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Forecasting Recharging Demand to Integrate Electric Vehicle Fleets in Smart Grids

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Abstract

Electric vehicle fleets and smart grids are two growing technologies. These technologies 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, the comparison of several evolutionary algorithms, genetic algorithm, genetic algorithm with evolution control, particle swarm optimization, and hybrid solution are shown in order to evaluate the proposed architecture. The proposed solution is presented to prevent the overload of the power grid.

Keywords: smart grids, vehicle-to-grid, electric vehicles, charging prioritization, electric vehicle fleets, evolutionary computation

1. Introduction

The electric vehicle (EV) means a new research field in smart grid (SG) ecosystems [1]. Currently, the new generation of EV provides different technologies that can be integrated in SGs [2]. However, these new technologies make the distribution grid management difficult [3, 4]. In particular, the EVs and the infrastructure needed to charge them have provided a great quantity of new standards and technologies. Currently, there are several research lines related to EVs, fast-charging networks (e.g., see [5], battery performance modeling [6], parasitic energy consumption, EV promotional policies, and increase in the range of the battery in EV [7], and other research lines related to EV energy management, contract models for consumption vehicle, market model to adopt the EVs, distributed energy resources management systems (DERMS), DER standards, faster charging technologies, demand response management systems (DRMS), the role of aggregators in the V2G (vehicle-to-grid), and energy efficiency (e.g., see [8], customer support, driver support, etc.). Additionally, all these lines are influenced by current regulations, and it could be very different among countries (e.g., the regulation between United States and Europe is very different in energy management). The charging infrastructure affects the SG on several levels. These levels concern transportation,

distribution, and retailer levels. The main affected frameworks inside these levels are energy management, distribution management, and demand response. The energy management systems compound several functions [9]. One of them is the control of energy flows. The charging of EV can be made in any point of the grid that 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 [10, 11]. The distribution management is related to distribution system operators (DSO). Usually, the charging infrastructure oversees DSOs. Thus, the DSOs must manage these facilities and maintain the information about them. Finally, the demand response concerns retailers and DSOs, and the main problem is demand curve flattening and price management [12]. Nevertheless, the new paradigm proposed by standard organizations, like National Institute of Standards and Technology (NIST), International Electrotechnical Commission (IEC), etc., related to the V2G proposed that the EV could charge or discharge the batteries [13]. 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 [14].

This paper proposed a solution for fleet charging prioritization, based on the concept of 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. Bibliographic review

There are several research lines that are related with EVs, involving batteries (e.g., in [15], renewable energy [16], battery management systems [17, 18], energy management systems [19], charging spots [20, 21], driver assistance system [22], etc.). The EVs in the last millennium [23] provided a scenario with several vehicles with different types of vehicles: EVs, hybrid electric vehicles (HEVs), fuel cell vehicles, etc. The introduction of EVs provides several advantages, like reduction in greenhouse gas emissions [24]. But people's acceptance is necessary of EVs for daily usage [85, 86] and to have additional energy resources [23] in order to include the associated infrastructure. Additionally, the acceptance of EVs for daily usage, 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 [25]. Additionally, there are several studies about the performance of batteries in Ref. [26] and battery degradation in [27]. The new generation of EVs has several requirements not only in power but also infrastructure in Ref. [28]. 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 [87, 88], photovoltaic resources [29], general congestion of EV charging based on renewables [30], etc. However, SGs have provided a good scenario to integrate EVs and charging infrastructure.

Another solution could be the application of the queue theory [31]. The queue theory has an application in several topics: boarding management in [32], healthcare in Refs. [89, 90], dynamic facility layout problem in [33], optimization

of traffic by means of signal-controlled management in [34], data acquisition in [35], etc. Usually, these references manage only one queue or several independent queues. However, there are more complex problems based on distributed software systems [36], 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.

There are other manners to manage the EV fleets that involve directly or indirectly the demand concept, improving the accuracy of energy forecasting [37]. The driver pattern modeling could improve fleet management, increasing the efficiency and sustainability and it could be used to forecast demand, some of these cases are: vehicular driving patterns in the Edinburgh region and to offer an option of battery electric vehicles for sustainable mobility is estimated in Ref. [38]; usage patterns and the user perception are the main objectives of a longitudinal assessment of the viability of EV for daily use study in Ref. [39]; the usage of autonomous vehicles and eco-routing like in [40]; or, ridesharing of shared autonomous vehicle fleet [41]. There are other examples oriented to transport management which includes in different ways the concept of demand: a bi-level optimization framework for EV fleet charging based on a realistic EV fleet model including a transport demand sub-model is proposed in Ref. [42]. Other references treated the problem from the point of view of the congestion management of the electrical distribution network in case of limited overall capacity, for example, a distributed control algorithm for optimal charging is proposed in reference [43], or depending on the routing problem [44], allowing partial battery recharging with hybrid fleets (conventional and electric vehicles). Other references provided a solution to integrate renewable energy sources, investigating the possibilities to integrate additionally loads of uncertain renewable energy sources by smart-charging strategies as is proposed in Ref. [45].

There are several algorithms which provide solutions related to peak saving in demand curve. A real-time EV smart-charging method that not only considers currently connected EVs but also uses a prediction of the EVs that are expected to plug in the future is proposed in Ref. [46].

The authors in Ref. [47] 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 [48] proposed the integration of combined heat and power (CHP) microunits based on VPP in a low voltage network from a technical and economical point of view. The authors of [49] presented a new concept where microgrids and other production or consumption units form a VPP. The authors of [50] 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 [51] 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 [52] provided a suitable software framework to implement GVPP with SOA. The FENIX European Project [53] 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 [54] described a general framework for future VPP to control low and medium voltage for DER management. The authors of [55] presented a case study which shows how a broker GVPP was developed based on the selection of appropriate functions. The

EDISON Danish project [56] 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 [57] proposed an architecture for EV fleet coordination based on V2G integrating VPP. The authors of [58] analyzed the possibility of using EVs as an energy storage system (V2G) within a VPP structure. The authors of [59] considered the EV as a mobile load and described a VPP containing aggregated microgeneration sources and EV, but it is centered around minimizing carbon emissions. The authors of [60] proposed and discussed three approaches for grid integration of EVs through a VPP: control structure, resource type, and aggregation. The authors of [61] presented a solution for integrating EVs in the SG through unbundled smart metering and VPP technology dealing with multiple objectives. The authors of [62] 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. Although the aggregation idea is not always implemented with a VPP, for example, the authors in [63] proposed an aggregate battery modeling approach for EV fleet, which is aimed for energy planning studies of EV-grid integration, they did not use the concept of VPP. The present paper proposes the charging prioritization of EV fleets to provide additional services [64], like EV fleet management or demand forecasting.

Of course, there are not a lot of examples of EV fleet currently with a complete charging infrastructure, notwithstanding several references papers in the simulation focused in EV fleet simulation, for example, an evolutionary approach is proposed in Ref. [65] or a planning simulation model is presented in Ref. [66] that evaluates the feasibility of electric vehicle driving range when recharging is considered at home, at work, or at quick charging stations. But some scenarios are more difficult to simulate, for example, the use of electric modules which can be added or removed from a freight vehicle proposed in Ref. [67]. However, the problem, in this case, is the recharging of electric modules, which is done in different nodes or point of reception, and they will have a charging infrastructure; the authors provide a good mathematical background to calculate the time windows of electric module availability. This problem is similar to battery exchange infrastructures proposed in Ref. [68].

Additionally, a charging management could provide a good contribution to the demand forecasting, although the different references did not treat the problem of demand forecasting, but the scheduling and suitable assignment of EVs to charging stations could provide information about the demand in the charging stations. For example, the optimal solution provided in Ref. [69] could be a contribution for an algorithm to provide an aggregated demand forecasting. Other solutions are oriented to specific sectors or infrastructures: EV fleet parking determining the minimum number of chargers that are required to charge all electric vehicles [70] or estimating total daily impact of vehicles aggregated in parking lots on the grid [71], taxi fleets [72], and taxi fleets with mixed electric and conventional vehicles [73].

On the other hand, some researchers have studied the impact of HEV and plug-in HEV (PHEV) [74]. In this sense, decentralized algorithms for coordinating the charging of multiple EVs have gained importance in recent years. The authors of [75] compared several approaches based on centralized, decentralized, and hybrid algorithm, with the latter showing better results. The authors of [76] 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 regard to fleet composition and vehicle routes, including the choice of recharging times and locations. The authors of [64] 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. Virtual power plants

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. The 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**. The proposed architecture is based on VPP concept [77]. 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 way, 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 in different levels was based on an extension of the Common Information Model (CIM) from IEC 61970, 61,968, and 62,325. The interface information is based on the Component Interface Specification (CIS) from the IEC. The Open Automated Demand Response (OpenADR) version 2.0 is included in the VPP, but it is only enabled in some levels. 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.

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 2**. The modules are shown in **Figure 2**. 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).

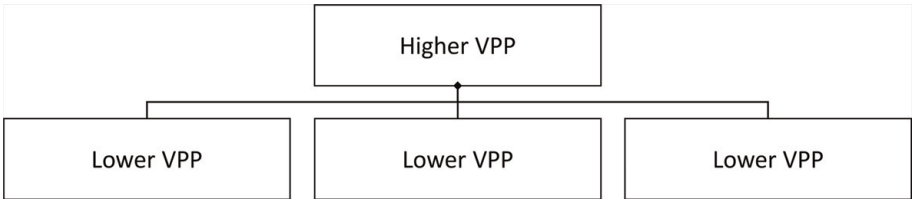


Figure 1.
Conceptual model of VPP.

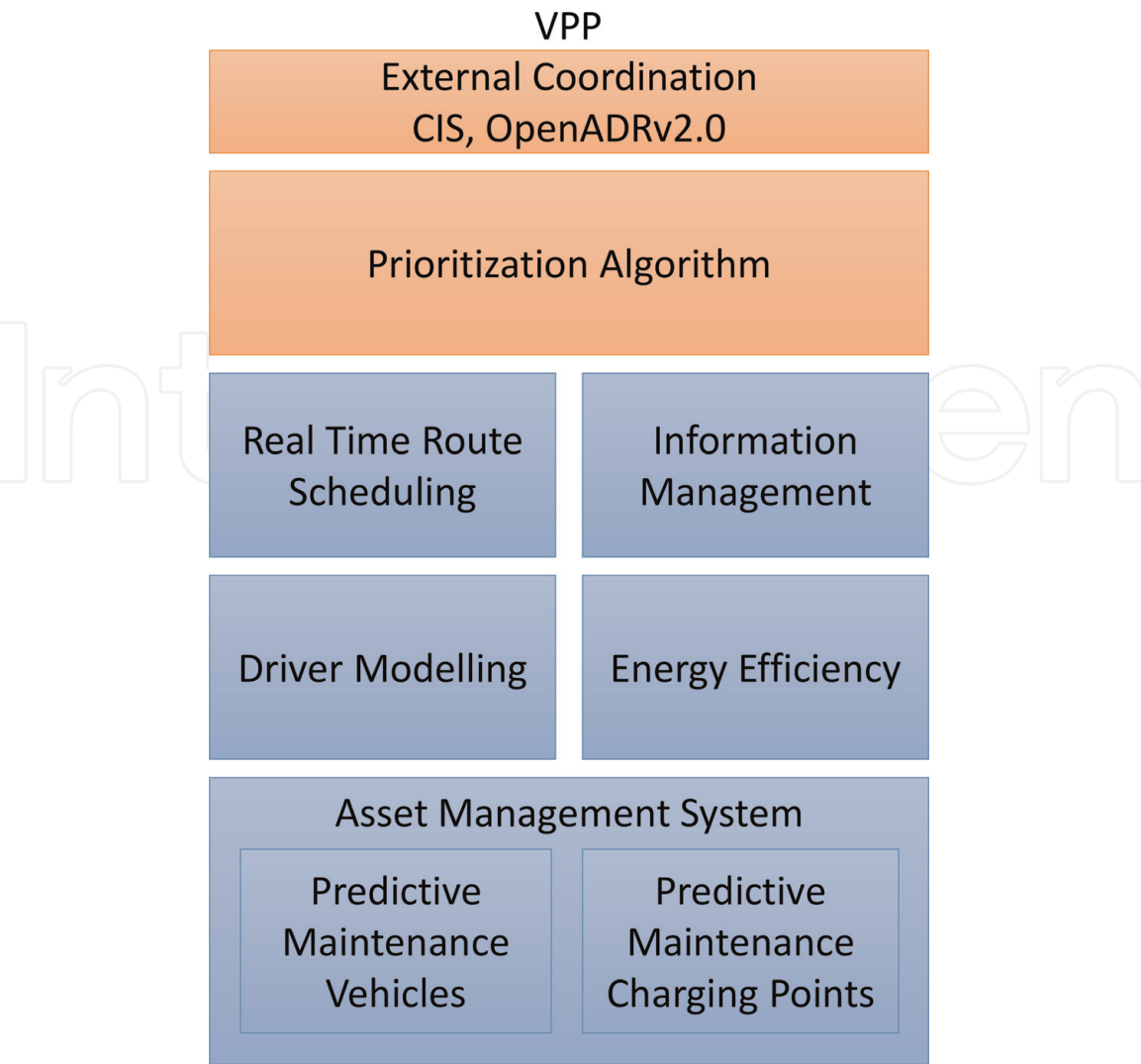


Figure 2.
Modules of distributed evolutionary prioritization framework.

- *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. This module oversees communications with other VPPs (higher or lower) by using CIS or OpenADR.

Some modules, such as external coordination, prioritization algorithm, and the SoC module, are available for all VPPs. The other modules are enabled depending on the available information in the VPPs.

The modules shown in blue are not included in this chapter. The asset management system is in development and will not be described in this chapter.

The prioritization algorithm includes different options of evolutionary computations, to test the best algorithm. Several approaches are tested: genetic algorithm, genetic algorithm with evolution control, particle swarm optimization, and a hybrid solution. All these algorithms use the information available from the different modules. The information in each module is described in Sections 4.1 to 4.4. The information is channeled through information management module.

4.1 Available information

Much information about different entities is available, depending on the level of VPP. 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 is stored in a relational database management system (RDBMS) that is based on the IEC CIM. This information includes the following data: information about asset management, current configuration for prioritization algorithm, technical information about charging stations, parametric information about technical characteristics of different connection types for vehicles and charging stations, information about driver patterns, different measures gathered from charging stations and power register, establishing the expected periods of availability and nonavailability for each vehicle and charging station, information about pending and assigned routes, technical information about vehicles and their batteries, and information about traffic, roadwork, and topology. In addition, stored information about previously 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. Furthermore, other historical information included historical information about usage of charging stations, configuration of prioritization, drivers that will be used in the driver pattern modeling, traffic related to roadworks, weather conditions, traffic conditions and accidents, periods configured in the system, different routes stored in the system, statistical information, mechanical problems and statistics from EVs, and 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 on 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.

4.3 Real-time routing scheduling

This module controls several conditions that can modify the current prioritization charging queues. This module notifies any change in the following conditions: charging station availability, driver and EV availability, route modifications, traffic and roadworks, and weather conditions.

The charging station availability updates the unavailability periods of the corresponding charging stations, in this case, if the higher VPPs can send commands or instructions to limit the consumption or availability of the power supply.

On a route, the driver and EV availability is related to a driver (or EV). The driver 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.

Three types of route modifications are possible: adding new stop, adding new stop to charge an EV, and adding new stop to change drivers.

The traffic and work road modeling is 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.

The weather conditions would take effect over the SoC module, prioritization algorithm, and asset management module.

4.4 SoC module: estimation of EV consumption

The proposed solution is based on the SoC instantaneous value of each EV. These algorithms require an estimation of some consumptions, according to its planned route and alternative routes to achieve different recharging spots. This consumption estimation is supported by a route planning tool. However, these estimations are not trivial and relate to the distance or time of the trip [91, 92]. Other factors (e.g., road [78] and vehicle characteristics, traffic [79], driving style [80], 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 chapter. 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) [81] and fuzzy neural networks (FNNs) [82]. 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.

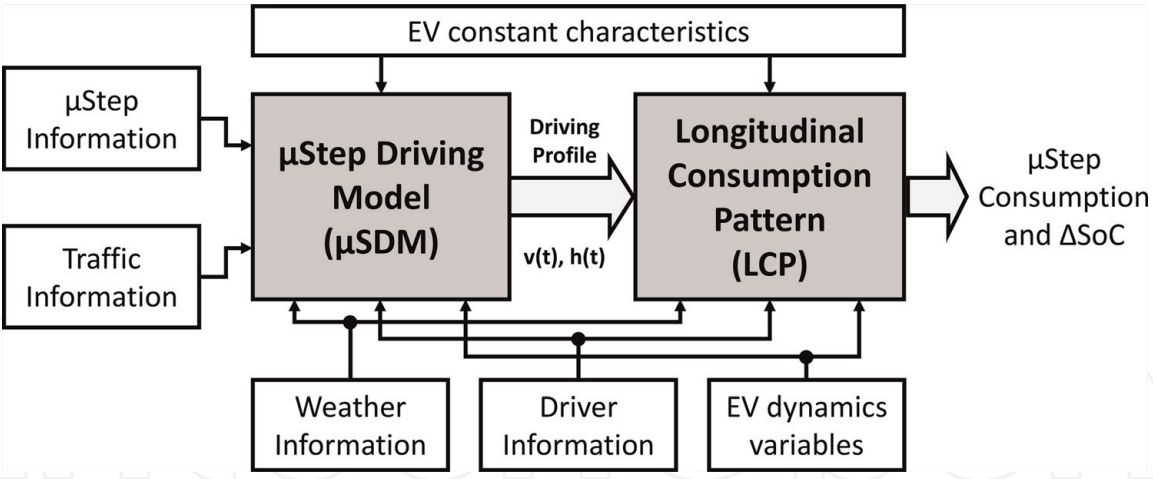


Figure 3.
Consumption model architecture.

- They 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 [43, 93]. 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) [83].

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 3**): the first block—the μ Step Driving Model (μ SDM)—is responsible for estimating the driving profile. This estimate 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 μ Step). A complete list of parameters in the model is shown in **Table 1**.

Parameter	Group	Associated to
μ Step distance	μ Step information	μ SDM
μ Step start elevation		μ SDM
μ Step final elevation		μ SDM
μ Step estimated time		μ SDM
Traffic congestion level	Traffic information	μ SDM
Driver style	Driver information	μ SDM, LCP
Precipitation level	Weather information	μ SDM, LCP
Average temperature		μ SDM, LCP
Sunrise/sunset time		μ SDM, LCP
ECO mode state		μ SDM, LCP
Additional mass (passengers, baggage, etc.)	EV dynamics variables	LCP
Initial SoC		LCP

Parameter	Group	Associated to
Vehicle mass	EV constant characteristics	LCP
Eq. mass of rotating parts		LCP
Maximum acceleration		μSDM, LCP
Frontal area		LCP
Friction resistance coefficient		LCP
Drag coefficient		LCP
Performance internal systems (inverter + engine + transmission)		LCP
A/C consumption		LCP
Heating consumption		LCP
Cooling consumption		LCP
Light consumption		LCP
Power steering consumption		LCP
Secondary consumptions (light panels, control systems, etc.)		LCP
Battery performance		LCP
Battery capacity		LCP
Battery voltage		LCP
Maximum recovery capacity		LCP

Table 1.
List of consumption model inputs.

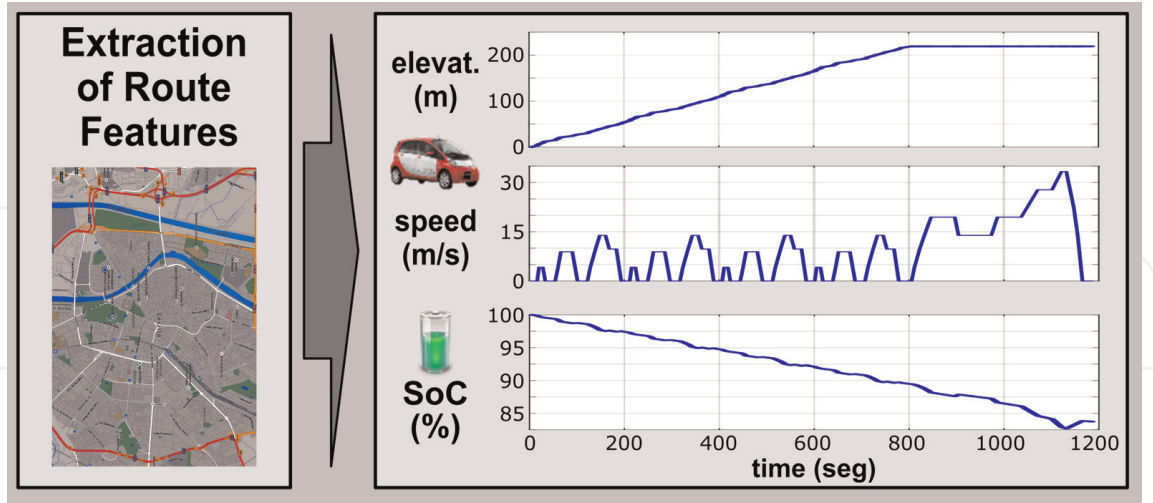


Figure 4.
Consumption and SoC estimation for a route.

The second block of the model—the longitudinal consumption pattern (LCP)—is responsible for estimating the consumptions and SoC variations associated with the velocity and elevation profiles for each μ Step. 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 1**.

The combination of part of the model and the initial SoC value enables the estimation of the SoC at the end of a trip or part there of (as shown in **Figure 4**).

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) [94, 95] 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
 - 4.1. Select parents from the population $P(t)$, number of elitism $n_e = p \cdot q$
 - 4.2. Perform the crossover on parents by creating the new population $P(t+1)$ with the probability c .
 - 4.3. Perform mutation of the population $P(t+1)$ with the probability m .
 - 4.4. Assess the population $P(t+1)$.
 - 4.5. If the stopping criteria are true, then return to step 3; 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 are 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
 - 4.1. Select parents from the population $P(t)$, number of elitism $n_e = p * q$
 - 4.2. 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.
 - 4.3. 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.
 - 4.4. Assess the population $P(t + 1)$.
 - 4.5. If the stopping criteria are true, then return to 3; 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 for the new solutions, where the fitness f can be calculated as the certain quality 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 Eq. (1). The new position is determined by the sum of the previous position, and the new velocity is determined by Eq. 2.

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

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

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.

Algorithm 3. PSO Algorithm
1. Initialize particles
2. Repeat
2.1. Calculate the fitness values for each particle
2.2. Is the current fitness value better than p_i ?
2.2.1. Yes. Assign the current fitness as the new p_i
2.2.2. No. Keep the previous p_i
2.3. Assign the best particle's p_i value to p_g
2.4. Calculate the velocity for each particle
2.5. Use each particle's velocity value to update its data values
3. Until stopping criteria are satisfied.

5.4 Configuration of prioritization algorithms

The system enables different restrictions to be specified for the prioritization algorithm: assignation prioritization of external charge, driver rest periods along a route, driver rest periods between different routes, external charging priority, external charging, maintenance periods for charging stations, maintenance periods for vehicles, possibility of partial charging, possibility of reuse drivers, possibility of several vehicles per route, possibility of specifying periods of unavailability of charging stations, possibility of specifying periods of unavailability of drivers, possibility of specifying periods of unavailability of vehicles, rest periods between vehicles that charge at charging stations, time interval to prioritize (1 day by default), and usage balancing of charging stations.

The external charging priority takes effect in the way which system will assign the first available slot in the queues to the external vehicles; however, the system moves the vehicles of the lowest VPPs (if possible). Furthermore, the system may accept a charging request from the different VPPs.

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 an end 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 and 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), maximum velocity (v_{\max}) for the PSO algorithm [84], maximum particle position ($x_{i,\max}$) for the PSO algorithm [84] to retain the value of the particle position in the interval $[-x_{i,\max}, x_{i,\max}]$, inertia weight (w) for PSO algorithm, modifiers for random number generation, self-recognition component (must be a positive value), coefficient of the social component (must be a positive value), and maximum and minimum velocities.

A GA and GAEC have similar parameters: population size, and, only in the GA, the operator probabilities (mutation and crossover).

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 to a vehicle and driver for the time requirements to perform the route and the number of routes that are assigned to a vehicle and driver but exceeds 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, external charging, external charging priority, reuse of vehicles, reuse of drivers, assignation prioritization of external charging, several vehicles per route, instructions from higher VPPs, or presence of autonomous vehicles.

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.

The different levels of VPPs are defined as shown in **Figure 5**. Each level runs the DEPF. The VPP level at which the DEPF is performed determines the availability of services, protocols, and data. Several VPP levels are proposed (**Figure 5**):

- *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. This VPP communication is based on CIS and OpenADR protocols.
- *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. This VPP communication is based on CIS and OpenADR protocols.

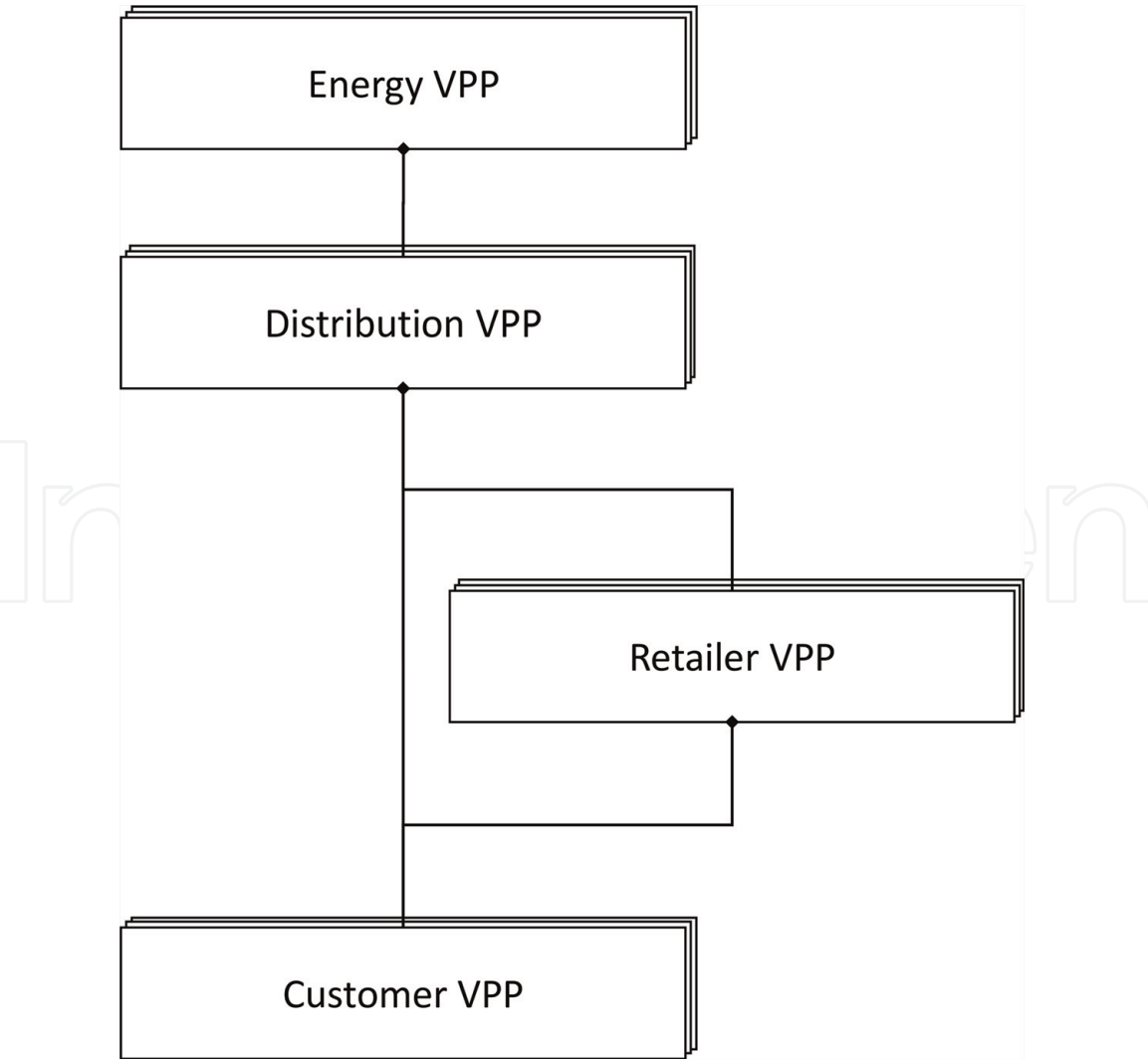


Figure 5.
Information aggregation between different VPP layers proposed.

- *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 charging stations of different companies. This VPP communication is based on OpenADR protocol.
- *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. The 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. This VPP communication is based on CIS and OpenADR protocols.

From the point of view of the power market:

- Two power retail companies. The first retailer has a contract to supply company A. The second retailer has a contract to supply company B. The retailer has three contracts to supply 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 171 routes: 68 routes from company A and 103 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 2**. 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.

The evaluation of the proposed solution is conducted in several scenarios based on algorithms: GA, GAEC, PSO, and hybrid solution. In case of hybrid solution, all possible combinations (81 cases) were tested; however, only the best hybrid

Characteristics	Company A	Company B
Number of routes	200	300
Number of EVs	4	7
Number of drivers	3	6
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 charging (0–80%)	30 minutes	30 minutes

Table 2.
Characteristics of both companies with EV fleets.

solution is shown in this chapter. The best hybrid solution applies PSO in SBVPP and GAEC in the higher VPPs.

The proposed solution is evaluated by checking two aspects (**Table 3**); 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 a number of generations.

The general best fitness curve for each scenario is shown in **Figure 6**. The first part (until generation 17) of the curve is the search of the best solution to schedule the routes (500 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 34 (**Figure 6**) with 258 scheduled routes (**Figure 7**); in the GAEC scenario, the command was fired in generation 19 with 456 scheduled routes; in the PSO scenario, the command was fired in generation 30 with 338 scheduled routes; and in the hybrid scenario, the command was fired in generation 39 with 378 scheduled routes. The command takes effect in a different number of routes in each scenario; the results did not agree with the fitness value (**Figure 6**) and the number of scheduled routes (**Figure 7**) between different scenarios, because there are different scheduling solutions. When the command is fired, the fitness is updated with

Test scenarios	t_c (number of generations)	t_t (number of generations)
Only GA	16	5
Only GAEC	11	2
Only PSO	17	5
Hybrid solution	11	3

Table 3.
Evaluation parameters for each scenario.

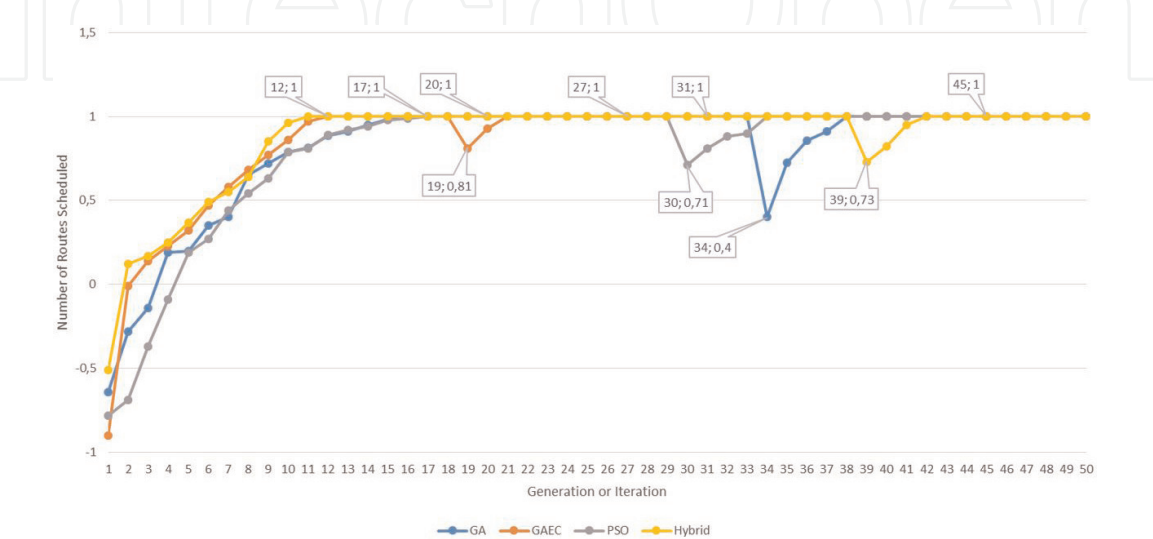


Figure 6.
General best fitness curve.

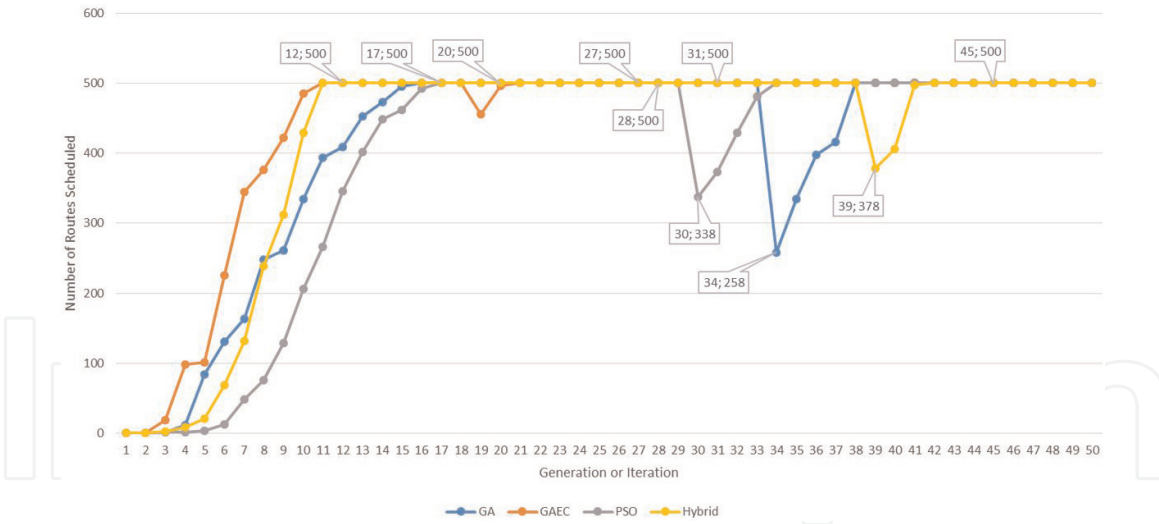


Figure 7.

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

the new restrictions. This updating changed the value of the best solution by converting it into another solution with lower fitness. However other solutions in the same population generation could have a good fitness in the new scenario. In the population (in the case of GA and GAEC) or swarm (in the case of PSO), several solutions were reassessed. 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.

7. Conclusions

A novel solution for the distributed prioritization of charging station queues is presented in this chapter. The proposed solution provides additional results:

- An algorithm to manage the EV fleet, to improve the efficiency of fleet.
- A model of mobile load inside a power grid. The algorithm provides a load forecasting of mobile loads, and it again calculates in real time in case an unexpected incident or an additional EV is added.

- The comparison between different energy management scenarios showing the hybrid solution as the best solution to different scenarios.
- The aggregation in different levels decreases the response time of system at different levels, allowing to respond in real time. In the consumer level, the EV is charging with minimized waiting periods. In the retailer level, the retailer can offer different rates and services according to the demand forecasting. In the distribution and energy level, 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 takes into account the minimization of the waiting time.
- The successful usage of CIM and CIS in a VPP-based environment.


Although the usage of EVs can be an excellent solution for decreasing pollution, it may cause serious problems in the power grid. Several solutions could be applied to solve this problem. In this chapter, 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 systems in the case of an alarm or emergency; in this case, the battery of EV (V2G) can serve as an energy resource.

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