Business Models for Flexibility of Electric Vehicles: Evolutionary Computation for a Successful Implementation

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ABSTRACT

The electrical grid is undergoing an unprecedented evolution driven mainly by the adoption of smart grid technologies. The high penetration of distributed energy resources, including renewables and electric vehicles, promises several benefits to the different market actors and consumers, but at the same time imposes grid integration challenges that must adequately be addressed. In this paper, we explore and propose potential business models (BMs) in the context of distribution networks with high penetration of electric vehicles (EVs). The analysis is linked to the CENERGETIC project (Coordinated ENErgy Resource manaGEment under uncerTainty considering electrIc vehiCles and demand flexibility in distribution networks). Due to the complex mechanisms needed to fulfill the interactions between stakeholders in such a scenario, computational intelligence (CI) techniques are envisaged as a viable option to provide efficient solutions to the optimization problems that might arise by the adoption of innovative BMs. After a brief review on evolutionary computation (EC) applied to the optimization problems in distribution networks with high penetration of EVs, we conclude that EC methods can be suited to implement the proposed business models in our future CENERGETIC project and beyond.

CCS CONCEPTS

• **Computing methodologies** → *Search methodologies*; • **Applied computing** → **Engineering**.

KEYWORDS

Business models, computational intelligence, electric vehicles, local markets

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1 INTRODUCTION

Technological developments and environmental issues have led to an unprecedented evolution of power systems and the electrical grid. Driven by the adoption of Smart Grid (SG) technologies, the high penetration of Distributed Energy Resources (DER), such as renewable generation and Electric Vehicles (EVs), is increasingly essential to our society, but at the same time is imposing grid integration challenges that need to be addressed [1]. In this new paradigm, the management and control of distribution networks require new roles and responsibilities from the Distributed System Operator (DSO) to provide high-quality services for end users [2].

Although several studies indicate that operational problems may arise in distribution networks because of the massive integration of EVs, several opportunities aiming at taking advantage of the significant flexibility that can be obtained from the optimal use of EVs' batteries are also envisaged. Some studies have identified various valuable services that can be related with the integration of EVs into distribution networks, e.g., balancing requirements for energy suppliers with renewables, regulation services for system operators, modification of demand curves to defer network expansion, congestion management mitigation for DSO, and so on [3]. As a result, opportunities for new Business Models (BM) arise in such context, with a keen interest from different stakeholders in the potential of EVs' flexibility as a resource of negotiation.

There is also a major concern when such BM are considered, related to the complexity of the necessary mechanisms behind the implementation of a given service. For instance, an EVs' aggregator may face a complex large-scale optimization problem to guarantee the optimal coordination of its EVs fleet when a large number of EVs users is considered, and the information related to their schedules is scarce. Several studies have identified the complexity in implementing control/marketing methods to maximize business values [2, 3]. When real-world scenarios are taken into account, current models and proposed solutions rely on unrealistic assumptions and simplifications to be able to tackle issues related to scalability, computational burden, or memory requirements, limiting the applicability of optimization tools. Therefore, in this paper, the application of innovative Computational Intelligence (CI) approaches, namely Evolutionary Computation (EC), is discussed as an alternative to solve the optimization problems more efficiently.

In summary, this paper explores and proposes potential BM in the context of distribution networks with high penetration of EVs. The analysis is linked to the P2020 project CENERGETIC-Coordinated ENErgy Resource manaGEment under uncerTainty considering electrIc vehiCles and demand flexibility in distribution networks. Due to the wide variety of services that can be procured by DSO, aggregators, or EVs users, we limit our study to congestion management and EVs charging coordination related services. This choice has been made based on the literature review which points out to the vast potential on the use of EVs' batteries for providing flexibility services. Through a simple framework, three BM are identified involving stakeholders such as DSO, market facilitators, aggregators, and EVs users. Mechanisms to fulfill such BM are also identified and, in some cases, translated into complex optimization problems. For this reason, CI techniques are envisaged as a viable option to provide more efficient solutions in the context of distribution networks with high penetration of EVs.

The rest of the paper is organized as follows: Sect. 2 presents a short literature review on the recent works regarding electric vehicles flexibility. Sect. 3 presents the proposed business models for EVs' flexibility in the scope of CENERGETIC project, Sect 4. presents an overview of the application of EC to EVs' flexibility optimization, Sect 5. presents the case study and, finally, Sect 6. fully draws the conclusions of this paper.

2 FLEXIBILITY OF ELECTRIC VEHICLES

Flexibility of EVs can defined as the amount of energy that the EVs users can offer by changing their charging patterns, i.e., shifting load consumption or reducing the charging load on a given moment. Literature has suggested significant potential of EVs' flexible demand. The work in [4] depicts the applicability of two demand technologies, namely electric vehicles and heat pumps, in electricity markets. The benefits of these technologies associated with the market participation is analyzed in the work. The research work in [5] quantifies the potential of EVs to utilize fluctuating renewables through optimized charging. The work also highlights that optimized charging can increase by twofold the utilization of renewables compared to simple charging, while trip information is more relevant than charger availability to utilize EVs' flexibility. Authors in [6] propose an algorithm to quantitatively analyze how much flexibility regarding duration and amount is used at various times of a day using a large dataset of 390k EVs. Authors in [7] propose the co-creation of distributed flexibility using 902 study participants in three domains of residential energy consumption, namely solar PV plus storage, electric mobility, and heat pumps. The results indicate that electric car and solar PV users show a higher willingness to co-create flexibility and adequate business models are required to take the prosumer perspective into account. Authors in [8] present an optimal approach to improve the flexibility of electric vehicles, namely by combining the effect of slow home charging of electric vehicles together with fast charging stations. The work also studies the benefits of stationary battery storage in fast charging stations to mitigate the negative effects on the power system operation. The work in [9] presents a framework for assessing the EV storage flexibility and distributed energy resource potential. The work highlights the importance of investing in nonresidential charging infrastructure to maximize the renewables potential arising from BEV storage flexibility. The work in [10] presents a set of strategies for solar and wind integration to leverage flexibility of EVs. Smart charging of EVs can facilitate integration of large shares of renewables and reduce the incremental generation cost and renewables curtailment. Vehicle-to-grid can reduce ancillary and electricity prices. Reference [11] presents an unsupervised algorithm to extract EV charging load patterns from smart meter data. Then, a method to define the flexibility of EVs based on the collective demand is proposed. Therefore, it is possible to quantify the flexibility achievable from the aggregated EV load in different time periods. This is especially relevant for aggregators of EVs aiming to participate in flexibility programs. Based on the studied benefits of EVs' flexibility claimed by the literature, we systematize the possible business models for EVs' flexibility interactions with DSO in the next section.

3 BUSINESS MODELS FOR EVs' FLEXIBILITY

According to [12], the definition of a BM starts by answering the question:how value for the customer can be created? and then by defining a business case around it. Therefore, a BM in SGs should describe: (i) the benefits that an enterprise will deliver to the SG players; (ii) how such benefits will be delivered to them; and (iii) how the enterprise will capture a portion of the value that is delivered.

The developments of SG technologies will enable DSO to assume new roles in the distribution context. For instance, Ancillary Services (AS) directed to the DSO at the distribution level of the grid is an example of a new business case, similarly to AS provided to the Transmission System Operator (TSO) at the power transmission level. Also, the integration of EVs and Renewable Energy Sources (RES) into the distribution grid make possible the emergence of a set of flexibility services as a viable solution to deal with operational challenges.

In [2], a systematic review of the services enabled by the integration of EVs into the distribution grid is presented. To avoid confusion with AS at the transmission level, the authors define the Distribution System Services (DSS) and divide them into three different categories: active power support, reactive power support, and RES integration support.

In the context of the CENERGETIC project, it is envisaged the integration of EVs enabling DSS for active power support. In this way, the DSO can use such service for solving different problems in the distribution grid (e.g., congestion management and power loss minimization are two of the most common problems related to the use of active power as a solution).

Figure 1 presents the illustration of three different BM considered in the scope of the CENERGETIC project. In the three cases, the product to be sold/bought is flexibility, while the players and interactions among them give the differences in the definition. In this way, BM1 is focused on the interactions between the DSO and EVs' aggregators. Therefore, in BM1 the DSO can request flexibility to the aggregators to alleviate management issues in the distribution network. The aggregators should receive monetary compensation for the service provided. Similarly, BM2 is focused on the interactions between the DSO and independent EVs users through a market place. As the flexibility provided by a single EV is lower than the flexibility provided by an EVs' aggregator, efficient communication/interaction processes, needed to obtain large amounts of the product, may increase the complexity of the transactions.

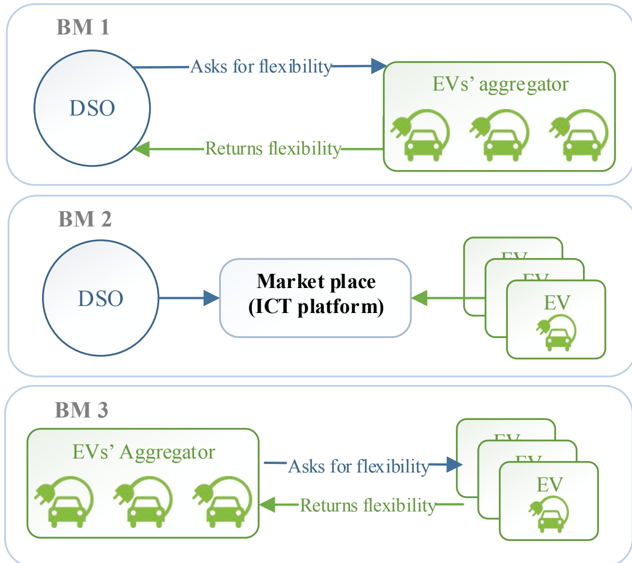

Figure 1: Distribution system services provided by different EVs' interaction schemes

Finally, BM3 defines the interactions between EVs' aggregators and EVs.

To better define the proposed BMs, in this paper we applied a BM framework with three different levels, namely (i) the strategic level (related to the governance and actors features), (ii) the costumers and market level (related to the business content and focus), and (iii) the value chain level (related to the delivery and financing structure). Table 1 presents the three BMs under this framework (AGG stands for aggregator in the table).

4 EVOLUTIONARY COMPUTATION IN THE CONTEXT OF EVs' OPTIMIZATION

EC is one of the main branches of CI[1], a sub-field of artificial intelligence (AI) that attempts to exhibit the intelligence observed in nature [1]. Different from classical deterministic mathematical methods, CI is tolerant to imprecision, uncertainty, and approximation, characteristics present in optimization problems that consider EVs' uncertainty, and large penetration of distributed resources. Even when CI-based approaches cannot guarantee an optimal outcome, they certainly can provide near-optimal, and in some cases even optimal solutions in acceptable computational times and with low memory requirements. Some studies suggest that the application of CI can be suitable to solve energy problems when such situations arise [13, 14].

This paper has considered some possible BM opportunities that may arise due to the interaction of DSO, EVs' aggregators, and EVs users. Conceptually speaking, the BMs can be translated into optimization problems, some of them very complex ones. We focus our attention on two main issues that need to be solved to fulfill the proposed BMs, namely the congestion management problem (DSO) and the coordination of EVs charging (aggregator). For instance, the DSO might want to take advantage of the flexibility that EVs can provide to solve congestion issues in the network. In fact, congestion management is an optimization problem that aims at efficiently making use of the power available without violating system/network constraints. Several methods have been proposed to tackle congestion management, such as nodal pricing, uplift cost, price area congestion management, available transfer capability, and flexible AC transmission systems devices. Due to the properties of the optimization problem, a nonlinear program typically involving a large number of variables, evolutionary computation and expert systems have also been applied to solve it [15]. On the other hand, the optimal scheduling of charging EVs, also known as EVs' charging coordination problem [16, 17], is usually a large-scale optimization problem that needs to be solved by an aggregator or network operator in order to satisfy the demand of its fleet. The complexity associated to this problem comes with the consideration of uncertainty in EVs user behavior, since current management systems typically rely upon highly accurate forecast of EVs trips and user preferences, which could not hold in realistic scenarios [18, 19]. Besides that, interactions between the DSO and the aggregators might give place to bi-level optimization problems, in which the coordination of such entities should be taken into account, posing a new degree of complexity to the problems.

Notice that despite the models and assumptions behind such optimization problems, some of them can be reduced to the form:

$$\min_{x \in \Omega} \quad f(x) \tag{1a}$$
$$\text{subject to} \quad g_i \leq 0, i = 1, \ldots, m \tag{1b}$$
$$h_j = 0, j = 1, \ldots, p \tag{1c}$$

where x is a D-dimensional decision variable vector $x = (x_1, \ldots, x_D)$ from some universe Ω. $g_i(x) \leq 0$ and $h_j(x) = 0$ represent constraints that must be fulfilled while optimizing (minimizing or maximizing) $f(x)$. The formulation can be extended to multi-objective optimization, bi-level optimization, dynamic optimization, many-objective optimization, consideration of uncertainty, and so on. In any case, an objective function ($f(x)$) and a decision variable vector (x) are part of the formulation. Those elements can be later translated to the so-called fitness function and encoded potential solutions (e.g., individuals in differential evolution (DE), particles in particle swarm optimization (PSO), chromosomes in genetic algorithms (GA), etc.), two of the requirements needed in the application of a wide variety of EC algorithms. Therefore, once the problem has been abstracted to this form, practically any EC algorithm can be applied to get optimal and near-optimal solutions. If an EC algorithm is tailored to tackle a specific problem, it can result in an efficient tool providing good-quality solutions with low memory requirements and in an acceptable amount of time (requirements that in real-world applications are usually crucial). In fact, it is important to mention that the use of EC is just justified when deterministic approaches (e.g., based in mixed-integer linear programming (MILP) or mixed-integer nonlinear programming (MINLP)) fail in providing efficient solutions to the problems [1, 14]. If a deterministic approach can be used to solve a given

[1] CI in a broader sense is formed by EC, artificial neural networks (ANN), and fuzzy systems (FS). In this paper, we focus on the EC branch for optimization.

Table 1: Business Models using EVs flexibility

Level	Name BM1 DSO-AGG	BM2 DSO-EV	BM3 AGG-EV
Strategic Level			
The provider (who?)	AGG	DSO	AGG
The strategy (why?)	The AGG can offer flexibility to the DSO for congestion management or as AS.	A market place for flexibility trading can be made available by the DSO to take advantage of demand response (DR) for congestion management.	The AGG can pay to EVs for the use of their flexibility.
The resources (who and what internally?)	The AGG might use forecast capabilities (e.g., EVs consumption and trip schedules) and energy management systems as internal resources.	The DSO might poses the necessary infrastructure (ICT capabilities) to communicate with the EVs.	The AGG might use forecast capabilities (e.g., EVs consumption and trip schedules) and energy management systems as internal resources.
The network (who externally?)	The ICT and trading platforms can be contracted externally.	The EVs can react to DSO locational marginal pricing (LMP) at different zones of the grid using their own control system. The possibility of acquire ICT and trading platforms externally is also an option.	The EVs' management capabilities can be used to react to AGG flexibility requests. The ICT and trading platforms can be contracted externally.
Customer and Market Level			
The customer model (to whom?)	DSO	EVs	EVs
The market offer model (what?)	Aggregated flexibility.	Flexibility market place to exploit EVs coordination.	Compensation for the use of EVs flexibility.
The revenue model (how they pay?)	The DSO will have to pay the flexibility required to the AGGs. The price per unit of flexibility (€/kW) can result from an asymmetric pool or a value contracted between to pears.	The EVs users can make a monthly/annual payment to participate in the market place. Additionally, DSO can pay incentives to users for making transactions between them, and thus avoid the congestion of lines.	The EVs users can make a monthly/annual payment to participate in the flexibility aggregation. Additionally, free fees can be considered assuming that the price per unit of flexibility (€/kW) is determined by the AGG considering DSO compensations.
Value chain level			
The delivery (how we deliver?)	The flexibility is delivered by the coordination of EVs and the modification of consumption patterns.	The market place can be set as a webservice. Synchronization between the EVs' control module and the market place configured by the DSO is another option.	The coordination of EVs is done through centralized systems or by price signals mechanisms.
The procurement (how is being delivered to us?)	The EVs can react to AGG coordination schemes by given direct control to AGG or using intelligent systems. Failure to comply with the agreement between AGG and EVs may be penalized.	The EVs transactions in the market place are intended to be done in function of LMP automatically, thus avoiding network congestion problems.	The flexibility is delivered to the AGG in response to the price signals issued for this purpose. Direct control mechanism are also an option.
The financial model (how we pay for it?)	The DSO pays to the AGG in function of the amount of flexibility used and considering the fees and compensations that AGGs might pay to EVs users (e.g., a penalization if the congestion occurred).	The DSO might pay incentives calculated in function of the penalty amount that is required to be paid if congestion problems exists.	The AGG will pay for the use of flexibility to the EVs in function of the amount sold to the DSO.

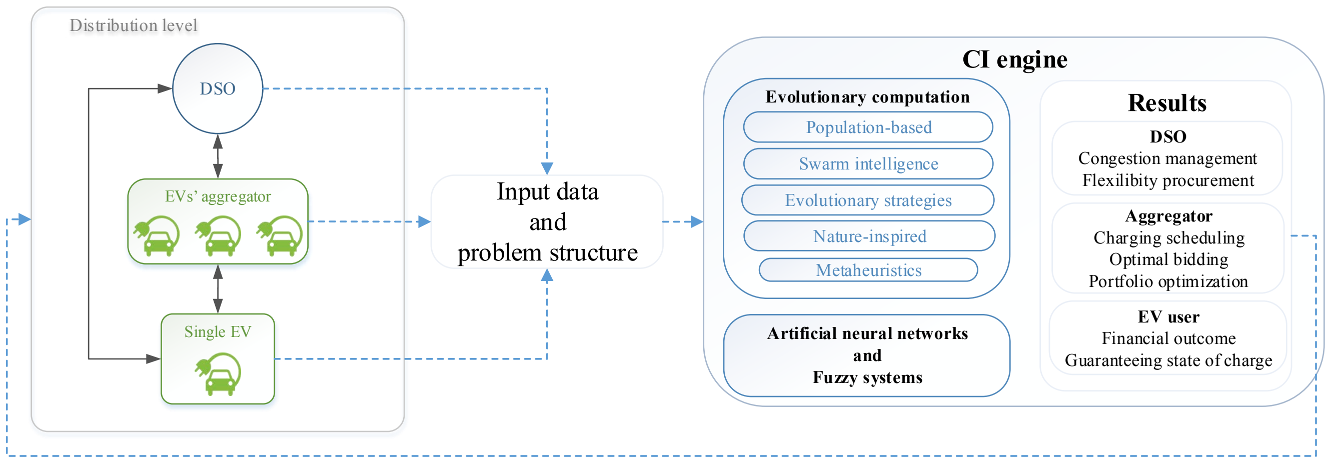

Figure 2: A CI-engine that can be used to optimize specific requests from DSO, aggregators, or EVs users.

optimization problem, it should always be preferred as a solution method.

We are not intended here to provide a comprehensive tutorial on the use of EC for solving optimization problems (the reader can be referred to [20–22] to that end). Rather, we want to conceptualize and suggest the use of EC as efficient computational methods to solve the optimization problems behind the proposed BMs. Fig. 2 shows a simple conceptualization of the idea, through the development of a CI engine as a decision support system. In this case, DSO, aggregators, or EVs users can abstract their optimization problems (defining the desired objective functions and decision variable vectors) and send the information to a CI engine (i.e., a platform with EC capabilities). The CI engine should have a module for optimal selection of the optimization approach depending on problem complexity. A set of EC approaches, including different types of algorithms (e.g., population-based, swarm intelligence, evolutionary strategies, etc.), should be available to tackle the burden of stochastic formulations solving more realistic scenarios, i.e., of high dimension and considering nonlinear constraints in acceptable execution times, that are crucial for the short-term decision making horizon. The engine can also include a module with ANN and FS methods either to forecasting and control purposes. The engine can later return the requested results to the users.

Finally, we provide a summary of EC techniques used in the context of EVs' charging coordination. Table 2 summarizes some works regarding EVs' charging coordination using EC approaches. The table also shows some characteristics taken into account in such studies. It can be highlighted the use of GA and PSO as the preferred solvers. Other approaches used include artificial bee colony (ABC), tabu search (TS), greedy randomized adaptive search procedure (GRASP), improved grey wolf optimization (IGWO), and firefly (FF) algorithm. Also, notice that most studies do not consider V2G capabilities. The reason behind that might be the complexity in incorporating a new set of variables into the formulation (requiring an extra set of binary variables in some cases to avoid the simultaneous charge and discharge actions). The work presented in [23, 24] relax this issue by using a clever encoding of individuals in which the same variable with negative values indicates injection of energy into the grid (V2G), while positives values indicate the battery charging process. However, this approach does not allow to set a minimum level of energy charging in the battery, so that a new set of variables for each EV, or a new set of constraints, will still be needed to make a correct formulation of such process. Also, most of the works focus on the charging process to meet user requirements, while neglecting congestion management problems. With the current high penetration of DGs and EVs, it is expected that congestion management problems will become critical, so it is expected to see more applications of EC combining EVs' coordination and DSO activities.

5 CONCLUSIONS AND FUTURE WORK

In this paper we overlook flexibility of electric vehicles for the smart grid, which is part of CENERGETIC project research. We analyze the works that highlight the potential of EVs in several challenges of the smart grid, including peak shaving, congestion management, optimize renewables' use, etc. We propose three different business models for EVs flexibility. The business models are different in the way the flexibility can be provided, e.g. if a market place to trade flexibility is present or not. To implement these business models in practise we identify evolutionary computation tools that are suited to tackle complex issues in this field, namely providing a review of the EC applied to EVs optimization problems. We believe that EC methods can be suited to implement the proposed business models in our future work of CENERGETIC project.

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Table 2: EC applied to EVs' optimization problems

Year	**Ref.**	**EC approach**	User requirements	Peak load reduction	Congestion management	Power constraints	Network constraints	V2G	DR
2012	[25]	GA	✓	✓		✓			
2012	[26]	GA	✓	✓		✓			
2012	[23]	SA	✓	✓		✓	✓	✓	
2013	[24]	PSO	✓	✓		✓	✓	✓	✓
2015	[27]	GA	✓				✓		
2015	[28]	GA	✓	✓		✓			
2017	[16]	TS GRASP Hybrid algorithm	✓	✓		✓	✓		
2018	[29]	ABC with LS and GA	✓				✓		
2018	[30]	IGWO FA PSO		✓	✓	✓	✓	✓	

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