also charged in a parking lot, with $0 < m < 1$ and $k = 1 - m$. The mobility patterns considered in the test cases and simulations are dictated by the island's road network constraints. Because the island has a road network of less than 30 km, it is reasonable to assume that the kN EVs used by permanent residents will be charged, at most, once a day and mostly during the night, while the mN rental EVs may be used for valley filling or peak shaving, during idle times at the rental service parking lot, based on a smart charging schedule. According to the IEC61851-1 standard and the existing regulatory framework, the "slow" charging Mode 3 AC supported by a 55 FkVA low-voltage power supply is used in all charging facilities. This is a reasonable assumption since on small islands, due to zoning laws, even privately owned cars are parked in public parking lots. This implementation allows the aggregation of demand and flexibility offered by EVs via a functionality of the central energy management system, as proposed in [30]. Because we assume that EV charging and discharging take place at a relatively slow rate, their impact on the load flow or the stability of the grid is not taken into consideration in this study. However, the genetic algorithm developed for the optimization problem presented in the remainder of the section is designed in such a way so as to allow for load flow constraints, price signals and user preferences to be taken into account.

The optimization problem aims to flatten the demand curve.

To achieve valley filling, the batteries of N EVs are fully or partially charged. The objective function given in (1) aims to minimize the difference between average daily demand, μ, and the power that needs to be supplied by the APS to meet the demand through management of the energy flowing in or out of the EV batteries over a given time interval Δt_t [21,33]. If a PV plant supplies a portion of the required energy, the energy that needs to be generated by the APS decreases:

$$minimize\ f = \sum_{t=1}^{T}\left(\sum_{i=1}^{N} P_{i,t}^{EV} + D_t - P_t^{PV} - \mu\right)^2 \tag{1}$$

$$\text{s.t. } \sum_{t=1}^{T} P_{i,t}^{EV}\Delta t_t - (1 - SOC_{in,i})\frac{E_b}{\eta_c} = 0 \tag{2}$$

$$(SOC_{i,t+1} - SOC_{i,t})\,\frac{E_b}{\eta_c} - P_{i,t}^{EV}\,\Delta t_t = 0 \tag{3}$$

$$(SOC_{i,t+1} - SOC_{i,t})\frac{E_b}{\eta_c} - \ [D_t - \mu]\ \Delta t_t \leq \ 0 \tag{4}$$

$$\left|P_{i,t}^{EV}\right| - P_{ch} \leq 0 \tag{5}$$

$$0.20 \leq SOC_{i,t} \leq 0.80 \tag{6}$$

where P_t^{PV} is the power generated by the PV plant at every time step Δt_t, D_t is the demand at a given time step Δt_t,D_t is the power absorbed by the battery (positive sign) of the i-th EV at time step Δt_t, $SOC_{i,t}$ is the state of charge of the battery of the i-th EV at time step Δt_t, E_b and η_c are the storage capacity and charging efficiency of the battery, respectively, and P_{ch} is the power rating of the charging facility. The state of charge of each battery is assumed to be independent of the open-circuit voltage, the charging (or discharging) efficiency is assumed to be equal to 1 and the power rating of the charging facility depends on the charging mode following IEC61851-1.

The optimization routine is executed for a period T, i.e., for a daily demand profile with hourly data T = 24 and $\Delta t_t = 1$ h.

The N EVs are assumed to enter the charging facilities in a consecutive manner. The i-th EV enters the charging facility with the available remaining charge in its battery denoted by $SOC_{in,i}$. $SOC_{in,i}$ depends on the mileage d_i of the i-th EV before connecting to the charging facility and the maximum number of kilometers R_i that the EV can travel without recharging:

$$SOC_{in,i} = \left(1 - \frac{d_i}{R_i}\right)100\% \tag{7}$$

where d_i is a random variable and R_i is the range given by the manufacturer of the i-th EV; in this study, the specifications of all EVs are considered identical and match those of a commercially available medium-sized EV.

The first constraint (2) ensures that the energy absorbed by or provided to the i-th battery during the total charging interval will not exceed the capacity allowed by $SOC_{in,i}$. The second constraint (3) controls the charging of the i-th EV; the amount of energy absorbed by the battery determines the change in the SOC between two consecutive time steps. The third constraint (4) prevents the i-th EV from charging to its maximum capacity if the remaining storage capacity of the i-th EV at time t is larger than the difference between the demand D_t and the average value μ in order to ensure the flattening of the curve. The fourth constraint (5) ensures that the $P_{i,t}^{EV}$, which is the power absorbed or delivered by the battery of the i-th EV, cannot exceed the power rating of the EV charging facility, P_{ch}. The fifth constraint (5) imposes lower and upper limits to the SOC as suggested in [34–36] for longer battery lifetime.

To achieve peak shaving, the problem is similar to (1)–(6), with constraints (2) and (3) being adjusted as follows and η_d being the discharging efficiency:

$$\sum_{t=1}^{T} P_{i,t}^{EV}\Delta t - SOC_{in,i}E_b\eta_d = 0 \tag{8}$$

$$(SOC_{i,t+1} - SOC_{i,t})\ E_b\eta_d - P_{i,t}^{EV}\ \Delta t = 0 \tag{9}$$

4. The Genetic Algorithm

The optimization problem, as described by (1)–(6), is a quadratic programming problem (QP) which can be efficiently solved with a QP solver. However, a genetic algorithm (GA) [37] has been used instead to allow for future problem formulations, with non-linear constraints, user-generated data, price signals, etc.

The GA uses tournament selection and applies a penalty when a solution violates a constraint. This way, no solutions are discarded but those violating one or more constraints are less likely to be chosen. In the pseudocode of the GA given below, G is the number of generations, P is the populations, l is the chromosome length, p_x is the probability of crossover, p_m is the probability of mutation and k is the number of solutions selected as parents each time in the tournament selection:

Set random $SOC_{in,i}$ for N EVs, gc = 1 (generations counter) and pc = 1 (population counter)
For i in range (Vehicles), 1 < i < N:
For t in range (Hours), 1 < t < T:
1. Set G, P, l, p_x, p_m, k
2. If (P/2) ! = 0 P = P − 1
3. Generate P of l-sized strings
4. Select 2 parent solutions through tournament selection
5. Apply crossover p_x to obtain children solutions
6. Apply mutation p_m to children solutions
7. While pc < P:
Repeat steps 5 to 7 P/2 times, pc = pc + 1
8. Get a new generation
9. While gc < G:
Repeat steps 5 to 9 G times, gc = gc + 1
10. Choose the optimum solution in each generation, min (f)
t = t + 1
Obtain $SOC_{i,t+1}$
i = I + 1
Update D_t after i-th EV has been charged

The fitness value is given as in [38]:

$$Q\left(\vec{x}\right) = \begin{cases} F\left(\vec{x}\right) & \text{if } \vec{x} \text{ is a feasible solution} \\ F\left(\vec{x}\right) + C\left(\vec{x}\right) & \text{if } \vec{x} \text{ is unfeasible} \end{cases} \quad (10)$$

$\vec{x} = \left[P_1^{EV}, P_2^{EV}, \ldots, P_N^{EV}\right]$ is the power absorbed or delivered by each EV car.
$C\left(\vec{x}\right)$ is a penalty imposed to any solution violating one or more constraints.

For the results shown below: P = 40, G = 20, l = 5, k = 3, $p_x = 1$, $p_m = 0.35$. Indicative execution times in the offline mode, using a computer equipped with an Intel Core i7-6700HQ CPU 2.60 GHz processor, 16 GB DDR4 RAM, Windows 10, range from 300 to 480 s based on the size N of the EV fleet.

5. Simulations and Results

All simulations were based on the hourly demand data of 2018. Two demand curves were used: LC1, corresponding to a typical winter day, and LC2, corresponding to a summer day, with sharp fluctuations of demand.

Four test cases have been developed reflecting various charging/discharging schemes: (a) valley filling; (b) valley filling and peak shaving with random EV mobility patterns; (c) valley filling and peak shaving with both random and predefined EV mobility patterns; (d) valley filling at predefined hours and peak shaving with random EV mobility pattern.

The size N of the EV fleet ranged from 25 to 150 vehicles for the winter curve LC1 and 50 to 250 vehicles for the summer curve LC2. The corresponding EV penetration level was calculated as the ratio of the total energy capacity of the N EVs over the total energy demand of the demand curve in each case. k, the fraction of EVs used by permanent residents, was set to 0.3, and m, the fraction of rental EVs, was set to 0.7 for all simulations.

All EVs were considered to be identical and their specifications correspond to a specific commercially available medium-sized EV: $E_b = 23.80$ kWh, $R = 145.00$ km. The charging rate was also assumed to be the same for all charging facilities and set to $P_{ch} = 7.40$ kW.

5.1. Valley Filling

The first test case allows for valley filling when the demand falls below μ.

Two cases were examined:

(a) EVs enter the charging facility randomly during the day. Charging can take place anytime during the day, as long as $D_t - \mu \leq 0$. During the winter period (LC1, Figure 3), valley filling is achieved with a fleet of 75 EVs, while during the summer period (LC2, Figure 4) the same result is obtained with a fleet of 150 EVs. Further increasing the number of vehicles would not affect the results, due to (4).

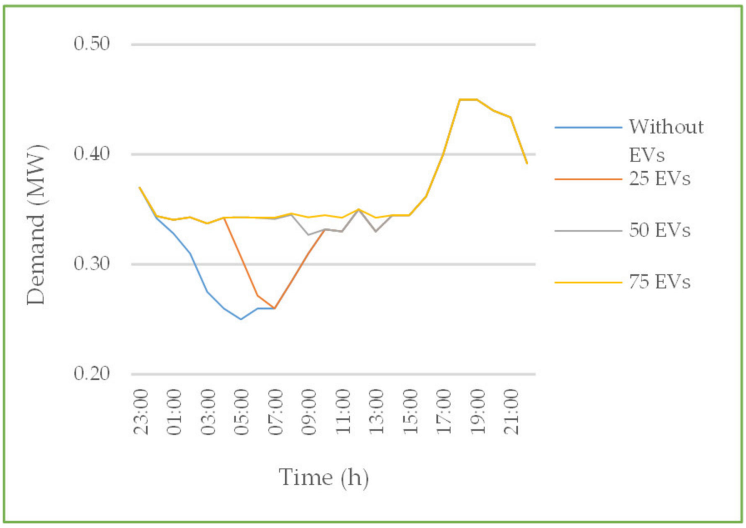

Figure 3. The effect of charging on load curve 1 (LC1) when N = 25, 50 and **75** cars are used for valley filling anytime during the day.

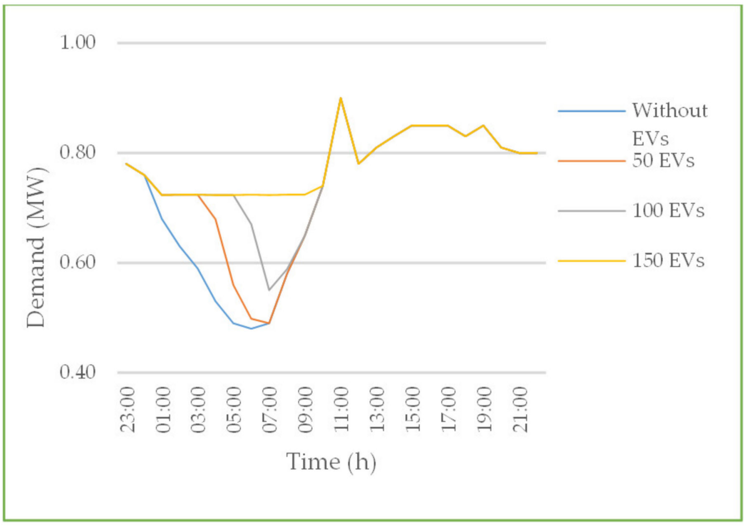

Figure 4. The effect of charging on load curve 2 (LC2) when N = 50, 100 and **150** cars are used for valley filling anytime during the day.

(b) All N EVs (rental and privately owned) may be charged only during a specific time interval $t_1 \leq t \leq t_2$. For the results shown here, charging is allowed only for $23:00 \leq t \leq 07:00$. During the winter period (LC1, Figure 5), valley filling is partially achieved with a fleet of 75 EVs, while during the summer period (LC2, Figure 6), the same is achieved with a fleet of 150 EVs. Further increasing the number of vehicles would not make a significant difference because of the restricted hours for charging. This charging schedule offers less flexibility.

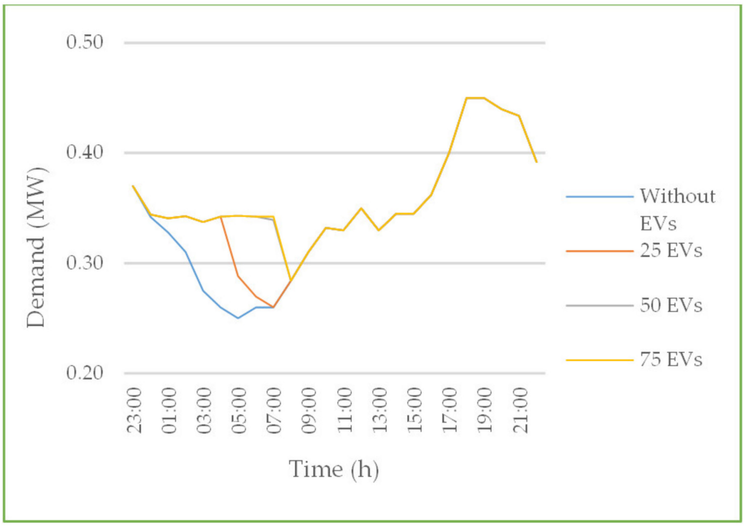

Figure 5. The effect of charging on LC1 when N = 25, 50 and **75** cars are used for valley filling between 23:00 and 07:00.

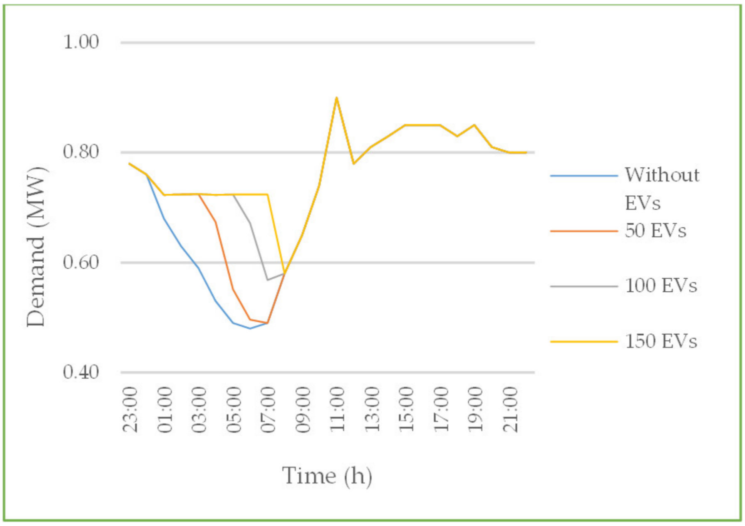

Figure 6. The effect of charging on LC2 when N = 50, 100 and **150** cars are used for valley filling between 23:00 and 07:00.

5.2. Valley Filling and Peak Shaving with Random EV Mobility Patterns

The second test case allowed for both valley filling and peak shaving to be performed at random hours of the day and in a random manner. To accomplish that, the algorithm randomly assigned a binary p value of 0 or 1 to each EV for each hour of the day: an EV with p = 1 at a given time interval Δt corresponds to an EV that is parked and, thus, is available for charging or discharging via the grid, while a vehicle with p = 0 corresponds to an EV that is moving and, therefore, unavailable for the specific time t. In this latter case, the SOC_t of a moving EV decreases according to the energy consumption rate and range R of the car. The assumption in this case is that the EV owners, following signals issued by the energy management system, will opt to charge their EVs anytime during the low-demand time and discharge to the grid anytime during high-demand time. Furthermore, they are not allowed to do the opposite.

During the winter period (LC1, Figure 7), valley filling is achieved with a fleet of merely 25 EVs. Peak shaving is observed around noon, but there is not much energy available overall for V2G services. During the summer period (LC2, Figure 8), valley filling and maximum peak shaving are achieved with a fleet of 100 EVs.

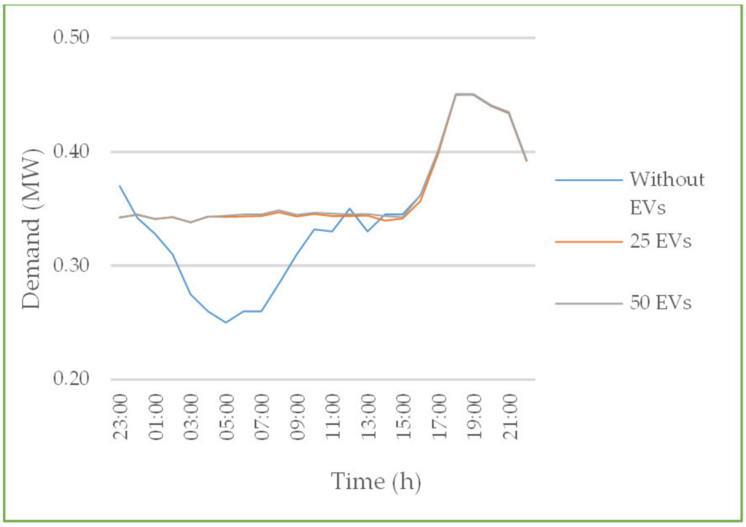

Figure 7. The effect of charging/discharging on LC1 when N = **25** and 50 cars with a random mobility pattern are used for valley filling or peak shaving.

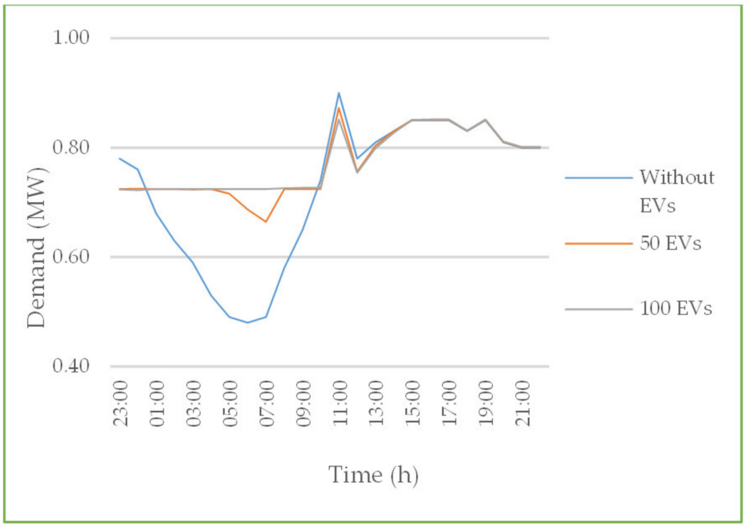

Figure 8. The effect of charging/discharging on LC2 when N = 50 and **100** cars with a random mobility pattern are used for valley filling or peak shaving.

5.3. Valley Filling and Peak Shaving with Random and Predefined EV Mobility Patterns

In the third test case, both valley filling and peak shaving are allowed, but the N EVs are now divided into two subgroups of populations, kN and mN. The first subgroup follows a predefined mobility pattern, as in test case 1: such is, for example, the case of permanent residents or workers in an office building who regularly work at predetermined hours. The predefined mobility pattern of the kN EVs, e.g., of the permanent residents, is largely shaped by the daily needs of their users: EVs are parked from 18:00 to 08:00 and are allowed to charge their battery, while in the remaining hours, they are assumed to be on the move and, therefore, unavailable. The second subgroup of mN EVs are allowed to charge or offer V2G services whenever they are parked, according to the random mobility pattern described in test case 2.

During the winter period (LC1, Figure 9), valley filling is achieved with a fleet of 50 EVs and peak shaving is only observed around noon. During the summer period (LC2, Figure 10), valley filling and maximum peak shaving are achieved with a fleet of 100 EVs.

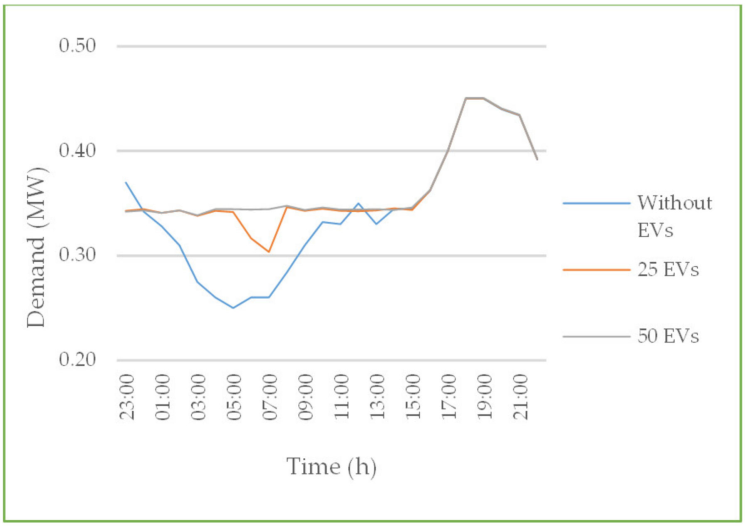

Figure 9. The effect of charging/discharging on LC1 when a fleet of N electric vehicles (EVs) is divided into subgroups of different mobility patterns and used for valley filling or peak shaving: N = 25 and **50**; $k = 0.3\ N$, $m = 0.7\ N$.

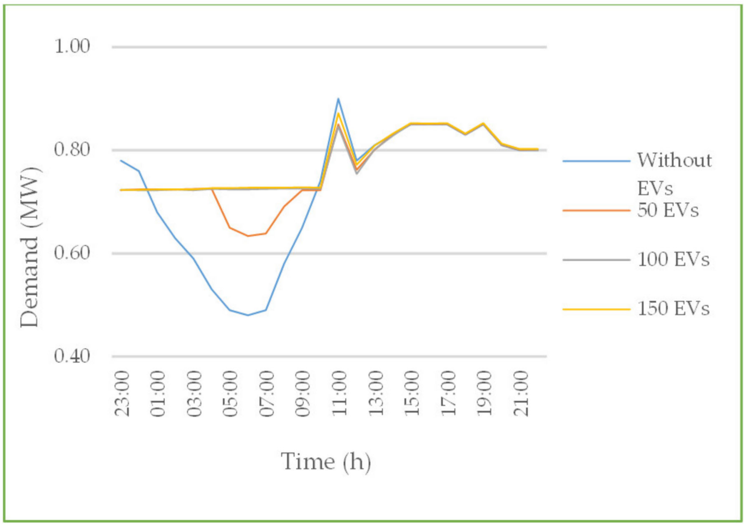

Figure 10. The effect of charging/discharging on LC2 when a fleet of N EVs is divided into subgroups of different mobility patterns and used for valley filling or peak shaving: N = 50 and **100**, 150; $k = 0.3\ N$, $m = 0.7\ N$.

5.4. Valley Filling at Predefined Hours and Peak Shaving with Random EV Mobility Pattern

The fourth test case dictates that all EVs must be fully charged during the hours at wich the demand is at its lowest, e.g., evening hours. This case has been designed in such a way so as to test whether the strategy of having all EVs fully charged at the beginning of each day would yield better results for peak shaving. To implement this scenario, the randomly assigned p-values, also used in the second test case, were activated: the EVs are assumed to be parked from 23:00 to 07:00, which means that $p = 1$ for these hours. During this time interval, they can either charge their battery or inject power into the grid. After 07:00, the status of the EVs, as parked or moving, is allowed to change: it is either randomly set to $p = 0$ and they are not available for charging or discharging or it remains as $p = 1$ and they can either charge their battery, inject power into the grid or move.

During the winter period (LC1, Figure 11), valley filling is achieved with a fleet of 75 EVs but there is little energy available for peak shaving. During the summer period (LC2, Figure 12), valley filling is achieved with a fleet of 150 EVs and maximum peak shaving is achieved for a fleet of 250 EVs. Overnight charging maximizes the flexibility for V2G services during the peak demand.

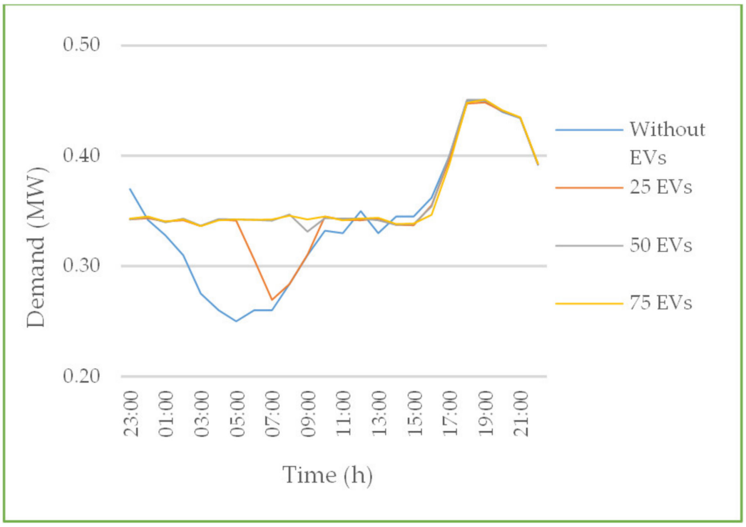

Figure 11. The effect of charging/discharging on LC1 when *N* cars have a custom mobility pattern for valley filling and random EV mobility pattern for peak shaving: *N* = 25, 50 and **75**.

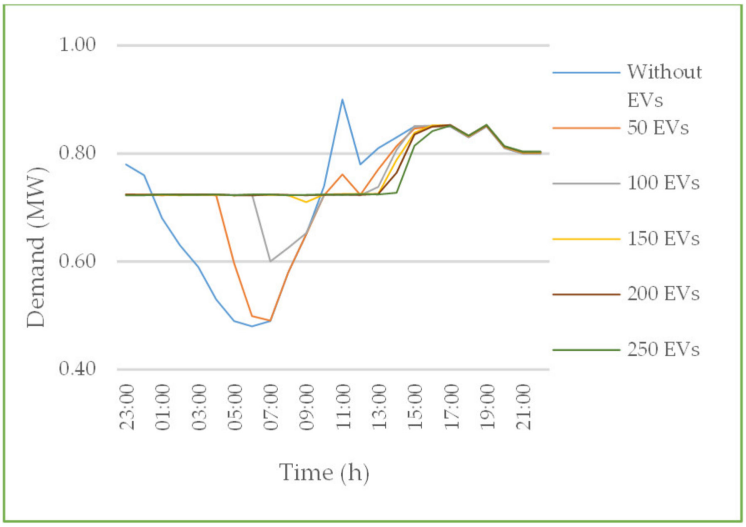

Figure 12. The effect of charging/discharging on LC2 when *N* cars have a custom mobility pattern for valley filling and random EV mobility pattern for peak shaving: *N* = 50, 100, **150**, 200, **250**.

5.5. The Effect of PV Penetration on the Power Generated by the Island's APS

The above test cases were also used to study the effect of a 140.0 kWp PV plant on the power that needs to be supplied by the island's autonomous power system (APS). Although the maximum yield of the PV plant (Figure 2) does not coincide with the peak demand of either the winter or the summer day, its operation significantly reduces the APS power output during daytime and allows for more flexibility in the shaping of the supply curve through the demand.

In test case 2, EVs have random mobility patterns and are not allowed to charge during the peak demand or discharge through the grid during the low demand. For the winter day LC1 (Figure 13), the energy generated by the PV plant enables EV charging to take place for the biggest part of the day, which also allows for more flexibility in V2G services. For the summer day LC2 (Figure 14), optimum valley filling and maximum peak shaving are achieved with a fleet of 150 EVs. More EVs are accommodated and peak shaving is enabled.

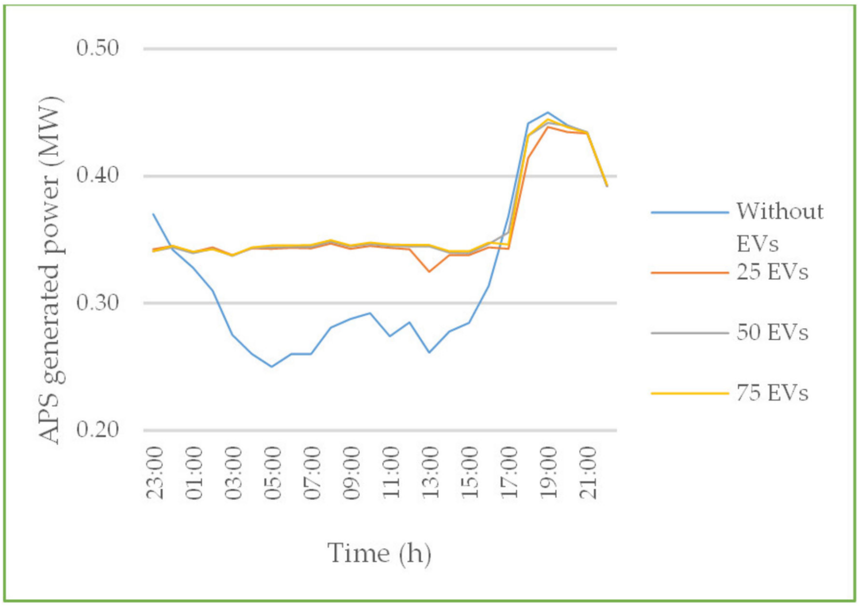

Figure 13. Autonomous power system (APS) output required in the presence of a 140.0 kWp PV plant for test case 2 and LC1.

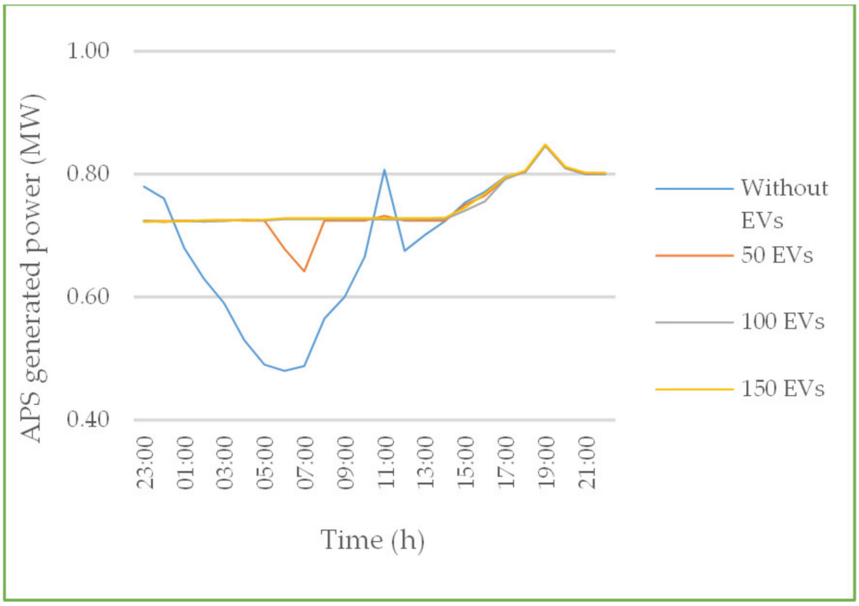

Figure 14. APS output required in the presence of a 140.0 kWp PV plant for test case 2 and LC2.

In test case 4, where all EVs are assigned random mobility patterns but must be fully charged during the night, peak shaving is achieved with a fleet of 75 EVs for the winter day LC1 (Figure 15). For the summer day LC2 (Figure 16), both valley filling and maximum peak shaving are achieved with a fleet of 200 EVs.

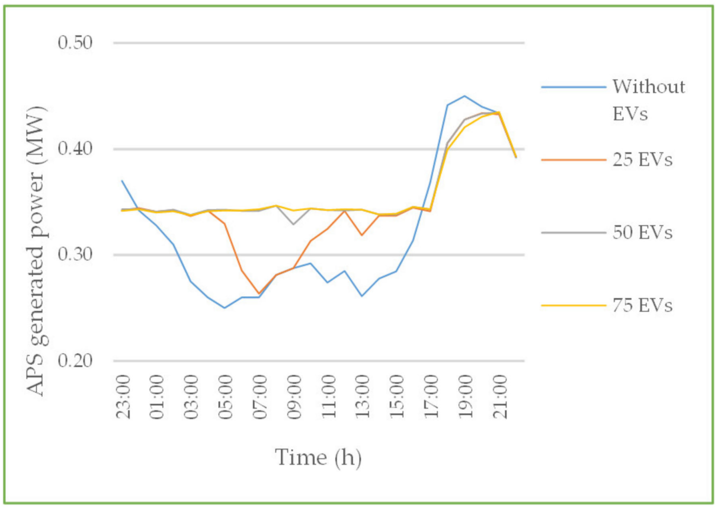

Figure 15. APS output required in the presence of a 140.0 kWp PV plant for test case 4 and LC1.

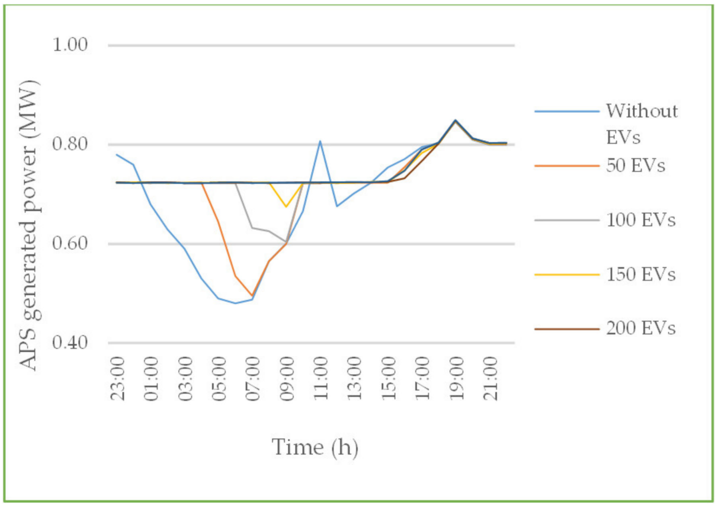

Figure 16. APS output required in the presence of a 140.0 kWp PV plant for test case 4 and LC2.

In the case of random charging during the day (test case 1a), a larger EV fleet may be charged, taking advantage of the PV energy; furthermore, a smaller number of EVs end up partially charged (Table 1). In test case 3, where the EV fleet is divided into two subgroups, one with a predefined mobility pattern and one with a random mobility pattern, the increased demand for EV charging is partly covered by PV generation and there is energy available for peak shaving services.

Table 1. Partially charged EVs for test cases 1a and 1b.

Load Curve 1 (Winter)					
Number of EVs (N)	**25**	**50**	**75**	**100**	**150**
Partially charged EVs (1a)	0	0	11	40	74
Partially charged EVs (1a) w/PV	0	0	0	0	43
Partially charged EVs (1b)	0	0	21	55	81
Partially charged EVs (1b) w/PV	0	0	24	45	93

Table 1. *Cont.*

Test Case 1—Load Curve 2 (Summer)					
Number of EVs (N)	**50**	**100**	**150**	**200**	**250**
Partially charged EVs (1a)	0	0	6	41	101
Partially charged EVs (1a) w/PV	0	0	0	37	85
Partially charged EVs (1b)	0	0	4	70	113
Partially charged EVs (1b) w/PV	0	0	16	55	122

6. Discussion

The genetic algorithm developed and implemented for optimum valley filling and peak shaving using the storage capacity of an EV fleet on a non-interconnected Greek island has highlighted some of the factors determining the optimum penetration level of EVs and the flexibility offered by them. The simulation experiments performed assumed various cases of mobility and charging patterns. The effect of PV generation has also been studied. In the following discussion, we first examine the case where all electricity on the island is supplied by the diesel autonomous power station (APS), and next, the effect of the PV plant.

In the first case of valley filling, which allows the EVs to charge anytime during the day, the demand curve is flattened at 22% and 28% EV penetration for the winter and summer periods, corresponding to 75 and 150 EVs, respectively. Considering that there are approximately 500 inhabitants, this level of penetration is reasonable. Increasing the size of the EV fleet will leave a number of cars partly charged (Table 1) if charging is allowed only during low-demand periods (valley filling). The presence of a PV plant allows for a larger EV fleet to be accommodated with relatively good quality of service, since the excess energy required for EV charging is supplied by the PV plant.

If a predefined time interval for charging is set, e.g., 23:00–7:00 (test case 1b), a large number of EVs will either be charged below the upper SOC limit or will not be charged at all (Table 1) if the average demand level μ, above which charging is not allowed, is not increased. Therefore, setting time restrictions for EV charging overnight is not advisable, especially when PV energy is available during the daytime.

In the second case, both peak shaving and valley filling services are offered with random EV mobility patterns. EV users, reacting to signals or pre-announced pricing options, may charge their EVs anytime during low-demand periods and discharge to the grid anytime during high-demand periods, but they are not allowed to do the opposite. Valley filling is achieved at merely 7% and 19% EV penetration for the winter and summer periods, corresponding to 25 and 100 EVs, respectively, which are reasonable numbers for the size of the island. Peak shaving, on the other hand, is not easily attainable due to the small number of EVs and the resulting storage capacity. In the wintertime, the available energy in EV batteries is not enough to both cover the EV owners' needs and offer services to the grid. In the summertime, the larger EV fleet allows some flexibility for peak shaving, with the maximum observed from 10:00 to 14:00 h, for N = 100 EVs; the demand peak is decreased by 6% of the original peak and the corresponding energy fed into the power grid is 0.10 MWh. The power supplied by a PV plant allows for more EVs to be accommodated and the flexibility offered by the EV storage is enhanced.

In the third test case, the EV fleet is divided into two subgroups, one with a random mobility pattern and one with a predefined mobility pattern. Valley filling is achieved at 15% and 19% EV penetration for the winter and summer periods, respectively. In the summertime, the larger EV fleet allows for some peak shaving, similar to the second test case.

To facilitate V2G services, the strategy proposed in the fourth test case was designed: EVs are fully charged overnight when demand is low in order to increase the EV capability for peak-shaving services when demand is higher. The potential for peak shaving is higher in the summer case, since a total of 0.47 MWh may be offered to the grid when N = 250. The maximum power shaved is 0.18 MW, which amounts to 20% of the peak demand. The flexibility for V2G services is significantly enhanced when PV generation is available.

For the case of an autonomous grid with low mobility and a restricted road network, such as the one studied here, the EV penetration level for optimum flexibility management is determined mainly by the difference between the low- and high-demand values of the demand profile.

In any case, the electricity required to charge the EVs increases the power that needs to be supplied by the island's fossil-fueled APS. However, replacing conventional cars by EVs and shaping the demand curve through valley-filling and peak-shaving operations partly counterbalances the environmental footprint of the increased APS supply.

On the road towards "green" islands, in order to phase out the local fossil-fueled power plants in favor of RESs, it is necessary to complement any RES generation with electrical storage. Except from absorbing any excess energy, electrical storage may be used to effectively shape the demand curve and minimize the energy required from the APS, leading to additional fuel and CO_2 emissions savings. However, the storage offered by EVs increases the demand and does not suffice for effective V2G services, but an appropriate charging and, when possible, discharging schedule may optimize the overall electricity demand profile.

For the case studied here, in the absence of EVs, a PV plant significantly reduces the power that needs to be supplied by the APS during daytime. However, in the evening hours, the APS must ramp up significantly to meet the high demand. In the presence of EVs, charging may be used to flatten the demand curve around a given value, thus allowing a more efficient operation of the APS even if it needs to generate more energy. The energy supplied by the PV plant contributes further towards that direction, favoring peak shaving and increasing the flexibility offered by the EV storage.

Based on the above results, a plausible strategy for EV charging and V2G services on non-interconnected islands is to either issue recommendations and price signals to EV users, using hourly forecasts and a tool such as the one depicted in Figure 17, or design daily schedules for EV charging and V2G services using day-ahead load forecasts and a tool such as the one shown in Figure 18.

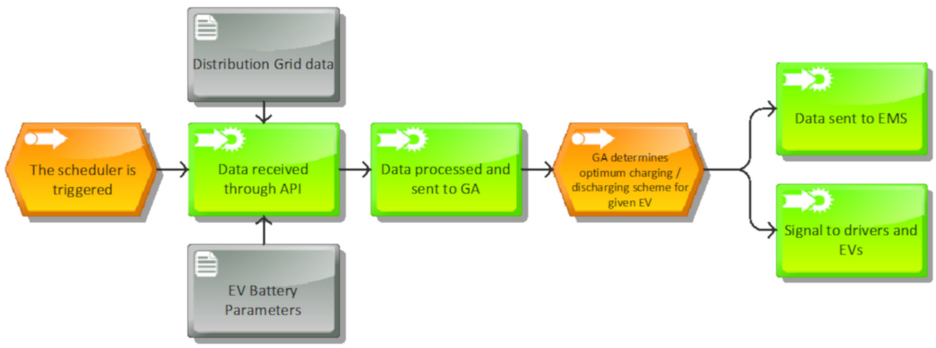

Figure 17. Genetic algorithm for online operations.

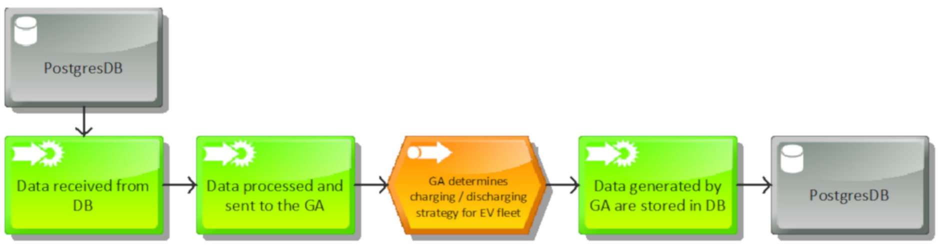

Figure 18. Genetic algorithm for offline operations.

These may be applied to all EV users regardless of their profile or, when profiling is possible, they may be adjusted to respective profiles' mobility patterns in order to enhance the impact of demand–response mechanisms.

The last part of the discussion is dedicated to the GA developed for this work. It has been designed so that it can be used in both an online and offline mode. In the online mode (Figure 17), it receives a signal from the grid every time a car is connected to it for charging or discharging (V2G) and retrieves all required data, such as SOC, energy balance and other grid-related data, from the EV battery controller and the energy management system linked to the grid. In future versions, the GA will be coupled to power flow equations and will be more detailed, AI-based and data-driven SOC models will be used. The output of the GA is signals to the driver and/or the EV battery controller, for fully automated systems, and data to the energy management system.

In the offline mode (Figure 18), the GA may be used to run simulations and design charging strategies and pricing schemes for the management of a given fleet of EV cars using next-day load forecasts or other data available in the database.

An overarching remark for the microgrid studied in this work is that increasing the EV fleet can offer more flexibility for demand-side management, but ultimately, the EV penetration levels should be subject to the mobility needs of the island and not the energy management system operations. In other words, the size of the EV fleet is limited by the population and size of the island itself. Moving towards carbon-free islands, electromobility relying on private or rental cars should not be encouraged. Instead, a strategy of small-scale mass electromobility [3], e.g., offered through frequently running minibuses, should be designed, which would serve both the locals and the visitors. In that case, the charging strategy would need to adjust accordingly, since the routes and charging schedules could be co-optimized as in [27].

7. Conclusions

The flexibility offered by an EV fleet on a Greek non-interconnected island in the Aegean Sea has been studied using a genetic algorithm to shape the demand curve and reduce the energy required of the autonomous power plant of the island. The EV flexibility is managed by an intermediate entity, e.g., an aggregator, or an energy management system linked to the distribution grid, which issues signals to EV owners or the EV battery controller.

Two operations were studied: charging for valley filling and discharging to the grid for peak shaving. The optimum size of the EV penetration which corresponds to the number of EVs participating in these two operations has been determined for four test cases with various mobility and charging patterns. Two demand curves have been examined: one for a winter day and one for a summer day, which typically has a much higher demand due to the influx of tourists.

The simulations show that time limits do not lead to better valley-filling services. Instead, more dynamic charging/discharging schemes are encouraged. The use of EVs as flexible loads and storage can flatten the demand curve, but peak shaving requires higher EV penetration levels so that the EVs have enough energy stored to also offer to the grid. The flexibility services depend on the size of the EV fleet. However, a larger EV fleet increases the total daily energy required. A PV plant allows for higher EV penetration levels and increases the peak-shaving capacity and flexibility for demand-side management operations.

Ultimately, the size of the EV fleet is subject to the mobility needs on the island and is, therefore, limited by the population and size of the road network itself. A strategy for optimum electromobility using small-scale mass transportation, such as frequently running minibuses with co-optimized routes and charging/discharging schedules, as part of a holistic approach towards "green" islands will be studied next. Certain assumptions made will be relaxed in future works to allow for the effect of time-dependent charging, pricing signals, battery degradation as well as uncertainties introduced by the stochastic nature of RESs to be studied. Load forecasting will be coupled to the genetic algorithm presented here in order to develop a tool for the design of charging schedules.

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

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

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

References

1. European Environment Agency. Indicator Assessment. *Greenhouse Gas Emissions from Transport in Europe*. 2019. Available online: https://www.eea.europa.eu/data-and-maps/indicators/transport-emissions-of-greenhouse-gases/transport-emissions-of-greenhouse-gases-12 (accessed on 6 December 2019).
2. IEA. *Global EV Outlook 2019: Scaling Up the Transition to Electric Mobility*; IEA: Paris, France, 2019. Available online: https://www.iea.org/reports/global-ev-outlook-2019 (accessed on 6 December 2019).
3. Ajanovic, A.; Haas, R. Electric vehicles: Solution or new problem? *Environ. Dev. Sustain.* **2018**, *20*, 7–22. [CrossRef]
4. Hacker, F.; Harthan, R.; Matthes, F.; Zimmer, W. *Environmental Impacts and Impact on the Electricity Market of a Large Scale Introduction of Electric Cars in Europe*; ETC/ACC Technical Paper 2009/4; Öko-Institut e.V.: Berlin, Germany, 2009.
5. Karakitsios, I.; Karfopoulos, E.; Hatziargyriou, N. Impact of dynamic and static fast inductive charging of electric vehicles on the distribution network. *Electr. Power Syst. Res.* **2016**, *140*, 107–115. [CrossRef]
6. Yanfei, W.; Haifeng, S.; Wenhao, W.; Yunjing, Z. The impact of electric vehicle charging on grid reliability. *IOP Conf. Ser. Earth Environ. Sci.* **2018**, *199*, 052033. [CrossRef]
7. Mousavi, S.; Flynn, D. Controlled Charging of Electric Vehicles to Minimize Energy Losses in Distribution Systems. *IFAC PapersOnLine* **2016**, *49*, 324–329. [CrossRef]
8. Díaz, A.R.; Ramos-Real, F.J.; Marrero, G.A.; Perez, Y. Impact of Electric Vehicles as Distributed Energy Storage in Isolated Systems: The Case of Tenerife. *Sustainability* **2015**, *7*, 15152–15178. [CrossRef]
9. Stavropoulou, E. The Electrical Systems of the Greek Non Interconnected Islands. In Proceedings of the 4th International Hybrid Power Systems Workshop, Heraklion, Crete, 22–23 May 2019.
10. Nieto, A.; Vita, V.; Maris, T.I. Power Quality Improvement in Power Grids with the Integration of Energy Storage Systems. *Int. J. Eng. Res. Technol.* **2016**, *5*, 438–443.
11. Kasten, P.; Bracker, J.; Haller, M.; Purwanto, J. *Electric Mobility in Europe—Future Impact on the Emissions and the Energy Systems*; Öko-Institut e.V.: Berlin, Germany, 2016.
12. *Smart Charging for Electric Vehicles*; Innovation Outlook; International Renewable Energy Agency (IRENA): Abu Dhabi, United Arab Emirates, 2019.
13. Ensslen, A.; Ringler, P.; Dörr, L.; Jochem, P.; Zimmermann, F.; Fichtner, W. Incentivizing smart charging: Modeling charging tariffs for electric vehicles in German and French electricity markets. *Energy Res. Soc. Sci.* **2018**, *42*, 112–126. [CrossRef]
14. DeForest, N.; Funk, J.; Lorimer, A.; Ur, B.; Sidhu, I.; Kaminsky, P.; Tenderich, B. *Impact of Widespread Electric Vehicle Adoption on the Electrical Utility Business-Threats and Opportunities*; Technical Report; Center for Entrepreneurship & Technology (CET), University of California: Berkeley, CA, USA, 2009.
15. Ramadan, H.; Ali, A.; Nour, M.; Farkas, C. Smart Charging and Discharging of Plug-in Electric Vehicles for Peak Shaving and Valley Filling of the Grid Power. In Proceedings of the 20th International Middle East Power Systems Conference (MEPCON), Nasr City, Egypt, 18–20 December 2018.
16. Ghofrani, M.; Detert, E.; Niromand, N.H.; Arabali, A.; Myers, N.; Ngin, P. V2G Services for Renewable Integration. In *Modeling and Simulation for Electric Vehicle Applications*; IntechOpen: Rijeka, Croatia, 2016. [CrossRef]
17. Paudyal, S.; Ceylan, O.; Bhattarai, B.; Myers, K.S. Optimal Coordinated EV Charging with Reactive Power Support in Constrained Distribution Grids. In *Proceedings of the 2017 IEEE Power & Energy Society General Meeting, Chicago, IL, USA, 16–20 July 2017*; IEEE: Piscataway, NJ, USA, 2017; pp. 1–5. [CrossRef]
18. National Energy and Climate Plan; Ministry of the Environment and Energy: Athens, Greece. 2019. Available online: https://ec.europa.eu/energy/sites/ener/files/el_final_necp_main_en.pdf (accessed on 2 February 2021).
19. Putrus, G.A.; Suwanapingkarl, P.; Johnston, D.; Bentley, E.C.; Narayana, M. Impact of Electric Vehicles on Power Distribution Networks. In Proceedings of the 2009 IEEE Vehicle Power and Propulsion Conference, Dearborn, MI, USA, 7–11 September 2009.
20. Alonso, M.; Amaris, H.; Germain, G.G.; Galan, J.M. Optimal Charging Scheduling of Electric Vehicles in Smart Grids by Heuristic Algorithms. *Energies* **2014**, *7*, 2449–2475. [CrossRef]

21. Erden, F.; Kisacikoglu, M.; Erdogan, N. Adaptive V2G Peak Shaving and Smart Charging Control for Grid Integration of PEVs. *J. Electr. Power Compon. Syst.* **2018**, *46*, 1494–1508. [CrossRef]
22. Finn, P.; Fitzpatrick, C.; Conolly, D. Demand side management of electric car charging: Benefits for consumer and grid. *Energy* **2012**, *42*, 358–363. [CrossRef]
23. Karfopoulos, E.; Hatziargyriou, N. Distributed coordination of electric vehicles for conforming to an energy schedule. *Electr. Power Syst. Res.* **2017**, *151*, 86–95. [CrossRef]
24. Kontou, E.; Yin, Y.; Ge, Y.E. Cost-effective and ecofriendly plug-in hybrid electric vehicle charging management. *Transp. Res. Rec.* **2017**, *2628*, 87–98. [CrossRef]
25. 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]
26. Traut, E.J.; Cherng, T.C.; Hendrickson, C.; Michalek, J.J. US residential charging potential for electric vehicles. *Transp. Res. Part D Transp. Environ.* **2013**, *25*, 139–145. [CrossRef]
27. Boewing, F.; Schiffer, M.; Salazar, M.; Pavone, M. A Vehicle Coordination and Charge Scheduling Algorithm for Electric Autonomous Mobility-on-Demand Systems. In *Proceedings of the 2020 American Control Conference (ACC), Denver, CO, USA, 1–3 July 2020*; IEEE: Piscataway, NJ, USA, 2020; pp. 248–255. [CrossRef]
28. Ortega-Vazquez, M.; Bouffard, F.; Silva, V. Electric Vehicle Aggregator/System Operator Coordination for Charging Scheduling and Services Procurement. In Proceedings of the 2013 IEEE Power & Energy Society General Meeting, Vancouver, BC, Canada, 21–25 July 2013.
29. Camus, C.; Farias, T. The electric vehicles as a mean to reduce CO2 emissions and energy costs in isolated regions. The Sao Miguel (Azores) case study. *Energy Policy* **2012**, *43*, 153–165. [CrossRef]
30. Efthymiopoulos, I. *Islands as testbeds for Innovative Energy Solutions*; Friedrich-Ebert-Stiftung: Athens, Greece, 2015.
31. Giannakaris, P.; Ktena, A.; Manasis, C.; Assimakis, N. Hybrid power plant with storage on a non-interconnected Greek island. *B H Electr. Eng.* **2020**, *14*, 46–52.
32. European Union 2001–2012. Solar Radiation and Photovoltaic Electricity Potential Country and Regional Maps for Europe. 2012. Available online: https://ec.europa.eu/jrc/en/pvgis (accessed on 3 December 2020).
33. Karfopoulos, E. Contribution of the Management of Electric Vehicles for Their More Efficient Integration in the Electricity Grids. Ph.D. Thesis, School of Electrical and Computer Engineering (NTUA), Athens, Greece, 2017.
34. Kostopoulos, E.; Spyropoulos, G.; Kaldellis, J. Real-world study for the optimal charging of electric vehicles. *Energy Rep.* **2019**, *6*, 418–426. [CrossRef]
35. Jiang, J.; Shi, W.; Zheng, J.; Zuo, P.; Xiao, J.A.; Chen, X.; Xu, W.; Zhang, J.G. Optimized Operating Range for Large-Format LiFePO4/Graphite Batteries. *J. Electrochem. Soc.* **2013**, *161*, 336–341. [CrossRef]
36. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. *J. Power Sources* **2013**, *226*, 272–288. [CrossRef]
37. Sheta, A.; Turabieh, H. A comparison between genetic algorithms and sequential quadratic programming in solving constrained optimization problems. *AIML J.* **2006**, *6*, 67–74.
38. Deb, K. An efficient constraint handling method for genetic algorithms. *Comput. Methods Appl. Mech. Eng.* **2000**, *186*, 311–338. [CrossRef]