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DC Nanogrids for Integration of Demand Response and Electric Vehicle Charging Infrastructures: Appraisal, Optimal Scheduling and Analysis

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With the development of electronic infrastructures and communication technologies and protocols, electric grids have evolved towards the concept of Smart Grids, by which is enabled the communication of the different agents involved in their operation, thus notably increasing their efficiency. In this context, microgrds and nanogrids have emerged as invaluable frameworks for optimal integration of renewable sources, electric mobility, energy storage facilities and demand response programs. This paper discussed a DC isolated nanogrid layout for integration of renewable generators, battery energy storage, demand response activities and electric vehicle charging infrastructures. Moreover, a stochastic optimal scheduling tool is developed for the studied nanogrid, quitable for operators integrated in local service entities along the energy retailer. A stochastic model is developed for fast charging stations in particular. A case study serves to validate the developed tool and analyse the economical and operational implications of demand response programs and charging infrastructures. Results evidence the importance of demand response initiatives in the economical profit of the retailer.

Introduction

The Smart Grid paradigm requires an active participation and coordination of all the agents involved in the electric system [1, 2]. With the advent of this concept, nanogrids (NGs) have emerged as invaluable framework for the integration of renewable generation, electric vehicles (EVs), storage facilities and demand response (DR) programs [3, 4]; as well as for electrical supplying of remote isolated areas [5]. In this context, the optimal coordination of the agents involved requires deploying advanced communication infrastructures and electronic interfaces on either AC, DC or hybrid networks [6, 7]. Communication channels enable an effective information exchange among the different assets that participate in the operation of the system. This novel paradigm allows to effectively coordinate the participation of the different agents, with the aim of pursuing a more efficient management of the generation and storage facilities [8]; while consumers can also actively participate through DR initiatives, modifying their consumption profiles on the basis of price or incentive signals [9].

Because the heterogeneity and conflicting interests of the different agents involved in the NG operation, their coordination is frequently addressed in a centralized fashion by the grid operator. This agent is usually integrated in the local service entity along the local retailer [10]. In remote isolated areas, the local service entity usually owns the onsite generation and storage assets [11]. In such a case, the operator must ensure the supplying quality and reliability at minimum cost, in order to maximize the benefits obtained by the retailer. To this end, the operator can exploit public infrastructures such as charging stations [12, 13], in order to complement the incomes obtained from energy supplying. Thereby, it is essential operating the grid in an optimal way, thus efficiently exploiting the different available resources and taking advantage of flexibility provided by DR programs.

The optimal operation of NGs (or microgrids) is a hot topic which has attracted huge attention recently. In [14], the authors developed an optimal scheduling model for EVs and battery swapping stations. The mode is formulated so that the costs of EVs is minimized while the profit of battery storage systems (BSSs) in energy markets is maximized. In islanded mode, this model aims at minimizing the total cost of grid operation. In [15], an energy management problem is formulated which considers renewable sources and a EV smart parking lot, with the objective of maximizing the EVs owner satisfaction. The authors in [16] developed a model predictive control for MGs which takes into account possible future variations in EVs demand, in order to consider increasing sizes of the fleet. The possibility of vehicle-to-grid capabilities from EVs is considered in [17], by which bidirectional flows are enabled from/to the on-board storage systems. In [18], an operation window constrained strategic energy management is proposed for MGs, which allows different formulations depending is the problem is treated by the EVs owner or the MG operator. In this case, energy the operator aims at minimizing the energy loss through the network while the drivers search their own benefit and satisfaction. The reference [19] deals with the optimal operation of isolated MGs in which EVs are exploited as storage facilities, enabling vehicle-to-grid capabilities. The authors in [20] developed a bi-level optimization problem for isolated MGs equipped with battery swapping stations. The idea is to minimize the operating cost in the upper level while the secondary problem aims at maximizing the profits of the stations. In [21], an optimal scheduling model for industrial MGs with plug-in EVs is developed, in which constraints related to industrial production are included. The reference [22] proposed a coordination model for charging stations supplied from photovoltaic (PV) panels, storage systems of EVs and the rest of the isolated MG. In [23] the optimal generation scheduling is combined with the optimal reconfiguration of the grid, in which EV penetration is modelled as an uncertain variable. The reference [24] proposed a real time control scheme for a smart EV fleet for optimal coordination of vehicle-to-grid and grid-to-vehicle modes. In [25], the EV fleet is considered as a mobile storage system in a hierarchical real time model predictive control for MGs. The authors in [26] considered the control of a hybrid AC-DC MG in which the EV charging system is directly connected to the DC side. To optimally control the hybrid MG, this reference developed a vector-decoupled control parameters of bidirectional converters based on the Particle Swarm optimizer. In [27], the authors developed a stochastic scheduling model for MGs including EVs, renewable sources and fuel cells. The reference [28] proposed a multi-objective problem for optimal network reconfiguration, generation dispatch and capacitor switching in the presence of controllable loads and EVs. The reference [29] developed a two-level robust optimization framework for optimal scheduling of grid-connected MGs including plug-in EVs. The reference [30] deals with the short term optimal planning of MG layout considering plug-in EVs with enabled vehicle-to-grid capability. The authors in [31] exploited metaheuristic techniques to solve the optimal scheduling of a MG with renewable sources, EVs and battery energy storage systems (BES). The authors in [32] considered three different charging modes for plug-in EVs, analyzing their impact on the MG optimal scheduling task. The reference [33] analyzed the role of EVs for critical load restoration in resilient MGs, exploiting vehicle-to-grid and grid-to-vehicle capabilities as well as on-board high-powered engine generators.

As deduced from the review above, optimal scheduling of MGs is essential to minimize their operating costs or maximizing their monetary profits. In this sense, flexible loads such as charging stations and DR initiatives play a vital role to boost up the efficiency of the system. To maximize the penetration of EVs, DC NGs emerge as the optimal solution for reducing system requirements. By this approach, charging stations can be directly connected to the DC bus through DC-DC converters, thus allowing a simplification in their control schemes. This paper develops an optimal day-ahead scheduling model for DC isolated NGs, which is suitable for grid operators that are integrated in the local service entity structure along the local retailer. This way, the developed formulation aims at maximizing the benefits obtained by the retailer optimally coordinating onsite generators, storage facilities, flexible consumers and public charging infrastructures. For the sake of clarity, the major contributions of this paper are summarized below:

- Describing a DC layout for isolated NGs with DR programs and public EV charging stations, commenting the electronic devices involved, the role of each agent and the necessary communication channels.
- Developing an optimal day-ahead scheduling model for the grid system described, which is suitable for a grid operator which is integrated in the local service entity structure along the local retailer. This way, the objective of the developed formulation is maximizing the benefits of the retailer, for which all the available infrastructures are exploited in an optimal way.
- Developing a stochastic model for the different uncertainties involved in the NG operation, including renewable generation, local demand and EV charging profiles.
- Analysing the influence of DR programs and EV penetration in the NG operation, also focusing on the economic impact of such aspects.

In the rest of the paper, Section 2 describes the analysed NG layout, the agents involved and their role in NG operation, as well as the enabled communications and interactions among them. Section 3 presents the developed optimal scheduling model for the NG described in the previous section. Section 4 develops a stochastic framework for considering uncertainties in renewable generation, demand and EV charging profiles. Section 5 presents various case studies which allow to analyse the impact of EV penetration and DR initiatives in MG operation. The main conclusions are duly drawn in Section 6.

Description of the NG under study

As commented, this paper is focused on isolated DC NGs. This kind of systems involve the participation of various agents. The more notable interactions among the agents involved is depicted in Fig. 1, while their roles are explained below.

- NG operator: this agent is integrated in an upscale structure called local service entity. It is responsible of operating the grid in an optimal way, ensuring the supplying quality and reliability. To this end, this agent daily performs a day-ahead optimal scheduling plan, by which the different onsite assets are coordinated with DR premises, such as those enabled by flexible consumers and public charging infrastructures. As a result, commitment signals, power set-points and DR information are sent to generators, storage systems and flexible consumers to address the resulted scheduling plan.
- Retailer: this agent provides fuel for conventional generators and is responsible of the monetary expenditures derived from generators operation (operation and maintenance). On the other hand, it receives monetary incomes from consumers through energy tariffs and public charging infrastructures, of which the local service entity is owner.
- Generators and storage facilities: they are onsite assets owned by the local service entity. They may be formed by conventional generators, such as diesel engine generators (DEGs); renewable generators, such as PV panels or wind turbines (WTs); and storage facilities like BES.
- Consumers: residential demand and public charging infrastructures are considered as consumers in this paper. The residential demand comprises inelastic and flexible consumption. While the first one does not response to price or incentive signals from the NG operator, the second one may be scheduled in order to increase the efficiency of the system or ensure its reliability. On the other hand, public charging stations are owned by the local service entity. They provide adequate charging infrastructures to private owned EVs, obtaining a monetary counterpart which is received by the retailer.

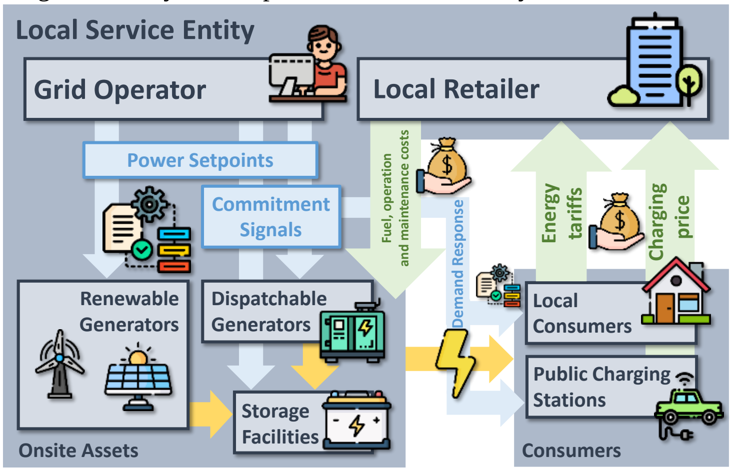

Figure 1 Pictorial representation of the agents involved in the operation of the NG under study and the more notable interactions among them

To effectively address the optimal coordination of the different participants, both energy and communication channels have to be enabled, which are illustrated in Fig. 2. Each controllable agent is connected through electronic interfaces, which allow an effective energy flow control from/to the different elements. This way, PV arrays, charging points and BES are directly connected to the DC bus through DC-DC converters. On the other hand, DEG and WTs require a rectified stage which converts the generated AC waveform to DC. It is assumed that residential consumers mostly comprise DC loads, therefore they can be connected directly to the DC bus without necessity of interface. In contrast, flexible consumers require a control mechanism which receives the commitment signals emitted from the NG operator. Each day, the operator receives forecasted data for weather and demand, which allow to perform the optimal scheduling plan for the grid. This plan is transferred to the conventional generators and storage systems in form of commitment and set-points signals, while renewable sources receive power set-points. DR programs are enabled through direct communication with flexible consumers. Thereby, the public charging station may be controlled through power set-points, so that EV demand may be totally satisfied or not, while flexible residential consumers can be actually scheduled, shifting their consumption to the more convenient hours of the day.

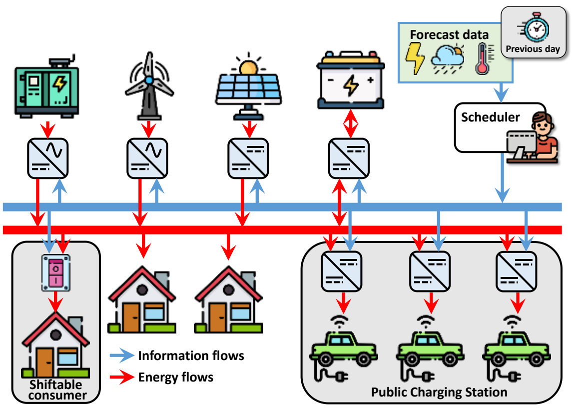

Figure 2 Layout of the NG under study

Optimal Scheduling Model for the NG under Study

In this section, the mathematical formulation for the optimal scheduling of the NG described in Section 2 is developed. The optimization problem is formulated as a Mixed-Integer-Lineal programming, which can be solved using conventional solvers.

Assumptions

It has been widely reported that electronic devices can delay the response of the device to which it is interconnected by several seconds [34]. This aspect has not been considered in the developed formulation because it is assumed that the time step scheduling is considerably larger than the delay introduced by electronic devices. This way, this aspect has not impact on the scheduling result yielded by the developed tool.

Objective Function

The optimal scheduling problem is formulated from the retailer point of view, which aims at maximizing its own profit. To this end, tis agent obtain monetary incomes from serving energy to flexible and non-flexible consumers as well as charging processes in EV stations. On the other hand, this agent incurs in monetary expenditures due to fuel consumption of DEG and operation derived costs of the other generation and storage assets. Keeping this on mind, the objective formulation can be formulated as follows:

$$F = \sum_{r\in\mathcal{R}} \left\{ \omega_r \Delta\tau \sum_{t\in\mathcal{T}} \left\{ \underbrace{\left[\lambda_t d_{r|t} + \lambda^{EV} d_{r|t}^{EV} + \sum_{q\in\mathcal{Q}}\{\lambda^q u_{r|t}^q p^q\}\right]}_{Incomes} - \underbrace{\left[\rho^{PV} p_{r|t}^{PV} + \rho^{WT} p_{r|t}^{WT} + \rho^{BES}\left(p_{r|t}^{BES,ch} + p_{r|t}^{BES,dch}\right)^2 + f_{r|t}^{DEG}\right]}_{Expenditures} \right\} \right\} \quad (1)$$

The objective formulation is formulated considering a stochastic model for uncertainties, so that the expression (1) takes into account the probability of occurrence of each scenario. The first term of the incomes stands for the energy consumption of inelastic residential consumers, the second term counts the profit from EV charging and the last element represents the payments of flexible consumers.

The monetary expenditures mainly comprise operation and maintenance costs of generation assets. For renewable-based generators, these costs are proportional to the energy generated [5], whereas in the case of BES the are quadratic function of the energy exchanged with the grid [35]. The last element of the expenditures stands for the fuel cost of DEG, which can be calculated as a quadratic function of the energy generated, as follows [36]:

$$f_{r|t}^{DEG} = a^{DEG} + b^{DEG} p_{r|t}^{DEG} + c^{DEG}\left(p_{r|t}^{DEG}\right)^2;\ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \quad (2)$$

In order to keep the lineal feature of the developed problem, quadratic functions can be efficiently linearized using piecewise representations [12] (see Appendix A).

DEG Modelling

DEG units can be modelled as other dispatchable generators by their upper and lower rated values and ramping constraints, as said the equations (3) and (4), respectively.

$$u_t^{DEG}\underline{p}^{DEG} \leq p_{r|t}^{DEG} \leq u_t^{DEG}\overline{p}^{DEG};\ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{3}$$

$$p_{r|t-1}^{DEG} - R^{DEG} \leq p_{r|t}^{DEG} \leq p_{r|t-1}^{DEG} + R^{DEG};\ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \backslash t > 1 \tag{4}$$

PV Modelling

PV generation is influenced by uncertain parameters such as solar irradiation and ambient temperature. Assuming these parameters known or sufficiently well-predicted, the available power generation can be calculated using an available PV array model. In this paper, the model considered in [5, 11] is used, which determines the PV generation capacity as a function of the solar irradiation and ambient temperature, as follows:

$$\phi_{r|t}^{PV} = \overline{p}^{PV}\left[0.25\vartheta_{r|t} + 0.03\vartheta_{r|t}\theta_{r|t} + (1.01 - 1.13\eta^{PV}) \times \left(\vartheta_{r|t}\right)^2\right];\ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{5}$$

As pointed out in [5, 11], the model (5) does not take into account the installed power of the PV generators. In other words, the second term in (5) may be higher than 1, which yields a value higher than the rated power of PV panels. In practice, inverters impose limitations in the PV power generation to avoid failure or fast degradation of components. Traditionally, equipment allows to exceed the nominal power by 10% [37], assuming that these overvalues may be eventually assumed without excessively deteriorating the components of the PV array. With these premises, the PV array model is completed with (6).

$$0 \leq p_{r|t}^{PV} \leq \begin{cases} \phi_{r|t}^{PV}, \text{if } \phi_{r|t}^{PV} \leq 1.1 \cdot \overline{p}^{PV} \\ 1.1\overline{p}^{PV}, \quad\quad\quad\quad \text{o.w.} \end{cases};\ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{6}$$

It is worth noting that the developed assumes the PV generation as a variable of the problem. It means that NG operator can schedule its production on the basis of forecasted data. In this sense, the scheduling result may occasionally set the PV generation below the available power calculated by (5). In such a case, the surplus energy is assumed to be dissipated in dummy loads [38, 39].

WT Modelling

As in the case of the PV panels, the power given by a WT depends on the available wind speed. Once this parameter is known or approximated, the available wind generation can be estimated on the basis of the wind speed-power curve of WTs [5]. A typical for this kind of curves is shown in Fig. 3. It can be distinguished three clear zones. For a wind speed below $\underline{\gamma}^{WT}$, the turbine is not able to extract energy from the wind and therefore the power produced is zero. After surpassing this threshold, the power given by the turbine increases until reaching the rated power of the device at $\gamma^{WT,*}$, which is a characteristic value of each turbine model. Beyond this point, the turbine is able to give its rated power until a maximum threshold $\overline{\gamma}^{WT}$, beyond which the turbine is braked to avoid breakdowns. The wind speed-power curve of a WT is typically represented by a set of equations as shown in (7), while the expression (8) takes into account the efficiency of the coupling rectifier.

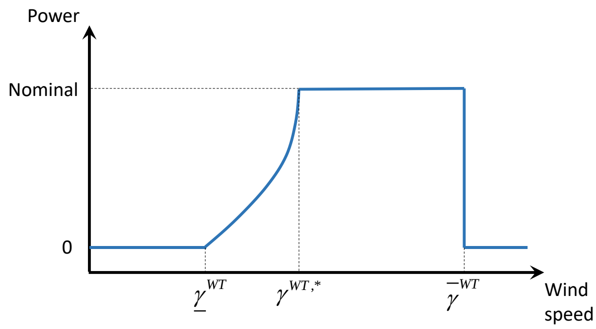

Figure 3 Typical wind speed-power curve of a WT

$$\phi^{WT}_{r|t} = \begin{cases} 0, & \text{if } \gamma_{r|t} < \underline{\gamma}^{WT} \\ \alpha^{WT} \cdot (\gamma_{r|t})^3 - \beta^{WT}\overline{p}^{WT}, & \text{if } \underline{\gamma}^{WT} \le \gamma_{r|t} \le \gamma^{WT,*} \\ \overline{p}^{WG}, & \text{if } \gamma^{WT,*} < \gamma_{r|t} \le \overline{\gamma}^{WT} \\ 0, & \text{if } \gamma_{r|t} > \overline{\gamma}^{WT} \end{cases}; \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{7}$$

$$0 \le p^{WT}_{r|t} \le \eta^{WT}\phi^{WT}_{r|t}; \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{8}$$

BES Modelling

The power that a BES can exchange with the system is typically upper bounded, as said the constraint (9), whose nominal values are determined by the nominal capacity and the energy to power ratio [40]. It is realistic to assume that charging and discharging processes are actually complementary, which is ensured by imposing the constraint (10). The equation (11) models the state of charge of the batteries, which is limited by their nominal capacity and depth of discharge settings [37], as said the equation (12).

$$0 \le p^{BES,i}_{r|t} \le u^{BES,i}_{r|t}\bar{p}^{BES}; \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge i \in \{ch, dch\} \tag{9}$$

$$\textstyle\sum_{i\in\{ch,dch\}}\{u^{BES,i}_{r|t}\} \le 1; \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{10}$$

$$\varepsilon^{BES}_{r|t} = \varepsilon^{BES}_{r|t} + \Delta\tau\left(\eta^{BES}p^{BES,ch}_{r|t} - \frac{p^{BES,dch}_{r|t}}{\eta^{BES}}\right); \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T}\backslash t > 1 \tag{11}$$

$$\bar{\varepsilon}^{BES}(1 - DOD^{BES}) \le \varepsilon^{BES}_{r|t} \le \bar{\varepsilon}^{BES}; \ \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{12}$$

The equation (11) models the energy stored in batteries as a function of the state of charge at $t-1$ and the total energy exchanged with the grid. However, as pointed out in other studies [5, 37], this model has to be completed by setting the state of charge at the beginning of the time horizon. As customary (e.g. see [38]), it is assumed in this work that the BES is fully charged at the beginning of the time horizon. In addition, to keep the model coherent, the state of charge of the BES is forced to be equal to the nominal capacity at the end of the time horizon. This working conditions are ensured by imposing the constraint (13).

$$\varepsilon^{BES}_{r|t=1} = \varepsilon^{BES}_{r|t=end} = \bar{\varepsilon}^{BES}; \ \forall r \in \mathcal{R} \tag{13}$$

Shiftable Consumers Modelling

As commented previously, it is considered that a part of the local demand may response to commitment signals emitted by the NG operator. This kind of responsible loads can therefore adjust their scheduling programs to achieve a more efficient operation of the grid. As in other related problems [11], it is assumed that these consumers have to be operated continuously, it means, once their operating cycle has started, it cannot be interrupted until completing their duty cycle, as modelled the equation (14).

$$u^q_{r|t} - u^q_{r|t-1} = on^q_{r|t} - off^q_{r|t}; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \wedge t \in \mathcal{T}\backslash t > 1 \tag{14}$$

It is assumed that these consumers have some preferences about when they prefer to be scheduled, in this sense, they have to be operated within allowable time windows, being the scheduling tool free to schedule their consumption in those time ranges. The constraint (15) ensures that shiftable consumers complete their duty cycles within the considered time windows. The model has to be completed by the equations (16) and (17), which ensure that responsible loads cannot be scheduled out of their time windows and are activated once over the time horizon, respectively.

$$\textstyle\sum_{t\in\Psi^q}\{u^q_{r|t}\} = \varphi^q; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{15}$$

$$\textstyle\sum_{t\notin\Psi^q}\{u^q_{r|t}\} = 0; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{16}$$

$$\textstyle\sum_{t\in\Psi^q}\{on^q_{r|t}\} = 1; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{17}$$

On the other hand, and with the aim of completing the analysis, it has been also considered the case in which the shiftable loads could not be operated in a flexible manner. In such a case, it is assumed that these consumers desire to start their operation at the first slot of the allowable time widow, which is ensured by the model (18)-(20).

$$\textstyle\sum_{t\in\Psi^q(1)+\varphi^q-1}\{u^q_{r|t}\} = \varphi^q; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{18}$$

$$\textstyle\sum_{t\notin\Psi^q(1)+\varphi^q-1}\{u^q_{r|t}\} = 0; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{19}$$

$$\textstyle\sum_{t\in\Psi^q(1)}\{on^q_{r|t}\} = 1; \forall r \in \mathcal{R} \wedge q \in \mathcal{Q} \tag{20}$$

Public EV Charging Station Modelling

The developed model assumes the public charging station can be operated in a flexible manner, however, in contrast to the flexible consumers considered in the previous section, the charging points response in this case to set-point signals rather than commitment orders, as said the equation (21).

$$p_{r|t}^{EV} \leq d_{r|t}^{EV}; \; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{21}$$

By the model (21), the expected EV demand may be only partially satisfied. This way, the operator has capability to decide if it is necessary to not fully cover or even ignore some charging events whether this supposes an actual benefit for the grid operation.

NG Balance

The energetic balance is ensured each time step by the constraint (22), which establishes the generation-consumption equilibrium. In this case, non-served load has not been contemplated, thus having to satisfy the inelastic expected demand entirely. Therefore, DR is in this case enabled by shiftable consumers and the public charging infrastructure.

$$p_{r|t}^{DEG} + p_{r|t}^{PV} + p_{r|t}^{WT} + p_{r|t}^{BES,dch} = d_{r|t} + p_{r|t}^{EV} + \sum_{q \in \mathcal{Q}} \{u_{r|t}^{q} p^{q}\} + p_{r|t}^{BES,ch}; \; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22}$$

Optimization Problem

The optimal scheduling model developed above is formulated from the retailer point of view, which aims at maximizing their profits while the operator ensures the quality of supplying. In this sense, the model is formulated as a maximization problem in which (1) supposes the objective function. Therefore, the result of the problem searches for the optimal scheduling of the different controllable assets that maximizes the monetary incomes of the retailer. For the sake of analysing, it has been also considered the case in which the shiftable consumers cannot be operated in a flexible way, minimizing the DR capability of the system. Both problems are stated in Table 1. In this table, $\mathbf{\Phi}$ stands for the vector of decision variables (see Nomenclature).

Table 1 The optimization problems developed for optimal scheduling of the NG under study

Model 1: *Shiftable consumers can be operated in a flexible fashion*	**Model 2:** *Flexible operation of shiftable consumers is not enabled*
$\max_{\mathbf{\Phi}} F$ Subject to: (3)-(14), (18)-(22)	$\max_{\mathbf{\Phi}} F$ Subject to: (3)-(17), (21), (22)

Uncertainties Modelling

The optimal scheduling model developed in Section 3 contemplates various uncertain parameters, which are reported in Table 2. For managing with such parameters, a stochastic framework has been proposed. Stochastic modelling is based on representing the uncertain parameters by means of probability distributions, from which one can generate a number scenarios [41]. The scenarios generated constitute the scenario-space ($\mathcal{S}$) which has to be formed by many members since a large number of scenarios have to be considered to properly catch the stochastic essence of the parameter (normally 1,000 [42]). Because the large size of the scenario-space, the optimization model may be intractable in practise. Indeed, one should note that all the variables and constraints would have size $\mathcal{S} \times \mathcal{T}$. To overcome such issues, some papers have proposed to use scenario reduction approaches [11, 42]. By these techniques, the original space is completely described by just a set of few representative members, which are considered a sufficiently descriptive image of the original space. Among the available space reduction approaches, clustering techniques are quite popular because their efficiency, adaptability accuracy and simplicity [43]. Specifically, the k-medoids method has been used in this paper because its overall good performance [43]. The k-medoids method is inspired in the optimal plant location problem. In such problem, a set of plant must be placed in a set of cities, so that the total distance from the plants to the cities is minimized. This approach thus grouping the set of scenarios into clusters, so that each cluster is fully described by just a member within it called medoid. This way, the scenario-space is reduced to the so-called representative scenario-space ($\mathcal{R}$), which is notably smaller scale. The k-medoid method presents a degree of freedom namely the total number of clusters to be created. To set this parameter, helpful indicators such as the total sum of distances and the Davies-Bouldin index along the methodology described in [44] have been used.

The flowchart in Fig. 4 summarizes the steps necessary for solving the optimal scheduling problem developed in Section 3 with stochastic modelling of uncertainties. One of the most interesting features of the k-medoids method is the possibility of easily calculating the probability of occurrence of each scenario, as follows:

$$\omega_r = \frac{\text{size}(\Omega_r)}{\text{size}(\mathcal{S})};\ \forall r \in \mathcal{R} \tag{23}$$

Table 2 Uncertain parameters involved in the operation of the NG under study

Uncertain parameter	**Explanation**
d	Local inflexible (non-shiftable) demand
d^{EV}	EV demand
ϑ	Solar irradiation
θ	Ambient temperature
γ^{WT}	Wind speed

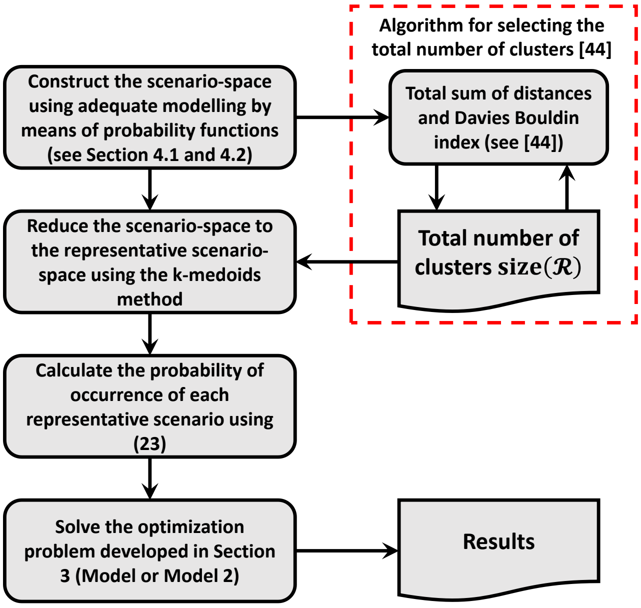

Figure 4 Proposed flowchart for solving the proposed optimal scheduling problem with stochastic modelling of uncertainties

It remains to be explained how the different uncertain parameters involved are modelled on the basis of probability functions, which is explained in the following sections.

Predictable Parameters

Some uncertain parameters can be day-ahead forecasted with sufficient accuracy [36]. Examples of these profiles are weather parameters or inflexible demand. For this kind of uncertainties, the forecasted data can be subjected to errors derived from the forecast technique or unpredictable events. Such errors can be modelled as normal distributions [45], taken the forecast parameter as mean and a preset standard deviation. Using this distribution function, the scenario-space can be generated for these parameters. For the model developed here in particular, the inflexible demand, solar irradiation, temperature and wind speed are assumed to be manageable by this approach [35, 46, 47].

EV Demand Modelling

In contrast to the other uncertain parameters, the EV demand, especially at low-aggregated levels, is hardly predictable due to generally random behaviours of drivers. In this sense, some references have considered specific probability distributions for EV demand [13, 48, 49].

In this paper, a stochastic model for the considered public charging stations has been developed. The developed model is based on the vehicle trip distribution ($\mathfrak{F}$), which is shown in Fig. 5 for a typical weekday in U.S. [13]. This distribution indicates the probability of a EV is driving on road at each hour of the day. As pointed out in [13], the probability of charging events can be modelled on the basis of this distribution.

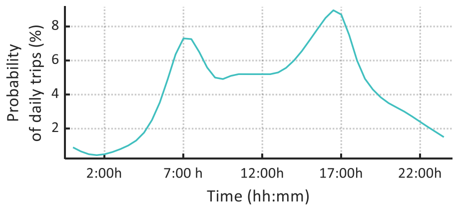

Figure 5 U.S. vehicle trip distribution on weekdays [13]

On the other hand, it is necessary to model the number of charging events that may occur in a day. It is assumed that this parameter can be either predicted based on historical data or directly estimated from for example market studies. In this sense, the number of daily charging events (N_V) is modelled with a normal distribution, where the mean μ stands for the daily expected number of charging events and σ models the standard deviation, as follows:

$$N_{V_s} = \mathrm{round}\left(\mathrm{rand}\big(\mathfrak{N}(\mu,\sigma)\big)\right); \forall s \in \mathcal{S}, \geq 0 \tag{24}$$

Once the total number of charging events has been determined, it can be used as entry of the vehicle trip distribution, in order to determine the arrival time of each vehicle, as follows:

$$\boldsymbol{T}_s = \mathrm{round}\big(\mathrm{rand}(\mathfrak{F})\big);\ \forall s \in \mathcal{S}, \boldsymbol{T}_{i|s} = \left[T_{1|s}, T_{2|s}, \dots, T_{N_{V_s}|s}\right] \tag{25}$$

Now, the vector $\boldsymbol{T}$ can be used to construct the vector $\boldsymbol{c}$, whose i^{th} element is equal to 1 if a vehicle arrives to the charging station at the i^{th} time instant and 0 otherwise, using the following simple loop:

$$\begin{cases} \boldsymbol{initialize}\ \boldsymbol{c}_s = \left[c_{s|1}, c_{s|2}, \dots, c_{s|\mathcal{T}}\right] = [0,0,\dots,0] \in \mathbb{B}^{\mathcal{T}} \\ \boldsymbol{for}\ i = 1{:}\,\mathrm{size}(\boldsymbol{T}_s)\ \boldsymbol{do} \\ \qquad \boldsymbol{c}_s\big(\boldsymbol{T}_s(i)\big) == 1 \\ \boldsymbol{end\ do} \end{cases} ; \forall s \in \mathcal{S} \tag{26}$$

Now, the vector $\boldsymbol{c}$ can be used for modelling the EV demand, as follows:

$$d_{s|t}^{EV} = c_t P_{Rated}^{EV};\ \forall s \in \mathcal{S} \wedge t \in \mathcal{T} \tag{27}$$

The model (27) considers two plausible assumptions:

- The EV demand is considered constant during all the charging process which, as indicated in [12], is a quite realistic assumption since only marginal variations with respect the rating values are observed during short time of the charging event.
- The EV charging process is completed within a unique time slot, which is quite realistic assuming fast charging processes, which can be completed in only 15-30 minutes [12].

Nevertheless, it is worth mentioning that the developed stochastic model for EV demand presents a modular structure that allows it to be adapted to any charging mode or more comprehensive charging profiles. Nevertheless, it has been assumed that the developed model is quite realistic and useful in practise, lying out of the scope of this work further analysing other more elaborated models. As a sake of example, Fig. 6 plots some EV demand profiles constructed with the developed model considering various number of expected charging events. In this figure, a rated power of 55 kW has been considered for the fast charging mode [12].

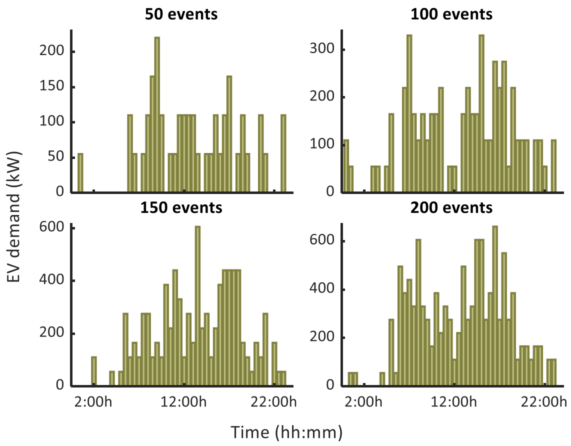

Figure 6 EV demand profiles generated with the developed stochastic model for various numbers of expected charging events

Case Study

This section presents a case study which is devoted on validating the developed stochastic optimal scheduling formulation, for the DC NG layout described in Section 2. The optimization model has been coded in Matlab R2019a, and solved using Gurobi [50] with 30-min resolution.

Data

For creating the scenarios for uncertain parameters, several public databases have been used. Fig. 7 shows the forecasted profiles for the solar irradiance, temperature, local demand and wind speed along the scenarios generated using the methodology described in Section 4. The considered weather profiles have been taken from [51] and correspond with real data observed at Virgin Islands at May 3rd, 2016. The forecasted profile corresponding to local demand has been adapted from real demand measurements at La Palma Island at same date, which are available in [52].

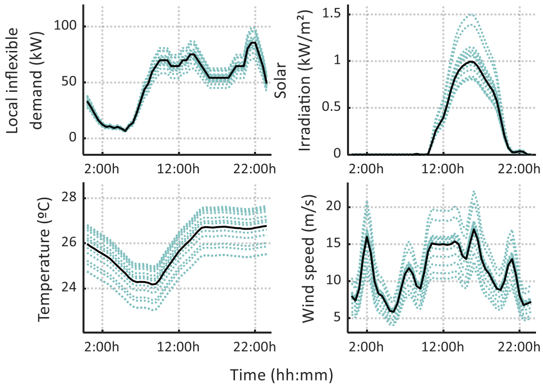

Figure 7 Forecasted profiles (solid lines) and scenarios (discontinuous lines) used for modelling uncertain parameters in simulations

The data corresponding to the other parameters involved are reported in Tables 3-7. For the EV charging the fast mode has been considered, with a rated power of 55 kW and a price of 1.5 $/kWh [12]. Finally, Fig. 8 shows the Time-of-Use tariff used for non-flexible consumers, which is based on typical dynamic tariffs [11].

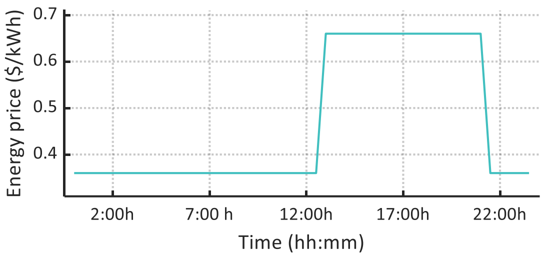

Figure 8 Time-of-Use tariff used in simulations

Table 3 Data of DEG [36]

Parameter	**Value**
$\overline{p}^{DEG}$	100 kW
$\underline{p}^{DEG}$	5 kW
R^{DEG}	50 kW
a^{DEG}	0.6 $/h
b^{DEG}	0.05 $/kWh
c^{DEG}	0.02 $/kWh²

Table 4 Data of PV array [5]

Parameter	**Value**
$\overline{p}^{PV}$	125 kW

η^{PV}	0.167
ρ^{PV}	0.4 \$/kWh

Table 5 Data of WT [5]

Parameter	Value
$\overline{p}^{WT}$	50 kW
η^{WT}	0.88
ρ^{WT}	0.19 \$/kWh
$\underline{\gamma}^{WT}$	2 m/s
$\gamma^{WT,*}$	11 m/s
$\overline{\gamma}^{WT}$	21 m/s

Table 6 Data of BES [11, 35]

Parameter	Value
$\overline{\varepsilon}^{BES}$	50 kWh
$\overline{p}^{BES}$	25 kW
η^{BES}	0.95
ρ^{BES}	10^{-6} \$/kWh^2
DOD^{BES}	0.7

Table 7 Data of shiftable consumers

Parameter	Consumer 1	Consumer 2
p	50 kW	30 kW
λ	0.36 \$/kWh	0.27 \$/kWh
φ	6 hrs.	7.5 hrs.
Ψ	2:30-17:30 h	4:30-15:30 h

Results

In this section, various results are presented and commented. For a further analysis, the operation of the NG under study is considered with and without flexibility in shiftable loads (models 1 and 2, respectively). Moreover, the model is tested for various number of expected charging events (μ in equation (24)). Fig. 9 shows the value of the objective function (retailer profit) for various cases. As observed, flexibility provided by consumers has a direct impact on economical profitability. In fact, the monetary balance for the retailer resulted negative (monetary losses) if the shiftable consumers are operated in a rigid manner, while the benefits may achieve up to ~400 \$ in case of flexible program. Logically, profitability of the system grows with the number of expected charging events, since more monetary incomes are obtained from the public charging station, as seen in Fig. 10.

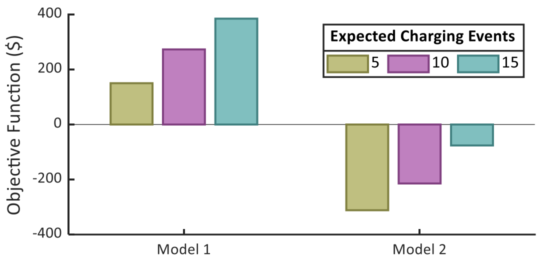

Figure 9 The value of the objective function for various scenarios

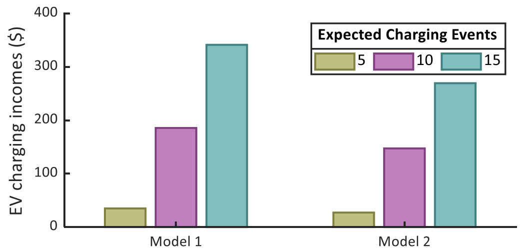

Figure 11 Monetary incomes obtained from EV charging processes in various scenarios

As seen in Fig. 11, flexibility of shiftable consumers has a direct impact on the profitability of the system. This is due to flexibility provided by consumers allows to further satisfy the expected EV demand. Indeed, as observed in Fig. 12, the EV demand satisfaction decreases in the case of considering the model, in which demand flexibility is not considered. In order to further analyse the behaviour of the charging station, Fig. 13 plots the expected and actual satisfied EV demand with model 2. As seen in this figure. some expected charging events were not covered, while other were just partially satisfied.

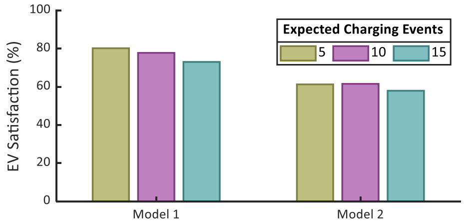

Figure 12 Percentage of the expected EV demand actually satisfied in various scenarios

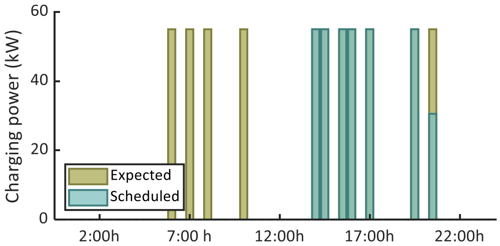

Figure 13 Expected and actual satisfied EV demand without considering flexibility (model 2)

In order to further analyse the role of the shiftable consumers, their scheduling results are plotted in Fig. 14 considering the optimization models 1 and 2. As seen, in case of flexible operation, both consumers are scheduled later, exploiting higher PV penetration and avoiding the use of DEG.

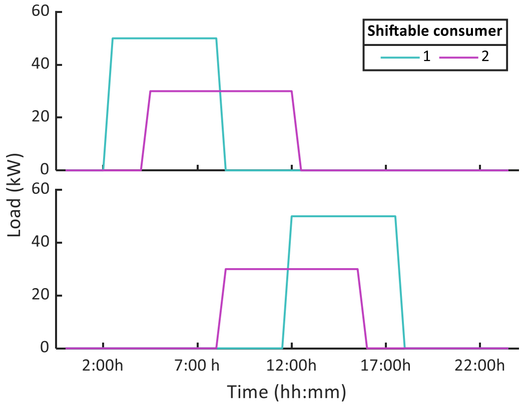

Figure 14 Scheduling result shiftable consumer with model 1 (upper) and 2 (bottom)

As commented, the main advantage of operating the shiftable consumers in a flexible way is reducing the dependency of costly generators like DEG. As seen in Fig. 15, expected DEG generation with flexibility barely surpassed 400 kWh, while it was higher than 600 kWh in case of no flexibility. These results are traduced in a lower fuel consumption and therefore a lower operational cost. As seen in Fig. 16, the expected fuel cost with the model 1 did not surpass 400 $, while the fuel cost was higher than 800 $ in the case of rigid operation of shiftable consumers. These results have also a direct impact in environmental concerns since, as commented in [37], the total CO_2 emissions are proportional to diesel consumption.

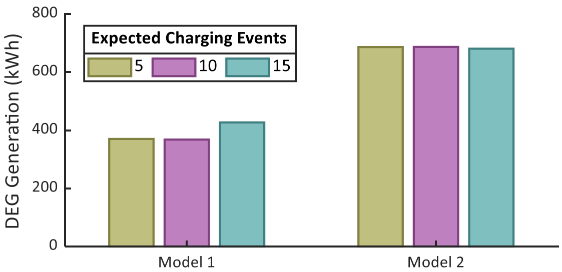

Figure 15 Total DEG generation in various scenarios

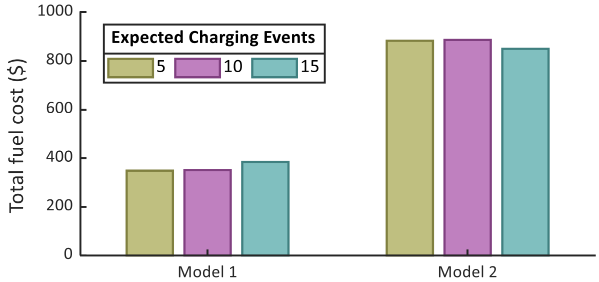

Figure 16 Total fuel cost in various scenarios

Conclusions

This paper has comprehensively analysed a possible DC isolated nanogrid layout for integration of renewable sources, energy storage facilities, demand response initiatives and electric vehicle charging infrastructures. In this sense, the necessary electronic interfaces and communication channels have been described. Moreover, the relationship among the different agents involved in the grid operation has been discussed. An optimal scheduling tool for the analysed nanogrid has been presented, along a stochastic framework for uncertainties modelling. In this regard, a specific stochastic model for fast charging stations has been developed.

A case study has been presented and various results have been commented, with the aim of validating the developed formulation and analysing the impact of demand response programs in the grid operation. Results obtained have served to evidence the importance of flexible consumption for boosting up the monetary incomes of the retailer and reducing diesel consumption and therefore CO_2 emissions. It has been also remarkable the role of public charging infrastructures in the profitability of the grid and how demand response programs affect their viability.

Future works should be focused on analysing the considered grid layout in grid-connected mode, for which the uncertainty of energy pricing along the possibility of selling energy to the upscale grid have to be considered.

Appendix A – Linearization of quadratic terms

In the developed optimization model, some quadratic terms have appeared in the objective function. To linearize these terms and therefore preserve the lineal character of the problem, a piecewise representation of such variables has been considered. By this approach, the quadratic function ψ is characterized by its piecewise representation $\tilde{\psi}$, for which n $(\tilde{x}_i)$ points are taken, as follows:

$$\tilde{\psi} = \langle \tilde{x}_i, \psi(\tilde{x}_i) \rangle; \forall i \in \{1,2,\dots,n\} \tag{28}$$

Usually, the higher the number of points considered, the more accurate the piecewise representation is, however, the optimization problem becomes computationally more expensive. The piecewise representation of quadratic terms allow to replace them by the dummy variable z wherever they appear in the problem. This variable is calculated, as follows:

$$z = \sum_{i=2}^{i=n}\{\delta_i(K_i x + L_i)\} = \sum_{i=2}^{i=n}\left\{K_i \underbrace{\delta_i x}_{w_i} + L_i\delta_i\right\} \tag{29}$$

where δ is a binary variable that ensures that only one segment of the piecewise curve is activated at once by imposing the following constraint:

$$\sum_{i=1}^{i=n-1}\{\delta_i \tilde{x}_i\} \le x \le \sum_{i=2}^{i=n}\{\delta_{i-1}\tilde{x}_i\} \tag{30}$$

In (29), the parameters L and K can be calculated as follows:

$$K_i = \frac{\psi(\tilde{x}_i) - \psi(\tilde{x}_{i-1})}{\tilde{x}_i - \tilde{x}_{i-1}};\ \forall i \in \{2,3,\dots,n\} \tag{31}$$

$$L_i = \psi(\tilde{x}_i) - K_i\tilde{x}_i;\ \forall i \in \{2,3,\dots,n\} \tag{32}$$

Finally, it is important to note that (29) involves the product of two variables (δ and x), which introduces further nonlinearities in the model. To avoid this issue, the product of variables can be replaced by the lineal variable w for which the following additional constraints are needed:

$$x - M(1-\delta_i) \le w_i \le x + M(1-\delta_i);\ \forall i \in \{2,3,\dots,n\} \tag{33}$$

$$-M\delta_i \leq w_i \leq M\delta_i; \ \forall i \in \{2,3,\dots,n\} \tag{34}$$

where M is a large positive constant.

Nomenclature

Indexes (Sets)

$t(\mathcal{T})$	Time
$s(\mathcal{S})$	Scenario
$r(\mathcal{R})$	Representative scenario
$q(\mathcal{Q})$	Shiftable load
Ω_r	Cluster of the representative scenario r
Ψ	Time window of a shiftable load

Superscripts

DEG	Diesel engine generator
EV	Electric vehicle
PV	Photovoltaic
WT	Wind turbine
$BES, ch/dch$	Battery energy storage in charging/discharging mode
$\overline{(\cdot)}/\underline{(\cdot)}$	Maximum minimum value of a variable or parameter

Constants and Parameters

ω	Probability (pu)
$\Delta\tau$	Time step (h)
λ	Energy price ($/kWh)
d	Predicted local demand (kW)
ρ	Operation and maintenance cost ($/kWh or $/kWh^2)
a, b, c	Fuel cost coefficients ($/h, $/kWh, $/kWh^2)
R	Ramping rate (kW)
ϑ	Solar irradiance (kW/m^2)
θ	Ambient temperature (ºC)
η	Efficiency (pu)
γ	Wind speed (m/s)
α, β	Speed-power wind turbine curve coefficients (kW·(m/s)$^{-3}$, -)
φ	Total number of hours of operation of shiftable load (h)

Electric Vehicles Demand Modelling

$\mathfrak{N}(\mu,\sigma)$	Normal distribution (with mean μ and standard deviation σ) for modelling the daily number of charging events
N_V	Total number of charging events
$T_{i\|s}$	Arrival time of the i^{th} vehicle corresponded to the s^{th} scenario
$\boldsymbol{c} \in \mathbb{B}^{\mathcal{T}}$	Binary vector whose i^{th} element is equal to 1 if a vehicle arrives to the charging station at the i^{th} time instant and 0 otherwise
$\mathrm{rand}(\cdot)$	Function that returns a random number based on a probability distribution function
$\mathrm{round}(\cdot)$	Function that rounds to the nearest integer
$\mathfrak{F}(\cdot)$	Vehicle trip distribution
P_{Rated}^{EV}	Rated power of Electric vehicles charging (kW)

Variables

p	Power (kW)
u	Commitment status (binary)
ε	Energy stored (kWh)
on/off	Flag variable that indicates the activation/deactivation of a shiftable load (binary)

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