Distributed Charging Prioritization Methodology Based on Evolutionary Computation and Virtual Power Plants to Integrate Electric Vehicle Fleets on Smart Grids

J.I. Guerrero *[ID]**, Enrique Personal**[ID]**, Antonio García, Antonio Parejo**[ID]**, Francisco Pérez and Carlos León**[ID]

Department of Electronic Technology, University of Seville, EPS. C/Virgen de África, 7, 41011 Seville, Spain; epersonal@us.es (E.P.); antgar@us.es (A.G.); aparejo@us.es (A.P.); fperez@us.es (F.P.); cleon@us.es (C.L.)
* Correspondence: juaguealo@us.es; Tel.: +34-954-557-192

Abstract: Electric vehicle fleets and smart grids are two growing technologies. These technologies have provided new possibilities to reduce pollution and increase energy efficiency. In this sense, electric vehicles are used as mobile loads in the power grid. A distributed charging prioritization methodology is proposed in this paper. The solution is based on the concept of virtual power plants and the usage of evolutionary computation algorithms. Additionally, a comparison of several evolutionary algorithms—namely genetic algorithm, genetic algorithm with evolution control, particle swarm optimization, and hybrid solution—is shown, in order to evaluate the proposed architecture. The proposed solution is presented as a means to prevent overload of the power grid.

Keywords: smart grids; vehicle-to-grid; electric vehicles; charging optimization; electric vehicle fleets; evolutionary computation

1. Introduction

The electric vehicle (EV) represents a new research field in smart grid (SG) ecosystems. Currently, the new generation of EVs provides different technologies which can be integrated in SGs. However, these new technologies make difficult the distribution of grid management. In particular, EVs and the infrastructure needed to charge them have resulted in a great quantity of new standards and technologies. Currently, there are several research lines related to EVs: fast charging networks, battery performance modeling, parasitic energy consumption, EV promotional policies, increasing the range of the battery in EV, etc.; and other research lines related to EV energy management: contract models for consumption vehicle, market model to adopt EVs, distributed energy resources management systems (DERMS), distributed energy resources (DER) standards, faster charging technologies, demand response management systems (DRMS), the role of aggregators in V2G (vehicle-to-grid), energy efficiency, customer support, driver support, etc. Additionally, all these lines are influenced by the current regulation and may different greatly between countries (for example, the regulation between United States and Europe is very different regarding energy management). The charging infrastructure affects SG on several levels. These levels concern the transportation, distribution, and retailer levels. The main affected frameworks inside these levels are energy management, distribution management, and demand response. The energy management systems include several functions, one of which is the control of energy flows. The charging of an EV can be made at any point on the grid which has a charging unit. If the system has information about the expected use of the charging unit, the energy flow will be easier to manage. The distribution management is related with distribution system

operators (DSO). Usually, the charging infrastructure oversees DSOs. Thus, the DSOs must manage these facilities and maintain information about them. Finally, the demand response concerns retailers and DSOs, and the main problem is demand curve flattening and price management. Nevertheless, the new paradigm proposed by standard organizations, including National Institute of Standards and Technology (NIST), International Electrotechnical Commission (IEC), among others, related with V2G proposed that EVs could charge or discharge batteries. Thus, the EV is a power source in specific scenarios. In these cases, the distributed resource management is affected by the new V2G technologies as a distributed power resource in low voltage without total availability, like some renewable energy resources, for example, wind and solar energy.

This paper proposed a solution for fleet charging prioritization based on the concept of a virtual power plant (VPP) and using distributed evolutionary computation algorithms to optimize the prioritization of EV fleets at different levels of SG ecosystems. A comparison of different evolutionary algorithms is performed.

This paper shows the proposed solution, starting with a bibliographical review. Then, the architecture over different levels of SG is described, including the information flows. The evolutionary algorithm is described at different levels of SG ecosystem. Finally, the results of test the evolutionary algorithms are shown.

2. Background

The introduction of EVs provides several advantages, but it is necessary to have additional energy sources [1,2] in order to include the associated infrastructure. One of the first EVs was the hybrid electric vehicle (HEV), and different types of HEVs were designed to reduce power requirements and increase vehicle autonomy, charging duration, and energy efficiency, selecting the appropriate battery [3]. Additionally, there are several studies about the performance of batteries [4] and battery degradation [5]. The new generation of EVs has several requirements not only in power but also infrastructure [6]. There are several studies to establish renewable energy sources to support the charging of EVs and HEVs and cover the power requirements, for example, based on wind energy [7,8], photovoltaic sources [9], general congestion of EV charging based on renewables [10], etc. However, SGs have provided a good scenario to integrate EVs and charging infrastructure.

Another solution could be the application of queue theory [11]. Queue theory has application in several topics: boarding management [12], healthcare [13,14], dynamic facility layout problem [15], optimization of traffic by means of signal-controlled management [16], data acquisition [17], etc. Usually, these references manage only one queue or several independent queues. However, there are more complex problems based on distributed software systems [18], which provide more difficult applications of queue theory. In these cases, queue theory should be adapted to a distributed environment. This paper proposes a novel solution to avoid this complexity.

The authors of [19] propose VPPs as a new solution for the implementation of technologies related to SGs, and several applications were developed to show the advantages of VPPs. The authors of [20] proposed the integration of combined heat and power (CHP) microunits based on VPPs into a low voltage network from technical and economical point of view. The authors of [21] presented a new concept where microgrids and other production or consumption units form a VPP. The authors of [22] presented a concept VPP as a primary vehicle for delivering cost efficient integration of distributed energy resources (DER) into the existing power systems. This study presented the technical and commercial functionality facilitated through the VPP and concluded with case studies demonstrating the benefit of aggregation and the use of the optimal power flow algorithm to characterize VPPs. The authors of [23] proposed the concept of generic VPP (GVPP), showing three case scenarios and overcoming challenges using a proposed solution framework and service-oriented architecture (SOA) as a technology which could aid in the implementation of GVPP. The authors of [24] provided a suitable software framework to implement GVPP with SOA. The FENIX European Project [25] delved into the concept of VPP and considered two types of VPP: the commercial VPP (CVPP), that tackles

the aggregation of small generating units with respect to market integration, and the technical VPP (TVPP), that tackles aggregation of these units with respect to services that can be offered to the grid. The authors of [26] described a general framework for future VPP to control low and medium voltage for DER management. The authors of [27] presented a case study which shows how a broker GVPP was developed based on the selection of appropriate functions. The EDISON Danish project [28] described an ICT-based distributed software integration based on VPPs and standards to accommodate communication and optimize the coordination of EV fleets. The authors of [29] proposed an architecture for EV fleet coordination based on V2G integrating VPP. The authors of [30] analyzed the possibility of using EVs as an energy storage system (V2G) within a VPP structure. The authors of [31] considered the EV as a mobile load and described a VPP containing aggregated microgeneration sources and EV, but is centered around minimizing carbon emissions. The authors of [32] proposed and discussed three approaches for grid integration of EVs through a VPP: control structure, resource type, and aggregation. The authors of [33] presented a solution for integrating EVs in the SG through unbundled smart metering and VPP technology dealing with multiple objectives. The authors of [34] addressed the design of an EV test bed which served as a multifunctional grid-interactive EV to test VPP or a generic EV coordinator with different control strategies.

The common point of these references is the utilization of the VPP concept in a simulation, but they only simulate the VPP which aggregates the information of EV. The present paper additionally analyzes the impact in VPP of higher levels, and how the distribution of charging is made.

On the other hand, some researchers have studied the impact of HEV and plug-in HEV (PHEV) [35]. In this sense, decentralized algorithms for coordinating the charging of multiple EVs have gained importance in recent years. The authors of [36] compared several approaches based on centralized, decentralized, and hybrid algorithm, with the latter showing better results. The authors of [37] introduced the electric fleet size and mix vehicle routing problem with time windows and recharging stations (E-FSMFTW) to model decisions to be made with regards to fleet composition and vehicle routes, including the choice of recharging times and locations. The authors of [38] presented a review and classification of methods for smart charging of EVs for fleet operators, providing three control strategies and their commonly used algorithms. Additionally, they studied service relationships between fleet operators and four other actors in SGs.

3. Architecture View

The viewpoint of the proposed solution treats vehicles as a mobile load. In this manner, the system must have data about these loads and the charging prioritization. Thus, the system will have information about the expected consumption or the expected generation of the resource (in the case of a fault in the grid), such as a battery.

The proposed system works like a service for large companies with EV fleets. Knowledge about the state and prioritization of vehicles may minimize the impact of charging loads. These services provide new tariffs for retailers and new policies for energy price management.

The conceptual architecture of the proposed solution is shown in Figure 1. Several VPPs are included. The information is aggregated on the lower level. Then, the aggregated information is sent by each lower VPP to a higher level. In this manner, each VPP aggregates the data and services from lower VPPs to higher VPPs. Each level may have one or more VPPs depending on the needs at each level and the power grid.

The information representation at different levels was based on an extension of the common information model (CIM) from IEC 61870, 61968, and 62325. The interface information is based on the component interface specification (CIS) from the IEC. The information representation and interface description are beyond the scope of this paper.

Each higher VPP can perform evolutionary algorithms to generate commands or instructions to modify the queues from lower VPPs. Additionally, lower VPPs can perform the same evolutionary

algorithms to request resources from other VPPs to prioritize the charging of vehicles that cannot be charged at their charging stations.
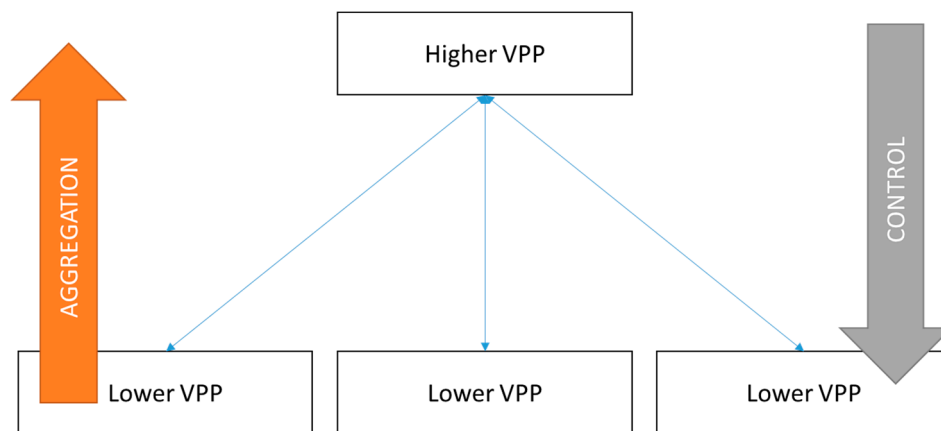

Figure 1. Conceptual model of virtual power plant (VPP) architecture.

The evolutionary algorithms are based on genetic algorithms and swarm intelligence. Each level runs the evolutionary algorithms depending on the available computational resources or option configured in the corresponding VPP. The level at which the VPP is performed determines the availability of services and data. In this paper, several levels are proposed:

- Smart business VPP (SBVPP). This is the lowest level. At this level, all information about vehicles, routes, and drivers from the same company is available. Thus, the charging prioritization of the charging stations of the company is treated at this level. The state of charge (SoC) is also calculated at this level. Some routes may be very long, which may cause a vehicle to use a charging station that is located outside of the company. This charging station may be administered by another company or the corresponding power distribution company. In this case, the algorithm sends the restrictions to higher VPP levels to obtain a solution for the charging needs.
- Distribution VPP (DVPP). At this level, information is aggregated from lower levels, and information about retailers and the presence of charging stations is stored. This information is sent to higher levels, such as an energy VPP (EVPP). Additionally, the restrictions from an EVPP to the corresponding retailer and SBVPP are addressed at this level.
- Retailer VPP (RVPP). At this level, a retailer needs to know when vehicles require charging at any point outside of the company points. The retailer can use this information to offer different tariffs to a company. This level acts as an intermediate between the charging stations of different companies.
- Energy VPP (EVPP). In this paper, the vehicles represent mobile loads. Thus, if an energy management system has information about the expected charging stations, it may take advantage of this information to improve the load flow forecasting algorithms. Load flow forecasting algorithm is not an objective of this paper. This paper proposes a distributed prioritization algorithm based on the VPP concept for SGs. The prioritization algorithm that is performed at this level treats the total load and establishes possible restrictions at any point of the grid.

The prioritization process is performed in several stages to aggregate information for the upper layers, as shown in Figure 2. The lowest levels implement functions that are related to consumers. The medium levels implement functions that are related to energy distribution and commercialization. The higher levels implement functions to guarantee the quality and continuity of a power supply. This architecture is highly scalable, increasing the interoperability between different enterprises and integration of heterogeneous ecosystems. The VPPs include evolutionary algorithms and some capabilities which makes the interoperability and integration possible:

1. The evolutionary algorithm in an SBVPP. This algorithm sorts the vehicles with their drivers according to the SoC and expected route. If the algorithm cannot include any vehicle, the algorithm classifies the vehicle as an external charge and sends the request to higher VPPs. The SBVPP can receive commands and warnings from the DVPP and RVPP. The higher VPP commands and warnings are considered to be external restrictions. Additionally, the RVPP commands and warnings can take effect over different elements of customer power facilities when the customer that implements a SBVPP has contracted additional services from a retailer to manage the customer power facilities.

2. The evolutionary algorithm in a DVPP. The DVPP gathers all requests from all SBVPPs. This information is employed in an evolutionary algorithm to prioritize charging in available charging stations. The prioritization of different vehicles is sent to the corresponding RVPP. The prioritization of all vehicles is aggregated and sent to the EVPP.

3. The EVPP gathers all information about the charging processes to provide information to the energy flow algorithm. The EVPP can send commands or warnings to the DVPP to notify changes in the prioritization.

4. The RVPP gathers all information about vehicles that may have contractual relationships with a retailer. The retailer can use this information to offer new services to clients. If any problems arise in the client contract, the retailer can send a command or alarm to change the prioritization for one or more vehicles and/or charging stations.

5. If any command or warning exists, the prioritization is re-calculated, which adds new restrictions. If no command or warning exists, the charging prioritization in the external charging stations is notified to the SBVPP.
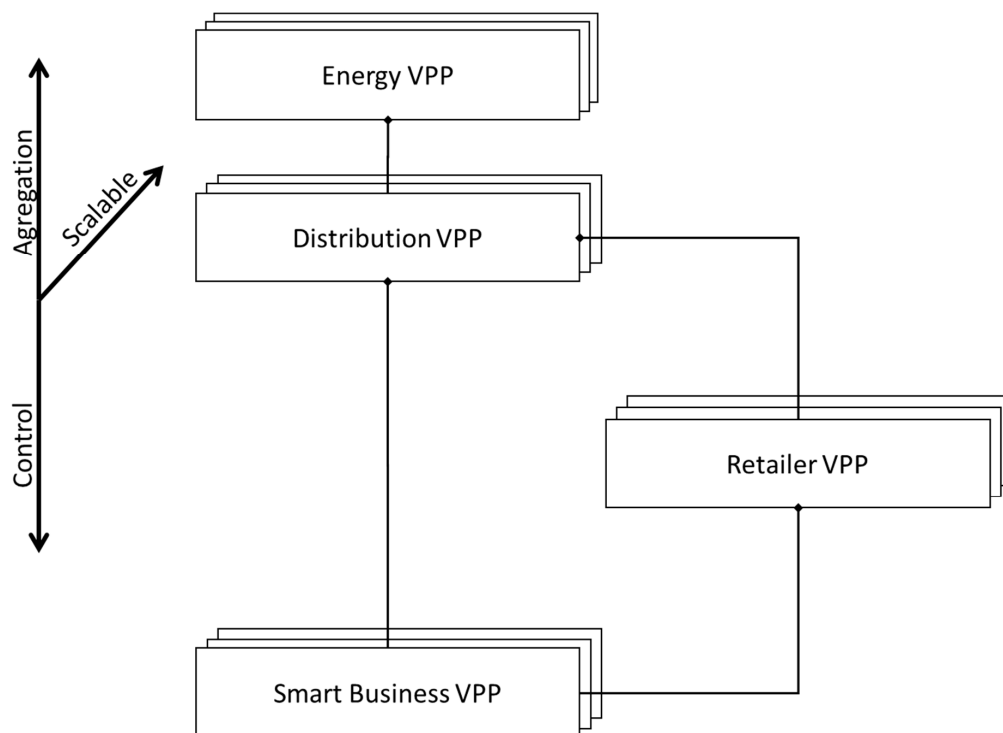

Figure 2. Scalability properties and information flow between different VPP layers.

Any evolutionary algorithm for the SBVPP and DVPP is possible because the algorithm works independently of other layers. Thus, several algorithms were tested in this paper, and a final configuration is proposed based on the results of the tests. However, the algorithms can be configured according to the resources of each level.

4. The Distributed Evolutionary Prioritization Framework

The distributed evolutionary prioritization framework (DEPF) is implemented in each VPP. The architecture of this framework is shown in Figure 3. The modules are shown in Figure 3. Each module has specific functions:

- Asset Management System. The asset management system is based on the predictive maintenance of vehicles and charging stations. These modules establish the maintenance periods and register the usage of all equipment (vehicles and charging stations).
- Driver Modeling. This module executes a modeling process of driver behavior. This module provides a driver pattern which is used to schedule the routes.
- Energy Efficiency. This module applies different techniques to optimize the energy consumption and reduce the maintenance periods and economic impact.
- Real-Time Route Scheduling. This module manages all information about vehicles, routes, drivers, and external conditions to establish better prioritization in each charging station.
- Information Management. This module manages all information of this VPP for reporting and visualization.
- Prioritization Algorithm. The prioritization algorithm in this layer is based on swarm intelligence.
- External Coordination. This module sends information to higher layers and gathers information about external requirements or vehicles to charge.
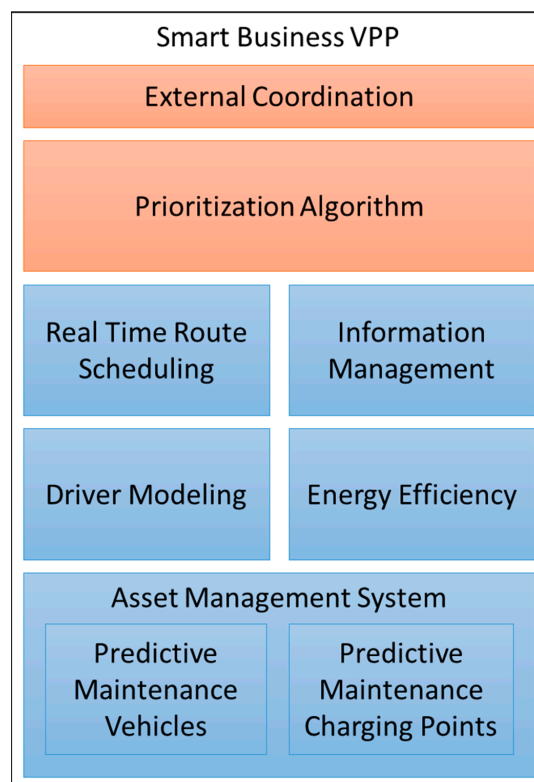

Figure 3. Modules of distributed evolutionary prioritization framework.

The blue modules included in Figure 3 are not the objective of this paper. The information required from these modules is specified in order to establish the constraints and requirements of prioritization algorithm. The external coordination is provided by the interoperability with higher VPP layers.

Some modules, such as external coordination, prioritization algorithm, and the SoC module, are available for all VPPs. The other modules depend on the available information in the VPPs. For example, the SBVPP has all information about the EV fleet (refer to Section 4.1); however, the SBVPP

may have additional services of energy efficiency if it shares the information with the RVPP (in this case, the RVPP would use the energy efficiency module).

The asset management system is in development and will not be described in this paper.

4.1. Available Information for SBVPP

At the SBVPP level, information about different entities is available. This information is used to calculate the SoC, the best driver for each router, and the prioritization at the charging stations of the company. When the route needs an external charging station (out of company supply), the final prioritization is assigned by higher VPP levels.

The available information for the SBVPP is stored in a relational database management system (RDBMS) that is based on the IEC CIM. This information includes the data in Table 1.

Table 1. Available information.

Entity	Description
Vehicle	Technical information about vehicles and their batteries.
Driver	Information about driver patterns.
Asset	Information about asset management.
Charging station	Technical information about charging stations.
Routes	Information about pending and assigned routes.
Charging configuration	Current configuration for prioritization algorithm.
Connection types	Parametric information about technical characteristics of different connection types for vehicles and charging stations.
Periods	Establishes the expected periods of availability and non-availability for each vehicle and charging station.
Measurement	Different measures gathered from charging stations and power register.
External contingencies	Information about traffic, roadwork, and topology.

Additionally, the algorithm stores the historical information described in Table 2.

Table 2. Historical information stored by algorithm.

Additional Entities	Description
Historical vehicles	Historical information about vehicles: mechanical problems and statistics.
Historical charging prioritization	Historical information about calculated charging prioritization and real information about charging stations. This information is stored to determine the difference between the expected charging process and the real charging process. This information will be useful to improve models for charging prioritization.
Historical routes	Historical information about different routes stored in the system, and statistical information.
Historical drivers	Historical information about drivers will be used in the driver pattern modeling.
Historical charging stations	Historical information about usage of charging stations.
Historical configurations	Historical information about configuration of prioritization.
Historical periods	Historical information about periods configured in the system.
Historical information about external contingencies	Historical information about traffic and roadwork.
Historical information about the weather	Information about weather conditions.
Historical information about traffic	Information about traffic conditions and accidents.
Historical information about the execution and configurations	Information about the execution, configuration, and results of configurations.

4.2. Driver Patterns

Driver behavior is stored in driver patterns. The driver pattern is a model that takes effect over the consumption of a vehicle in route scheduling. The driver pattern affects the calculated SoC calculated for each section of a route; it depends on the terrain topology and traffic data. Driver behavior is calculated according to the historical data of a driver. If historical information about a driver is not available, this pattern cannot be calculated.

The driver pattern consists of the deviation from the original predicted SoC. This pattern considers information about traffic and weather to explain the variation from the original predicted SoC.

Although a default driver pattern can be defined, information about driver patterns is currently unavailable. A default "average" driver pattern can be created when a system has adequate information. Currently, this pattern does not include the utility factor [39] because the EV fleets are treated as mobile loads and they do not include PHEVs. The analysis of utility factor in the proposed scenario is beyond the scope of this paper.

4.3. Real-Time Route Scheduling

This module controls several conditions that can modify the current prioritization charging queues. This module notifies any change in the following conditions:

- Driver and EV availability. On a route, a driver (or EV) may have an accident or a driver (or EV) may notify temporary unavailability. In this case, the module updates the calendar for the driver (or EV). This new condition takes effect in the prioritization process by a fitness function of evolutionary algorithms. Sometimes, the temporal unavailability of an EV can be notified by the asset management module.
- Route modifications. Three types of route modifications are possible:

  ○ Adding a new stop.
  ○ Adding a new stop to charge an EV.
  ○ Adding a new stop to change drivers.

- Traffic and roadwork. The traffic and work road modeling are translated into a penalty coefficient for different sections of a route. In this case, the route scheduling algorithm may provide the route with lesser penalties. These penalties take effect on the calculated SoC and the driver selection. The penalty coefficient is stored for each geographical zone and is associated with driver information. If a driver has a very high deviation from the original predicted value, the penalty is increased. This pattern did not consider any information about the origin of the traffic load. The pattern only assigns a penalty coefficient according to the fluidity of traffic.
- Weather conditions. The weather conditions would take effect over the SoC module, prioritization algorithm, and asset management module.
- Charging station availability. If the higher VPPs can send commands or instructions to limit the consumption or availability of the power supply. In this case, this module updates the unavailability periods of the corresponding charging stations.

4.4. SoC Module: Estimation of EV Consumption

The proposed solution is based on the instantaneous SoC value of each EV. These algorithms require an estimation of some consumption according to its planned route and alternative routes to reach different recharging spots. This consumption estimation is supported by a route planning tool. However, these estimations are not trivial and are related to the distance or time of the trip [40,41]. Other factors (e.g., road [42] and vehicle characteristics, traffic [43], driving style [44], and weather conditions) are essential for this estimation.

Typical approaches to estimating route consumptions must be reviewed and briefly explain the architecture that supports the main algorithm in this paper. The two approaches can be easily distinguished in the literature:

- Knowledge-based models are the most common approach. This type of model performs a consumption characterization based on records of vehicle operations using computational intelligence techniques, such as artificial neural networks (ANNs) [45] and fuzzy neural networks (FNNs) [46]. However, these techniques have the disadvantage of requiring a large amount of data which must contain different conditions to model realistic vehicle behaviors in as many situations as possible.
- There are analytical models (also known as longitudinal models) that study the necessary energy to move a vehicle by analyzing the losses along its different mechanical and electronic elements [47,48]. Thus, these models are typically more complex than knowledge-based models. However, analytical models do not require as much information as knowledge-based models because their parameters can be characterized based on information provided by a manufacturer (i.e., New European Driving Cycle (NEDC) standards test [49]).

Based on these philosophies and due to the lack of availability of necessary sets of registered data (especially in the initial phases of the project), an analytical model was chosen to estimate the consumption of this system. It provides the different SoCs that are associated with each route stage. This estimation is based on a model that can be divided into two blocks (refer to Figure 4): First block—the μStep driving model (μSDM)—is responsible for estimating the driving profile. This estimation consists of the velocity and elevation profiles accomplished by the analyzed EV. The velocity profile is constructed from the averaged inferred patterns for different situations which are characterized by the different input parameters. The elevation profile is directly estimated from the route information (in each μStep). A complete list of parameters in the model is shown in Table 3.

The second block of the model—the longitudinal consumption model (LCM)—is responsible for estimating the consumptions and SoC variations associated with the velocity and elevation profiles for each μStep. This consumption is obtained by adding the different losses and consumptions that are required to generate these profiles which are associated with the trip. This analysis also considers the vehicle configuration, as listed in Table 3.

The combination of this model (μSDM + LCM) and the initial SoC value makes it possible to estimate of the SoC at the end of a trip or part thereof. Figure 5 shows an example of this process, in which by using the path, car, driver, and meteorology data, the SoC after this route is estimated. Additionally, in this figure, the velocity and elevation values are also shown (intermediate data estimated by the μSDM).
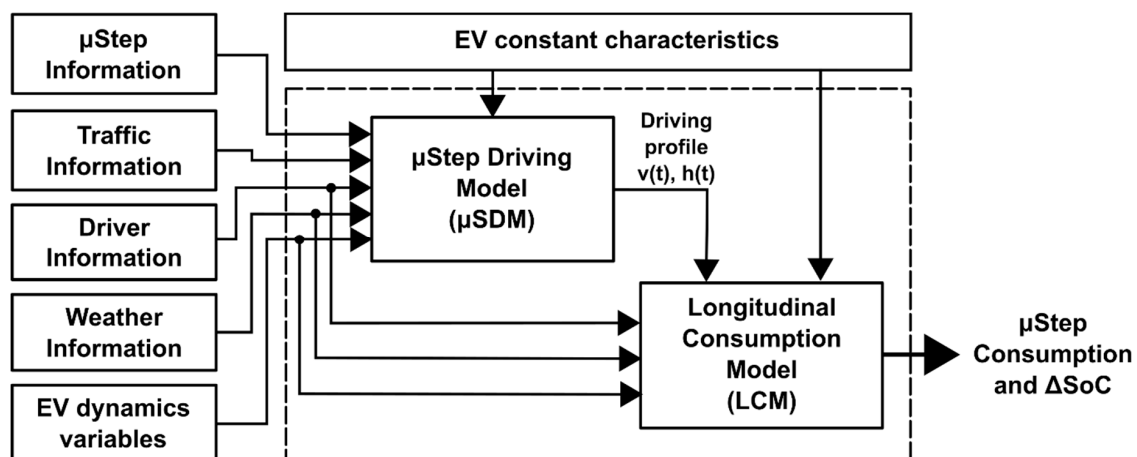

Figure 4. Consumption model architecture. EV, electrical vehicle; SoC, state of charge.

Table 3. List of consumption model inputs.

| Parameter	Group	Associated to
μStep distance		μSDM
μStep start elevation	μStep information	μSDM
μStep final elevation		μSDM
μStep estimated time		μSDM
Traffic congestion level	Traffic information	μSDM
Driver style	Driver information	μSDM, LCM
Precipitation level		μSDM, LCM
Average temperature	Weather information	μSDM, LCM
Sunrise/sunset time		μSDM, LCM
ECO mode state	EV dynamics variables	μSDM, LCM
Additional mass (passengers, baggage, etc.)		LCM
Initial SoC		LCM
Vehicle mass		LCM
Eq. mass of rotating parts		LCM
Maximum acceleration		μSDM, LCM
Frontal area		LCM
Friction resistance coefficient		LCM
Drag coefficient		LCM
Performance internal systems (inverter + engine + transmission)	EV constant characteristics	LCM
A/C consumption		LCM
Heating consumption		LCM
Cooling consumption		LCM
Light consumption		LCM
Power steering consumption		LCM
Secondary consumptions (light panels, control systems, etc.)		LCM
Battery performance		LCM
Battery capacity		LCM
Battery voltage		LCM
Maximum recovery capacity		LCM
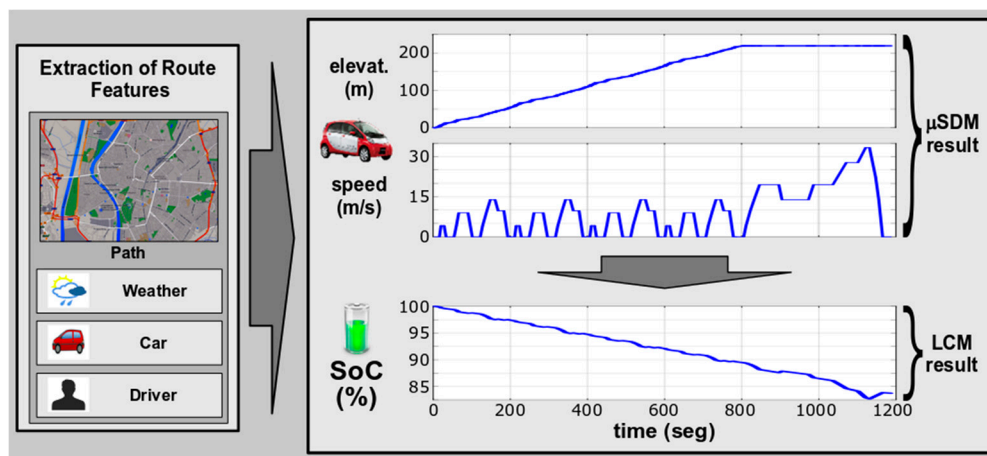
Figure 5. Steps for the SoC estimation process.

5. Prioritization Algorithm

Three algorithms are proposed to prioritize the charging queues:

- Genetic algorithm (GA).
- Genetic algorithm with evolution control (GAEC) based on fitness evolution curve.
- Swarm intelligence based on particle swarm optimization (PSO).

These algorithms were applied in the same scenario and different layers to determine the best combination of algorithms.

The application of these algorithms is performed after a preprocessing stage after the following steps:

1. The routes are sorted by starting timestamp, route distance, and ending timestamp.
2. The vehicles are sorted by range or battery capacity.
3. The drivers are sorted according to the difference between the real and expected routes, in ascending order. The new drivers or drivers without historical information are positioned in first place.
4. The charging stations are ordered by connector type according to the estimated charging period.

5.1. Genetic Algorithm (GA)

The genetic algorithm (GA) [50,51] is a bioinspired algorithm. This algorithm is based on the evolution of populations in which only the best individuals survive. Everyone from a population is a possible solution to a problem, and a fitness value is assigned according to an indicator that determines the distance from the final solution. In each evolution, a new generation from the previous population is created based on cross, mutation, and selection processes. After some evolutions (iterations), the algorithm converges to a best solution or a solution that complies with the threshold.

Algorithm 1. Genetic Algorithm (GA): size p of population ($P(t)$), rate q of elitism, rate c of crossover (default 0,9), and rate m of mutation (default 0,1).

---

1. Randomly generate p feasible solutions,
2. Save them in the population $P(t)$,
3. Evaluation of the population $P(t)$; thus, the fitness of each solution of the population $P(t)$ are determined.
4. Repeat

   a. Select parents from the population $P(t)$, number of elitism $n_e = p*q$.
   b. Perform the crossover on parents by creating the new population $P(t+1)$ with the probability c.
   c. Perform mutation of the population $P(t+1)$ with the probability m.
   d. Evaluation the population $P(t+1)$; thus, the fitness of each solution of the population $P(t+1)$ are determined.
   e. If the stopping criteria are true, then return to step 4.a; otherwise, proceed to step 5.

5. If the threshold is active then obtain all solutions for which the fitness value complies with the threshold; otherwise, obtain the best solution (the best evaluation value).

The stopping criteria is specified in the configuration of the prioritization algorithm.

5.2. Genetic Algorithm with Evolution Control (GAEC) Based on Fitness Evolution Curve

The GAEC is a genetic algorithm with additional restrictions that influence the probability of mutate and cross operators according to the fitness evolution curve. The fitness evolution curve is created in each evolution and stores the best fitness value of each evolution. The angle of the tangent line in each point of the fitness evolution curve determines the probability of the operators.

Algorithm 2. Genetic Algorithm with Evolution Control (GAEC): size *p* of the population (*P(t)*), rate *q* of elitism.

---

1. Randomly generate p feasible solutions,
2. Save them in the population *P(t)*,
3. Evaluation of the population *P(t)*; thus, the fitness of each solution of the population *P(t)* are determined.
4. Repeat

   a. Select parents from the population *P(t)*, number of elitism $n_e = p*q$.
   b. Perform the crossover on parents by creating the new population *P(t+1)*. with the probability based on the absolute value of the sine of the angle of the tangent line to the fitness evolution curve.
   c. Perform a mutation of the population *P(t+1)* with the probability based on the absolute value of the cosine of the angle of the tangent line to the fitness evolution curve.
   d. Evaluation the population *P(t+1)*; thus, the fitness of each solution of the population *P(t)* are determined.
   e. If the stopping criteria are true, then return to 4.a; otherwise, proceed to 5.

5. If the threshold is active, then obtain all solutions for which the fitness value complies with the threshold; otherwise, obtain the best solution (the best evaluation value).

5.3. Particle Swarm Optimization (PSO) Algorithm

The prioritization algorithm works as a swarm intelligence algorithm. The application of the algorithm is performed after a preprocessing of information.

The prioritization algorithm is based on the parametric optimization until a solution is obtained. This optimization is executed depending on the capabilities of a system. The algorithm employs a PSO to establish the initial prioritization for the charging stations in the company area. The canonical PSO model consists of a swarm of particles, which are initialized with a population of random candidate solutions. They iteratively move through the *d-dimension* problem space to search the new solutions, where the fitness *f* can be calculated as the certain qualities measure. Each particle has a position that is represented by the position-vector x_{id} (*i* is the index of the particle, and *d* is the dimension)) and a velocity represented by the velocity-vector v_{id}. Each particle remembers its best position in the vector $x_{i\#}$ and its *j-th* dimensional value is $x_{\#ij}$. The best position-vector among the swarm is stored in the vector x_*, and its *j-th* dimensional value is x_{*j}. At the iteration time *t*, the update of the velocity from the previous velocity to the new velocity is determined by Equation (1). The new position is determined by the sum of the previous position, and the new velocity is determined by Equation (2).

$$v_{id}(t+1) = w \cdot v_{id}(t) + c_1 \cdot \psi_1 \cdot (p_{id}(t) - x_i(t)) + c_2 \cdot \psi_2 \cdot (p_g(t) - x_{id}(t)), \tag{1}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), \tag{2}$$

where c_1 and c_2 are constant weight factors, p_i is the best position achieved by particle *i*, p_g is the best position obtained by the neighbors of particle *i*, ψ_1 and ψ_2 are random factors in the [0,1] interval, and w is the inertia weight. Some references denote c_1 and c_2 as the self-recognition component and the coefficient of the social component, respectively.

Different constraints can be applied to ensure convergence of the algorithm. In the cases proposed in this paper, the stopping criteria are based on a fitness threshold.

Algorithm 3. PSO Algorithm

---

1. Initialize particles.
2. Repeat

   a. Calculate the fitness values for each particle.
   b. Is the current fitness value better than p_i?

      i. Yes. Assign the current fitness as the new p_i.
      ii. No. Keep the previous p_i.

   c. Assign the best particle's p_i value to p_g.
   d. Calculate the velocity for each particle (Equation (1) and (2)).
   e. Use each particle's velocity value to update its data values.

3. Until stopping criteria are satisfied (fitness threshold).

5.4. Configuration of Prioritization Algorithms

The system enables different restrictions to be specified for the prioritization algorithm:

- Time interval to prioritize (one day by default).
- External charging. The system may accept a charging request from the DVPP.
- External charging priority. The system will assign the first available slot in the queues to the external vehicles; however, the system moves the vehicles of the SBVPP (if possible).
- Partial charging. The prioritization algorithm may accept the queue calculation based on the energy needs of a route. This option takes effect over the asset management system and the predictive maintenance of vehicles.
- Possibility of reuse drivers. A driver may be assigned to one or more routes and vehicles on the same day. The routes must be separated by time.
- Possibility of specifying periods of unavailability of charging stations. Time periods at the charging stations may be established or reserved. This option is employed by the predictive maintenance of the charging stations of the asset management system to establish non-periodical maintenance.
- Possibility of specifying periods of unavailability of vehicles. Time periods of the vehicles may be established or reserved. This option is employed by the predictive maintenance of the vehicles of the asset management system to establish non-periodical maintenance.
- Possibility of specifying periods of unavailability of drivers. Time periods for drivers may be established in case of time off for sick or medical leave.
- Driver rest periods along a route. Driver rest periods along routes are set to two hours by default.
- Driver rest periods between different routes. This period is dependent on the reuse driver parameter and the driver rest periods along a route. Thus, this time considers the last rest period for a driver along a route.
- Rest periods between vehicles that charge at charging stations. This time is configured in the system to establish the time invested in disconnecting a vehicle and connect the next vehicle.
- Maintenance periods for charging stations. The periods specified for this parameter are periodically performed.
- Maintenance periods for vehicles. The periods specified for this parameter are periodically performed.
- Usage balancing of charging stations. The calculated queues are calculated to balance the usage of charging stations.
- Assignation prioritization of external charge. If this option is enabled, the prioritization algorithm gives precedence to charging vehicles at charging stations that are outside of the company area.
- Possibility of several vehicles per route.

These parameters can be modified while the algorithm is running. These parameters take effect over the convergence of evolutionary algorithms because the parameters can modify the fitness function.

The evolutionary algorithms are based on an iterative algorithm. In this case, the proposed algorithms have several similarities. These algorithms have stopping criteria to control the iterative part of the algorithm. In the proposed algorithms, the end criteria can be configured by the user by specifying one or more parameters:

- Maximum number of iterations: the optimization process is terminated after a fixed number of iterations.
- Number of iterations without improvements: the optimization process is terminated after a fixed number of interactions without any iterations without any improvement.
- Minimum objective function error: the error between the obtained objective function value and the best fitness value is less than a prefixed anticipated threshold.

The value of these parameters is dependent on the size of the search space and the complexity of the problem. These values are established by the default value according to the number of vehicles, number of drivers, number of routes, and number of charging stations, as well as the system characteristics in the installation stage. Other parameters in the PSO algorithm are dependent on the same parameters:

- Maximum number of particles (swarm size or number of neighbors). This parameter establishes the maximum number of particles that are generated in the prioritization algorithm based on the particle swarm optimization (PSO) algorithm.
- Maximum velocity (v_{max}) for the PSO algorithm [52] to ensure convergence. If this parameter is set to *0*, a maximum velocity will not be obtained.
- Maximum particle position ($x_{i,max}$) for the PSO algorithm [52] to retain the value of the particle position between *[−$x_{i,max}$, $x_{i,max}$]*. If this parameter is set to *0*, a maximum position will not be obtained.
- Inertia weight (*w*) for PSO algorithm. A large inertia weight favors a global search, whereas a small inertia weigh favors a local search. If inertia is applied, it is sometimes linearly decreased during the iteration of the algorithm, beginning at an initial value that is close to 1.
- Modifiers for random number generation.
- Self-recognition component (must be a positive value).
- Coefficient of the social component (must be a positive value).
- Maximum and minimum velocity. These values establish the maximum variation of the solution.

A GA and GAEC have similar parameters:

- Population size.
- Only in a GA, the operator probabilities (mutation and crossover). These operators have a default value (0,1 for mutation and 0,9 for crossover); different values can be set.

These factors are employed in the algorithm to fix the evolution of each particle and dimension, in the case of PSO, or everyone in a population, in the case of a GA and GAEC. The previously defined parameters and the parameters defined in this section can modify the convergence of an algorithm. These parameters are automatically adjusted in each evolution and running.

5.5. Fitness Function

The fitness function is calculated to test the validity of a particle. The fitness function is based on the following items:

- The number of routes that have been assigned a vehicle and driver for the time requirements to perform the route. The first routes in time will have greater weight than the other routes.

- The number of routes that are assigned a vehicle and driver but exceed the time requirements to perform the route are significantly penalized.

Additionally, the parameters that are configured in the system can modify the final fitness value that is calculated for each solution:

- Queue balancing of a charging station. Standard deviation but with the total number of vehicles assigned to a route divided by the total number of charging stations.
- External charging. If external charging is configured, the system multiplies the fitness value by the total number of vehicles with external charging divided by the total number of vehicles assigned to a route.
- External charging priority. If external charging is permitted.
- Reuse of vehicles.
- Reuse of drivers.
- Assignation prioritization of external charging.
- Several vehicles per route.
- Instructions from higher VPPs.

Several of these configurations can change at any time. Thus, the fitness value can change for each generation of evolutionary algorithm.

The proposed fitness function is performed in the proposed evolutionary algorithms. Thus, the fitness value is normalized in the interval [−1,1]. This fact simplifies the comparison of different options.

6. Experimental Results

The proposed algorithm was tested in different scenarios. These scenarios were simulated using a computer. Several entities are created:

- Two smart business parks (A and B) with separate EV fleets. Company A is a company in the logistics sector, and company B is a company in the transport sector.
- Three public charging stations.
- Five private EVs.

From the point of view of the power market:

- Two power retail companies. The first retailer has a contract for supply to company A. The second retailer has a contract for supply to company B. The retailer has three contracts for supply to private consumers.
- One power distribution company.
- An EMS is simulated. This system is configured to randomly generate a power consumption command in the EVPP. This power consumption command takes effect on 343 routes: 137 routes from company A and 206 routes from company B. This power consumption will be generated after a solution is obtained to assess the algorithm and address any changes in conditions.
- Companies A and B have an SBVPP. The characteristics of these companies are listed in Table 4. For each driver, EV, and charging station, some periods of unavailability are defined to check the capability of the algorithms to manage these contingencies.
- In this case, the private consumers are managed by the RVPP. In future research (refer to Section 8), the system will attempt to include a consumer VPP.

| Characteristics	Company A	Company B
Number of routes	400	600
Number of EVs	6	10
Number of drivers	5	7
Number of charging stations	2	2
Number of plugs by charging station	2	3
Power of charging stations	DC 50 kW/AC 43 kVA	DC 50 kW/AC 43 kVA
Time of fast-charge (0–80%)	30 minutes	30 minutes

The evaluation of the proposed solution is conducted in several scenarios:

- Using only evolutionary algorithms based on GA.
- Using only evolutionary algorithms based on GAEC.
- Using only evolutionary algorithms based on PSO.
- Hybrid solution. All possible combinations (81 cases) were tested; however, only the best hybrid solution is shown in this paper. The best hybrid solution applies PSO in SBVPP and GAEC in the higher VPPs.

The proposed solution is evaluated by checking two aspects; both aspects are evaluated in the general best fitness curve:

- Convergence time (t_c). Time to reach a solution. The convergence time is measured in number of generations.
- Transient time (t_t). Time to obtain a new solution when changes occur in the conditions of the problem. The transient time is measured in number of generations.

Figures 6 and 7 shows fitness curves. The fitness curves show the evolution of the fitness value in each new iteration, extracting the best fitness value in each population and in each iteration of PSO algorithm. The different algorithms are based in the elitism feature, so the best fitness value will be always preserved until the conditions change: a new car is added, a new route is added, etc. These situations provoke the fitness value variations in the evaluation stage, and the algorithm finds a new solution for the new scenario.
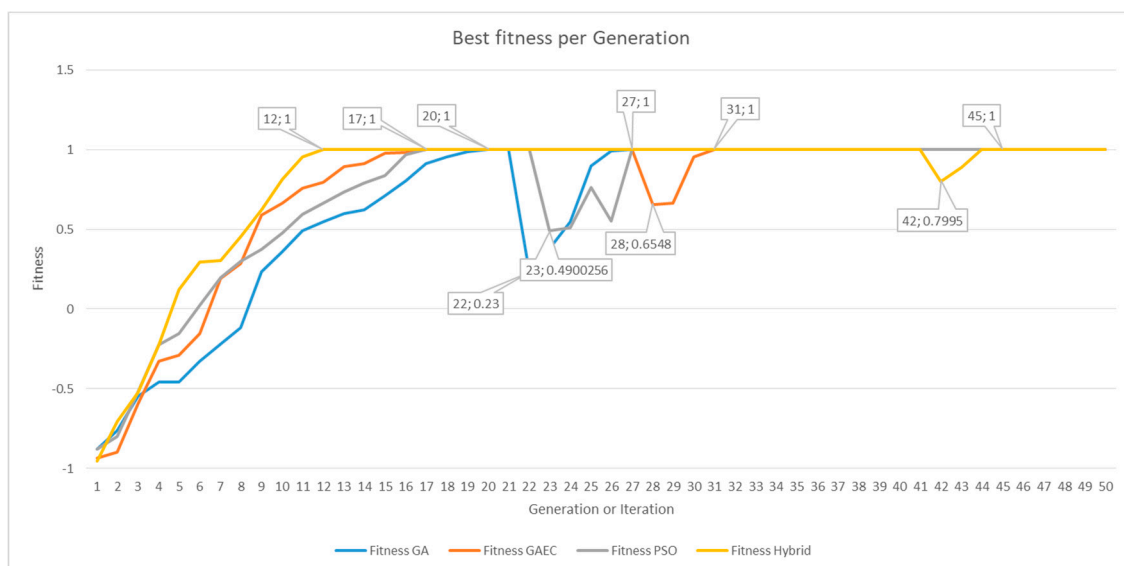
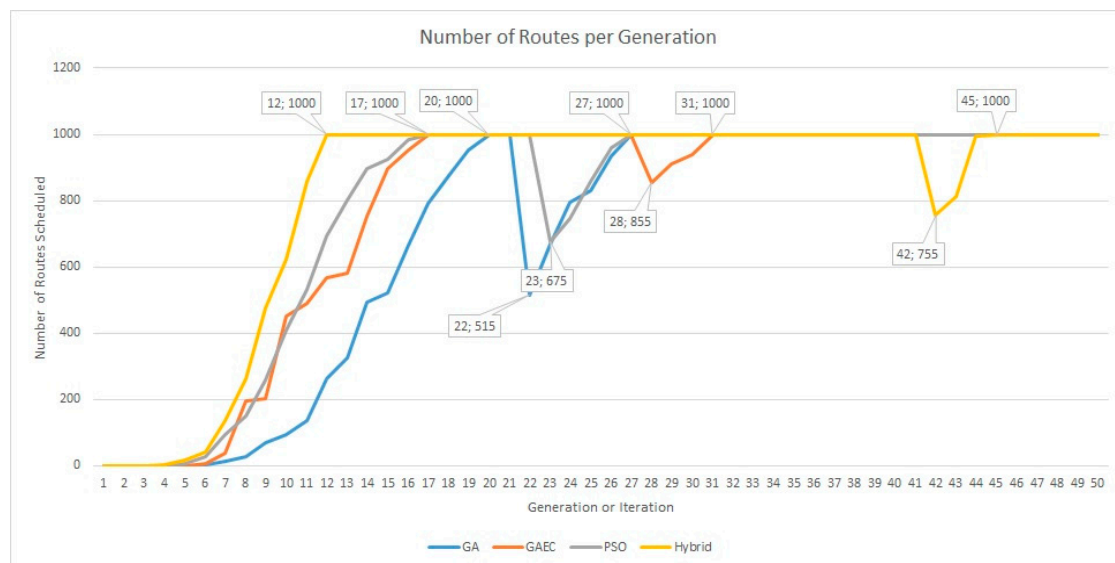**Figure 6.** General best fitness curve.

Figure 7. Translate of general best fitness curve to the number of assigned routes.

The general best fitness curve for each scenario is shown in Figure 6. The first part (until generation 20) of the curve is the search of the best solution to schedule the routes (1000 routes). The corresponding number of scheduled routes is shown in Figure 7. After the best solution is obtained, the simulated EMS randomly generates several commands in each scenario. In the case of the GA scenario, the command was fired in generation 22 (Figure 6) with 515 scheduled routes (Figure 7); in the GAEC scenario, the command was fired in generation 23 with 675 scheduled routes; in the PSO scenario, the command was fired in generation 28 with 855 scheduled routes; and in the hybrid scenario, the command was fired in generation 42 with 755 scheduled routes. Although the command takes effect in the same 343 routes in all scenarios, the results did not agree with the fitness value (Figure 6) and the number of scheduled routes (Figure 7) between different scenarios. When the command is fired, the fitness is updated with the new restrictions. This updating changed the value of the best solution by converting it into another solution with lower fitness. In the population (in the case of GA and GAEC) or swarm (in the case of PSO), several solutions were re-assessed. Although some solutions were not the best solutions in the initial scenario, after the command was fired, the new fitness value improved, and the solutions were sorted according to this new assessed fitness.

In the same manner, the transient time is less than the initial part of the algorithm because the current solutions are disseminated in the space of possible solutions. Thus, the solution is obtained at a faster rate.

According to the results, some conclusions are formed:

- GA and PSO exhibit the best trend.
- GAEC performs better in transient situations.
- The hybrid solution obtains better results because it takes advantage of all evolutionary algorithms.

One of the most interesting effects is shown in Figure 6 in GAEC (fitness GAEC) scenario. This algorithm has several steps. In these steps, the mutation probability is increased, and the crossover is decreased. This fact disseminates the solutions in the space of possible solutions, which increases the probability of obtaining better solutions. In Figures 6 and 7, the convergence of the fitness GAEC is better than the others. Although, the hybrid solution shows the best results, as shown in Table 5, this algorithm includes GAEC and others. The usage of GAEC or the same algorithm in all VPPs will simplify the deployment of proposed architecture.

Table 5. Evaluation parameters for each scenario. GA, genetic algorithm; GAEC, genetic algorithm with evolution control; PSO, particle swarm optimization.

Test Scenarios	t_c (Number of Generations)	t_t (Number of Generations)
Only GA	20	5
Only GAEC	17	3
Only PSO	17	4
Hybrid Solution	12	3

7. Conclusions

A novel solution for the distributed prioritization of charging station queues is presented in this paper. This novel solution provides several contributions to the state of art:

- A model for the implementation of VPP, based on the interaction between different roles in the power supply: transportation, distribution, commercialization, and consumption (especially in the case of companies with EV fleets).
- Organizational chart functionality according to the level of VPP.
- Several distributed prioritization algorithms to manage the queues for private and public charging stations.

A comparison of several evolutionary algorithms with the same fitness function. The proposed solution provides additional results:

- A scalable framework to manage the EV fleet, to improve the efficiency in its management.
- A model of mobile load inside a power grid. The algorithm provides a load forecasting of mobile loads (storage or resources) and it calculate again in real time in case of unexpected incident or an additional EV is added.
- The reductions of emissions by vehicle fleet are about 75.2% compared with the conventional vehicles with fossil combustible. Additionally, the forecasting of mobile loads provided to the energy management systems could reduce the peaks in demand curve, decreasing the emissions by using cycled combined (which usually are based in fossil combustibles).
- The comparison between different energy management scenarios showing the Hybrid solution as the best solution to different scenarios.
- The aggregation in different levels decrease the response time of system at different levels, allowing to respond in real time. On the consumer side, the EV is charging with minimized waiting periods. On the retailer side, the retailer can offer different rates and services according to the demand forecasting. In the distribution and energy side, the asset management, the energy flow, and the demand peak shaving are simplified based on demand forecasting.
- The reduction of waiting time to charge the EV. The prioritization considers the minimization of the waiting time.

Although the usage of EVs can be an excellent solution for decreasing pollution, it may cause serious problems in the power grid. Several solutions can be applied to solve this problem. In this paper, the proposed solution is to establish prioritization queues that enable control of the mobile loads or EV charging by taking advantage of the fact that this EV can only be plugged into charging stations. This type of knowledge can help energy management systems and other participants of power distribution to maintain a high quality of service and supply. Additionally, this knowledge provides information for distributed energy resource management system in the case of an alarm or emergency; in this case, the battery of EV (V2G) can serve as energy storage and support the needs of the power grid.

8. Future Research

Future research is based on the evolution of the solution and focuses on several topics:

- Develop an asset management system.
- Test the solution for personal EV vehicles in the prioritization process. The consumer VPP for an EV is in development.
- Update the fitness function to provide additional functionality in the emergency mode of the power grid.
- Develop a new algorithm to provide the best configuration options for the corresponding VPP.
- Develop a demand response management system to integrate an energy and capacity market based on blockchain and big data technologies.

Acronyms

Acronym	Definition
ANN	artificial neural network
CHP	combined heat and power
CIM	common information model
CIS	component interface specification
DEPF	distributed evolutionary prioritization framework
DER	distributed energy resources
DERMS	distributed energy resources management system
DRMS	Demand Response Management System
DSO	distribution system operators
DVPP	distribution virtual power plant
E-FSMFTW	electric fleet size and mix vehicle routing problem with time windows and recharging Stations
EV	electric vehicle
EVPP	energy virtual power plant
FNN	fuzzy neural network
GA	genetic algorithm
GAEC	genetic algorithm with evolution control
GVPP	generic virtual power plant
HEV	hybrid electric vehicle
ICT	information and communication technologies
IEC	international electrotechnical commission
LCM	longitudinal consumption model
NEDC	new European driving cycle
NIST	National Institute of Standards and Technology
PHEV	plug-in hybrid electric vehicle
PSO	particle swarm optimization
RDBMS	relational database management system
RVPP	retailer virtual power plant
SBVPP	smart business virtual power plant
SG	smart grid
SOA	service-oriented architecture
SoC	state of charge
TVPP	technical virtual power plant
V2G	vehicle to grid
VPP	virtual power plant
μSDM	μStep driving model

References

1. Meissner, E.; Richter, G. Battery Monitoring and Electrical Energy Management: Precondition for future vehicle electric power systems. *J. Power Sources* **2003**, *116*, 79–98. [CrossRef]
2. Chau, K.T.; Wong, Y.S.; Chan, C.C. An overview of energy sources for electric vehicles. *Energy Convers. Manag.* **1999**, *40*, 1021–1039. [CrossRef]
3. Nelson, R.F. Power requirements for batteries in hybrid electric vehicles. *J. Power Sources* **2000**, *91*, 2–26. [CrossRef]
4. Gerssen-Gondelach, S.J.; Faaij, A.P.C. Performance of batteries for electric vehicles on short and longer term. *J. Power Sources* **2012**, *212*, 111–129. [CrossRef]
5. Martel, F.; Dubé, Y.; Kelouwani, S.; Jaguemont, J.; Agbossou, K. Long-term assessment of economic plug-in hybrid electric vehicle battery lifetime degradation management through near optimal fuel cell load sharing. *J. Power Sources* **2016**, *318*, 270–282. [CrossRef]
6. Marra, F.; Sacchetti, D.; Træholt, C.; Larsen, E. Electric vehicle requirements for operation in smart grids. In Proceedings of the 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), Manchester, UK, 5–7 December 2011; pp. 1–7.
7. Masuch, N.; Keiser, J.; Lützenberger, M.; Albayrak, S. Wind power-aware vehicle-to-grid algorithms for sustainable EV energy management systems. In Proceedings of the Electric Vehicle Conference (IEVC), Greenville, SC, USA, 4–8 March 2012; pp. 1–7.
8. Valentine, K.; Temple, W.; Thomas, R.J.; Zhang, K.M. Relationship between wind power, electric vehicles and charger infrastructure in a two-settlement energy market. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 225–232. [CrossRef]
9. Giannouli, M.; Yianoulis, P. Study on the incorporation of photovoltaic systems as an auxiliary power source for hybrid and electric vehicles. *Sol. Energy* **2012**, *86*, 441–451. [CrossRef]
10. Romero-Ruiz, J.; Pérez-Ruiz, J.; Martin, S.; Aguado, J.A.; De la Torre, S. Probabilistic congestion management using EVs in a smart grid with intermittent renewable generation. *Electr. Power Syst. Res.* **2016**, *137*, 155–162. [CrossRef]
11. Ross, S.M. 8—Queueing Theory. In *Introduction to Probability Models*, 12th ed.; Ross, S.M., Ed.; Academic Press: Cambridge, MA, USA, 2019; pp. 507–589. ISBN 978-0-12-814346-9.
12. Bachmat, E. Airplane boarding meets express line queues. *Eur. J. Oper. Res.* **2019**, *275*, 1165–1177. [CrossRef]
13. Strielkina, A.; Uzun, D.; Kharchenko, V. Modelling of healthcare IoT using the queueing theory. In Proceedings of the 2017 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Bucharest, Romania, 21–23 September 2017; Volume 2, pp. 849–852.
14. Lakshmi, C.; Appa Iyer, S. Application of queueing theory in health care: A literature review. *Oper. Res. Health Care* **2013**, *2*, 25–39.
15. Pourvaziri, H.; Pierreval, H. Dynamic facility layout problem based on open queuing network theory. *Eur. J. Oper. Res.* **2017**, *259*, 538–553. [CrossRef]
16. Babicheva, T.S. The Use of Queuing Theory at Research and Optimization of Traffic on the Signal-controlled Road Intersections. *Procedia Comput. Sci.* **2015**, *55*, 469–478. [CrossRef]
17. Fedorenko, V.; Fedorenko, I.; Sukmanov, A.; Samoylenko, V.; Shlaev, D.; Atanov, I. Modeling of data acquisition systems using the queueing theory. *Aeu-Int. J. Electron. Commun.* **2017**, *74*, 83–87. [CrossRef]
18. Apte, V. Performance Analysis of Distributed Software Systems: Approaches Based on Queueing Theory. In Proceedings of the 2007 Working IEEE/IFIP Conference on Software Architecture (WICSA'07), Mumbai, India, 6–9 January 2007; p. 39.
19. Dielmann, K.; van der Velden, A. Virtual power plants (VPP)—A new perspective for energy generation? In Proceedings of the 9th International Scientific and Practical Conference of Students, Post-graduates Modern Techniques and Technologies, Tomsk, Russia, 7–11 April 2003; 18–20; pp. 18–20.
20. Schulz, C.; Roder, G.; Kurrat, M. Virtual power plants with combined heat and power micro-units. In Proceedings of the 2005 International Conference on Future Power Systems, Amsterdam, The Netherlands, 16–18 November 2005; 2005; p. 5.

21. Dimeas, A.L.; Hatziargyriou, N.D. Agent based control of Virtual Power Plants. In Proceedings of the International Conference on Intelligent Systems Applications to Power Systems, Kaohsiung, Taiwan, 5–8 November 2007; pp. 1–6.
22. Pudjianto, D.; Ramsay, C.; Strbac, G. Virtual power plant and system integration of distributed energy resources. *IET Renew. Power Gener.* **2007**, *1*, 10–16. [CrossRef]
23. Andersen, P.B.; Poulsen, B.; Decker, M.; Traeholt, C.; Ostergaard, J. Evaluation of a Generic Virtual Power Plant framework using service oriented architecture. In Proceedings of the Power and Energy Conference, Langkawi, Malaysia, 2–4 April 2008; pp. 1212–1217.
24. Andersen, P.B.; Poulsen, B.; Træholt, C.; Østergaard, J. Using Service Oriented Architecture in a Generic Virtual Power Plant. In Proceedings of the Sixth International Conference on Information Technology: New Generations (ITNG '09), Las Vegas, NV, USA, 27–29 April 2009; pp. 1621–1622.
25. Kieny, C.; Berseneff, B.; Hadjsaid, N.; Besanger, Y.; Maire, J. On the concept and the interest of virtual power plant: Some results from the European project Fenix. In Proceedings of the IEEE Power Energy Society General Meeting (PES '09), Calgary, AB, Canada, 26–30 July 2009; pp. 1–6.
26. Mashhour, E.; Moghaddas-Tafreshi, S.M. The opportunities for future virtual power plant in the power market, a view point. In Proceedings of the 2009 International Conference on Clean Electrical Power, Capri, Italy, 9–11 June 2009; pp. 448–452.
27. You, S.; Træholt, C.; Poulsen, B. Generic Virtual Power Plants: Management of distributed energy resources under liberalized electricity market. In Proceedings of the 8th International Conference on Advances in Power System Control, Operation and Management (APSCOM), Hong Kong, China, 8–11 November 2009; pp. 1–6.
28. Binding, C.; Gantenbein, D.; Jansen, B.; Sundström, O.; Andersen, P.B.; Marra, F.; Poulsen, B.; Træholt, C. Electric vehicle fleet integration in the danish EDISON project—A virtual power plant on the island of Bornholm. In Proceedings of the IEEE PES General Meeting 2010, Minneapolis, MI, USA, 25–29 July 2010; pp. 1–8.
29. Jansen, B.; Binding, C.; Sundstrom, O.; Gantenbein, D. Architecture and Communication of an Electric Vehicle Virtual Power Plant. In Proceedings of the 2010 First IEEE International Conference on Smart Grid Communications (SmartGridComm), Gaithersburg, MD, USA, 4–6 October 2010; pp. 149–154.
30. Musio, M.; Lombardi, P.; Damiano, A. Vehicles to grid (V2G) concept applied to a Virtual Power Plant structure. In Proceedings of the 2010 XIX International Conference on Electrical Machines (ICEM), Rome, Italy, 6–8 September 2010; pp. 1–6.
31. Skarvelis-Kazakos, S.; Papadopoulos, P.; Grau, I.; Gerber, A.; Cipcigan, L.M.; Jenkins, N.; Carradore, L. Carbon optimized Virtual Power Plant with Electric Vehicles. In Proceedings of the 45th International on Universities Power Engineering Conference (UPEC), Cardiff, UK, 31 August–3 September 2010; pp. 1–6.
32. Raab, A.F.; Ferdowsi, M.; Karfopoulos, E.; Unda, I.G.; Skarvelis-Kazakos, S.; Papadopoulos, P.; Abbasi, E.; Cipcigan, L.M.; Jenkins, N.; Hatziargyriou, N.; et al. Virtual Power Plant Control concepts with Electric Vehicles. In *Proceedings of the 2011 16th International Conference on Intelligent System Application to Power Systems (ISAP)*; IEEE: Piscataway, NJ, USA, 2011; pp. 1–6.
33. Sanduleac, M.; Eremia, M.; Toma, L.; Borza, P. Integrating the Electrical Vehicles in the Smart Grid through unbundled Smart Metering and multi-objective Virtual Power Plants. In Proceedings of the 2011 2nd IEEE PES International Conference and Exhibition on Innovative Smart Grid Technologies (ISGT Europe), Manchester, UK, 5–7 December 2011; pp. 1–8.
34. Marra, F.; Sacchetti, D.; Pedersen, A.B.; Andersen, P.B.; Traholt, C.; Larsen, E. Implementation of an Electric Vehicle test bed controlled by a Virtual Power Plant for contributing to regulating power reserves. In Proceedings of the 2012 IEEE Power and Energy Society General Meeting, San Diego, CA, USA, 22–26 July 2012; pp. 1–7.
35. He, Y.; Chowdhury, M.; Ma, Y.; Pisu, P. Merging mobility and energy vision with hybrid electric vehicles and vehicle infrastructure integration. *Energy Policy* **2012**, *41*, 599–609. [CrossRef]
36. Mansour, S.; Harrabi, I.; Maier, M.; Joós, G. Co-simulation study of performance trade-offs between centralised, distributed, and hybrid adaptive PEV charging algorithms. *Comput. Netw.* **2015**, *93*, 153–165. [CrossRef]
37. Hiermann, G.; Puchinger, J.; Ropke, S.; Hartl, R.F. The Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations. *Eur. J. Oper. Res.* **2016**, *252*, 995–1018. [CrossRef]

38. Hu, J.; Morais, H.; Sousa, T.; Lind, M. Electric vehicle fleet management in smart grids: A review of services, optimization and control aspects. *Renew. Sustain. Energy Rev.* **2016**, *56*, 1207–1226. [CrossRef]
39. Wu, X.; Aviquzzaman, Md.; Lin, Z. Analysis of plug-in hybrid electric vehicles' utility factors using GPS-based longitudinal travel data. *Transp. Res. Part C Emerg. Technol.* **2015**, *57*, 1–12. [CrossRef]
40. De Cauwer, C.; Van Mierlo, J.; Coosemans, T. Energy Consumption Prediction for Electric Vehicles Based on Real-World Data. *Energies* **2015**, *8*, 8573–8593. [CrossRef]
41. Shankar, R.; Marco, J. Method for estimating the energy consumption of electric vehicles and plug-in hybrid electric vehicles under real-world driving conditions. *IET Intell. Transp. Syst.* **2013**, *7*, 138–150. [CrossRef]
42. Park, J.; Chen, Z.; Kiliaris, L.; Kuang, M.L.; Masrur, M.A.; Phillips, A.M.; Murphey, Y.L. Intelligent Vehicle Power Control Based on Machine Learning of Optimal Control Parameters and Prediction of Road Type and Traffic Congestion. *IEEE Trans. Veh. Technol.* **2009**, *58*, 4741–4756. [CrossRef]
43. Boriboonsomsin, K.; Barth, M.J.; Zhu, W.; Vu, A. Eco-Routing Navigation System Based on Multisource Historical and Real-Time Traffic Information. *IEEE Trans. Intell. Transp. Syst.* **2012**, *13*, 1694–1704. [CrossRef]
44. Bingham, C.; Walsh, C.; Carroll, S. Impact of driving characteristics on electric vehicle energy consumption and range. *IET Intell. Transp. Syst.* **2012**, *6*, 29–35. [CrossRef]
45. Lee, J.; Kang, M.-J.; Park, G.-L. Battery Consumption Modeling for Electric Vehicles Based on Artificial Neural Networks. *Lect. Notes Comput. Sci.* **2014**, 733–742.
46. Lee, D.-T.; Shiah, S.-J.; Lee, C.-M.; Wang, Y.-C. State-of-Charge Estimation for Electric Scooters by Using Learning Mechanisms. *Ieee Trans. Veh. Technol.* **2007**, *56*, 544–556. [CrossRef]
47. Schaltz, E. Electrical Vehicle Design and Modeling. *Electr. Veh.-Model. Simul.* **2011**.
48. Chan, C.C.; Bouscayrol, A.; Chen, K. Electric, Hybrid, and Fuel-Cell Vehicles: Architectures and Modeling. *IEEE Trans. Veh. Technol.* **2010**, *59*, 589–598. [CrossRef]
49. Regulation No 101 of the Economic Commission for Europe of the United Nations (UN/ECE). *Off. J. Eur. Union* **2007**, *158*, 34–105.
50. Holland, J.H. *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence*; MIT Press: Cambridge, MA, USA, 1992; ISBN 978-0-262-08213-6.
51. Goldberg, D.E. *Genetic Algorithms in Search, Optimization and Machine Learning*, 1st ed.; Addison-Wesley Longman Publishing Co., Inc.: Boston, MA, USA, 1989; ISBN 978-0-201-15767-3.
52. Clerc, M.; Kennedy, J. The particle swarm—Explosion, stability, and convergence in a multidimensional complex space. *IEEE Trans. Evol. Comput.* **2002**, *6*, 58–73. [CrossRef]