# Co-optimization of Generation Expansion Planning and Electric Vehicles Flexibility

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***Abstract*—The envisaged de-carbonization of power systems poses unprecedented challenges enhancing the potential of flexible demand. However, the incorporation of the latter in system planning has yet to be comprehensively investigated. This paper proposes a novel planning model that allows co-optimizing the investment and operating costs of conventional generation assets and demand flexibility, in the form of smart-charging/discharging electric vehicles (EV). The model includes a detailed representation of EV operational constraints along with the generation technical characteristics, and accounts for the costs required to enable demand flexibility. Computational tractability is achieved through clustering generation units and EV, which allows massively reducing the number of decision variables and constraints, and avoiding non-linearities. Case studies in the context of the UK demonstrate the economic value of EV flexibility in reducing peak demand levels and absorbing wind generation variability, and the dependence of this value on the required enabling cost and users' traveling patterns.**

***Index Terms*—Demand flexibility, electric vehicles, generation expansion planning, mixed-integer programming, unit commitment, vehicle-to-grid.**

## NOMENCLATURE

### A. Indices, Sets and Sub-sets

| | |
|---|---|
| $i \in I$ | Generation technology types. |
| $l \in L$ | Piecewise linear heat consumption function segments. |
| $n \in N$ | Weeks. |
| $t \in T$ | Hours. |
| $v \in V$ | Electric vehicle (EV) types. |
| $I^{\mathrm{MR}} \subseteq I$ | Sub-set of must-run generation technologies. |
| $I^{\mathrm{SPR}} \subseteq I$ | Sub-set of generation technologies that can provide spinning reserve. |
| $T^{\mathrm{ed}} \subseteq T$ | Sub-set of last hour of each day. |
| $T_v^{\mathrm{gc}} \subseteq T$ | Sub-set of hours during which each EV of type $v$ is plugged into the grid. |
| $\Omega^{\mathrm{DV}}$ | Set of all discrete decision variables. |
| $\Omega^{\mathrm{CV}}$ | Set of all continuous decision variables. |

### B. Parameters

| | |
|---|---|
| $\tau$ | Time resolution. |
| $\Phi_n$ | Weighting factor of week $n$. |
| $\pi^{\mathrm{CO_2}}$ | $CO_2$ price. |
| $\pi^{\mathrm{LC}}$ | Load curtailment price. |
| $\pi^{\mathrm{GC}}$ | Conventional generation curtailment price. |
| $\pi^{\mathrm{WC}}$ | Wind generation curtailment price. |
| SEI | System-wide $CO_2$ emissions intensity limit. |
| $\mathrm{RR}_{nt}^{\mathrm{U}}$ | System-wide upward spinning reserve requirement at week $n$ and hour $t$. |
| $\mathrm{RR}_{nt}^{\mathrm{D}}$ | System-wide downward spinning reserve requirement at week $n$ and hour $t$. |
| $L_{nt}$ | Non-EV system demand at week $n$ and hour $t$. |
| $P_{nt}^{\mathrm{W\text{-}pwr}}$ | Wind power available at week $n$ and hour $t$. |
| $\sigma_{nt}^{\mathrm{WFE\text{-}4h}}$ | 4-hours wind forecast error at week $n$ and hour $t$. |
| $\mathrm{FC}_i$ | Fixed costs of a generation unit of technology $i$. |
| $K_i$ | Capacity of a generation unit of technology $i$. |
| $\pi_i^{\mathrm{O\&M}}$ | Variable O&M cost of a generation unit of technology $i$. |
| $\pi_i^{\mathrm{fuel}}$ | Fuel cost of a generation unit of technology $i$. |
| $\pi_i^{\mathrm{SU}}$ | Start-up cost of a generation unit of technology $i$. |
| $\pi_i^{\mathrm{SD}}$ | Shut-down cost of a generation unit of technology $i$. |
| $\mathrm{NLH}_{il}^{0}$ | Hypothetical no-load heat usage at zero power output of a generation unit of technology $i$ at segment $l$ of the piecewise linear heat consumption function. |
| $\mathrm{HR}_{il}^{\mathrm{inc}}$ | Incremental heat rate of a generation unit of technology $i$ at segment $l$ of the piecewise linear heat consumption function. |
| $\mathrm{EF}_i^{\mathrm{CO_2}}$ | $CO_2$ emissions factor of a generation unit of technology $i$. |
| $\mathrm{H}_i^{\mathrm{SU}}$ | Heat consumed during the start-up event of a generation unit of technology $i$. |
| $\mathrm{H}_i^{\mathrm{SD}}$ | Heat consumed during the shut-down event of a generation unit of technology $i$. |
| $\mathrm{ER}_i^{\mathrm{CCS}}$ | $CO_2$ emissions reduction factor due to a CCS system in a generation unit of technology $i$. |
| $p_i^{\mathrm{min}}$ | Minimum stable power output of a generation unit of technology $i$. |
| $p_i^{\mathrm{Max}}$ | Maximum power output of a generation unit of technology $i$. |
| $\Delta_i^{\mathrm{U}}$ | Ramp-up rate limit of a generation unit of technology $i$. |
| $\Delta_i^{\mathrm{D}}$ | Ramp-down rate limit of a generation unit of technology $i$. |
| $\mathrm{MT}_i^{\mathrm{U}}$ | Minimum up time of a generation unit of technology $i$. |
| $\mathrm{MT}_i^{\mathrm{D}}$ | Minimum down time of a generation unit of technology $i$. |

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$\mathrm{R}_i^{\text{Max-U}}$ Maximum upward spinning reserve deployment of a generation unit of technology $i$.

$\mathrm{R}_i^{\text{Max-D}}$ Maximum downward spinning reserve deployment of a generation unit of technology $i$.

$N_i^{I\text{-Max}}$ Upper bound for $N_i^I$.

$N_v^{\text{EV}}$ Total number of EV of type $v$.

$\mathrm{FC}_v^{\text{EV}^+}$ EV flexibility enabling cost per EV of type $v$.

$c_v^{\text{bat}}$ Battery cost of each EV of type $v$.

$d_{ntv}^{\text{EV}^-}$ Electricity demand of an inflexible EV of type $v$ at week $n$ and hour $t$.

$\eta_v^{\text{chg}}$ Charging efficiency of each EV of type $v$ (battery's and grid connection power electronics' charging efficiency).

$\eta_v^{\text{dis}}$ Discharging efficiency of each EV of type $v$ (battery's and grid connection power electronics' discharging efficiency).

$\eta_v^{\text{el}}$ Self-discharging energy efficiency of the battery of each EV of type $v$.

$\kappa_v$ Slope of the linear approximation of the battery life of each EV of type $v$ as a function of charge/discharge cycles.

$e_v^{\text{bat-cap}}$ Energy capacity of the battery of each EV of type $v$.

$e_v^{\text{bat-min}}$ Minimum state of charge of the battery of each EV of type $v$.

$e_v^{\text{bat-Max}}$ Maximum state of charge of the battery of each EV of type $v$.

$p_v^{\text{chg-Max}}$ Maximum charging power rate of the battery of each EV of type $v$.

$p_v^{\text{dis-Max}}$ Maximum discharging power rate of the battery of each EV of type $v$.

$e_{ntv}^{\text{tr}}$ EV type $v$ user's energy requirements for travelling purposes at week $n$ and hour $t$.

$e_v^{\text{ed}}$ Required energy level in the battery of an EV of type $v$ at the end of each day.

### C. Integer Variables

$N_i^I$ Number of installed generation units of technology $i$.

$U_{nti}$ Number of committed generation units of technology $i$ at week $n$ and hour $t$.

$S_{nti}^{\text{U}}$ Number of start-up events of generation technology $i$ at week $n$ and hour $t$.

$S_{nti}^{\text{D}}$ Number of shut-down events of generation technology $i$ at week $n$ and hour $t$.

$N_v^{\text{EV}^+}$ Number of flexible EV of type $v$.

### D. Continuous Variables

$P_{nti}$ Power output of generation technology $i$ at week $n$ and hour $t$.

$H_{nti}$ Heat consumption of generation technology $i$ at week $n$ and hour $t$.

$\mathrm{EMI}_{nti}^{\mathrm{CO_2}}$ $CO_2$ emissions of generation technology $i$ at week $n$ and hour $t$.

$R_{nti}^{\text{U}}$ Upward spinning reserve provided by generation technology $i$ at week $n$ and hour $t$.

$R_{nti}^{\text{D}}$ Downward spinning reserve provided by generation technology $i$ at week $n$ and hour $t$.

$L_{nt}^{\text{C}}$ Load curtailment at week $n$ and hour $t$.

$P_{nt}^{\text{GC}}$ Conventional generation curtailment at week $n$ and hour $t$.

$P_{nt}^{\text{W}}$ Wind power dispatched at week $n$ and hour $t$.

$P_{nt}^{\text{WC}}$ Wind generation curtailment at week $n$ and hour $t$.

$P_{ntv}^{\text{EV}^+\text{-chg}}$ Total power demand of all flexible EV of type $v$ at week $n$ and hour $t$.

$P_{ntv}^{\text{EV}^+\text{-dis}}$ Total power discharged from all flexible EV of type $v$ at week $n$ and hour $t$.

$\chi_{ntv}^{\text{EV}^+\text{-dis}}$ Total energy drawn from all flexible EV of type $v$ at week $n$ and hour $t$ due to V2G.

$E_{ntv}^{\text{EV}^+}$ Total battery energy level of all flexible EV of type $v$ at week $n$ and hour $t$.

$R_{ntv}^{\text{U-EV}^+\text{-chg}}$ Total upward spinning reserve provided by all flexible EV of type $v$ at week $n$ and hour $t$ through reduced charging.

$R_{ntv}^{\text{U-EV}^+\text{-dis}}$ Total upward spinning reserve provided by all flexible EV of type $v$ at week $n$ and hour $t$ through increased discharging.

$R_{ntv}^{\text{D-EV}^+\text{-chg}}$ Total downward spinning reserve provided by all flexible EV of type $v$ at week $n$ and hour $t$ through increased charging.

$R_{ntv}^{\text{D-EV}^+\text{-dis}}$ Total downward spinning reserve provided by all flexible EV of type $v$ at week $n$ and hour $t$ through reduced discharging.

## I. Introduction

ENVIRONMENTAL and energy security concerns have paved the way for the wide de-carbonisation of energy systems through the large-scale integration of renewable generation and the electrification of transport and heat sectors. However, this paradigm change introduces significant challenges to the operation and development of modern power systems. The limited controllability and predictability of renewable generation is expected to require large volumes of flexible generation, implying adverse economic effects. Furthermore, the electrification of transport and heat sectors will lead to disproportionately larger demand peaks–and subsequently higher generation and network costs–than the increase in the total electrical energy consumption, due to the temporal patterns of users' driving and heating requirements [1].

In this context, flexible demand technologies attract great interest due to their ability to redistribute users' demand requirements in time, through the use of different types of storage [2]. Smart coordination of such demand flexibility could reduce the requirements for flexible generation capacity and limit peak demand levels, improving significantly the economic efficiency of future low-carbon power systems. Despite the significant potential and great interest in flexible demand, its incorporation into system planning has yet to be analyzed in depth and with sufficient detail.

In [3], flexible demand is incorporated in generation expansion planning (GEP) as an equivalent peak generator without inter-temporal operational constraints, while authors in [4]–[6], represent it through the concept of self-price elasticity. However, the temporal redistributing capability of flexible demand is not captured in any of the above approaches. In [7] and [8], flexible demand is modeled through both self-price and cross-price elasticities, allowing a more accurate representation of its inter-temporal characteristics. Although this representation expresses the main properties of manually-facilitated flexible demand participation, it fails in the characterization of the inherent technology-specific operational complexity and dynamics of different flexible loads, which are likely to be automatically controlled in future power systems.

Amongst such loads, electric vehicles (EV) exhibit a particularly significant flexibility potential due to their inherent ability to store electrical energy in their batteries, their stationary character (parked for more than 90% of the time in average [9]), their low energy consumption requirements with respect to the significant capacity of their batteries [9]–[11], and the Vehicle-to-Grid (V2G) capability which enables the EV to inject stored energy in their battery into the grid [12], [13]. The impact of EV on GEP is analyzed in [14] and [15], but both studies underestimate the value of EV demand flexibility since they use a set of pre-defined fixed EV charging profiles, disregarding the capability of optimally scheduling EV demand.

Apart from the significant limitations of the employed flexible demand modeling approaches, all the above papers consider fixed flexible demand penetrations and do not account for the cost of introducing and coordinating flexibility at the demand side. In reality, the realization of the flexible demand potential involves the installation and operation of suitable metering, control and communication infrastructure. The benefits of flexible demand in system development can only be accurately captured by an integrated investment planning model which takes into account the costs of such enabling infrastructure, and determines the optimal number of flexible loads along with the optimal portfolio of generation assets.

This paper develops a novel planning model in which the investment and operating costs of generation assets and demand flexibility, in the form of smart-charging EV with or without V2G capability, are co-optimized. Along with the full set of different generation technologies' technical characteristics, the capability of optimally scheduling EV demand and V2G injections, according to a detailed model of the EV operational constraints, is explicitly incorporated into the model. Furthermore, the costs required to introduce and coordinate such EV flexibility, as well as those related to the degradation of the EV battery due to V2G, are accounted for and balanced against generation investment and operating costs, in order to determine the optimal number of flexible EV.

The model is formulated as a large-scale mixed-integer linear optimization problem in which generation units and EV of similar characteristics are clustered, in order to reduce the number of decision variables and constraints, and to avoid non-linearities in the objective function and constraints. Case studies in the context of the UK demonstrate the economic value of EV flexibility in reducing peak demand levels and absorbing wind generation variability, and reveal that this value is enhanced with an increasing electrification of the transport sector and increasing wind generation capacity levels. The results also analyze and illustrate the dependence of this value on the required enabling cost, the place of charging, the deployment of V2G capability, and EV users' traveling patterns, with EV plugged into the grid during demand peak periods and EV with larger traveling distances yielding higher system benefits when becoming flexible.

The rest of this paper is organized as follows. Section II details the properties, assumptions and mathematical formulation of the proposed optimization model. Section III presents the examined case studies and provides illustrative results regarding the impact of EV flexibility and the computational performance of the model. Finally, Section IV discusses conclusions and future extensions of this work.

## II. Proposed Optimization Model

### A. Key Properties and Assumptions

The proposed model is based on a deterministic long-run equilibrium approach, where the total system cost is minimized by a central planner. In order to capture the diversity of system conditions in a computationally manageable fashion, an approach based on the definition of typical weeks is used [16].

Flexible demand involves EV with smart (controllable) charging and V2G capabilities. Although the total EV penetration constitutes a fixed input for the model, the proportion of flexible EV is a decision variable. The demand and V2G injections of flexible EV are optimally scheduled in the operational timescale and constitute decision variables for the model, whilst the demand of inflexible EV is a fixed input and is derived by assuming that they start charging their batteries immediately after they are plugged into the grid and until they are fully charged [11]. It is assumed that only day-ahead information will be employed for the coordination of flexible EV in the operational timescale and thus the energy requirements of flexible EV can only be redistributed on an intraday basis. The realization and coordination of flexible EV operation requires certain enabling costs (associated with metering, control and communication infrastructure) per EV, while the exercise of the V2G capability yields additional costs associated with the accelerated degradation of the EV battery. The EV battery degradation cost is modeled as a function of the energy drawn from the battery due to V2G injections, following the approach adopted in [17]. The total EV population is categorized into different types according to the EV users' driving requirements, and the operational properties of EV batteries and grid connections.

Generation units are also grouped into different technology types, each characterized by their specific technical characteristics. The installed wind generation capacity is given as fixed input for the model, determined by the national and international targets for renewable energy integration and carbon emissions reduction.

The model is formulated as a large-scale mixed-integer linear optimization program (MIP) [18], which can be solved using commercially available software [19]. The optimization model's objective function, decision variables and constraints are presented in the following section.

### B. Model Formulation

$$\underset{\Omega^{\mathrm{DV}},\Omega^{\mathrm{CV}}}{\text{Minimize}} \Bigg\{ \sum_{i\in I} \mathrm{FC}_i K_i N_i^I + \sum_{n\in N}\sum_{t\in T}\Phi_n \Bigg[ \sum_{i\in I}\Big(\pi_i^{\mathrm{SU}} S_{nti}^{\mathrm{U}} + \tau\pi_i^{\mathrm{O\&M}} P_{nti} + \tau\pi_i^{\mathrm{fuel}} H_{nti} + \tau\pi^{\mathrm{CO_2}}\mathrm{EMI}_{nti}^{\mathrm{CO_2}} + \pi_i^{\mathrm{SD}} S_{nti}^{\mathrm{D}}\Big) + \tau\pi^{\mathrm{LC}} L_{nt}^{\mathrm{C}} + \tau\pi^{\mathrm{GC}} P_{nt}^{\mathrm{GC}} + \tau\pi^{\mathrm{WC}} P_{nt}^{\mathrm{WC}} \Bigg] + \sum_{v\in V}\mathrm{FC}_v^{\mathrm{EV^+}} N_v^{\mathrm{EV^+}} + \sum_{n\in N}\sum_{t\in T}\sum_{v\in V}\Phi_n \left|\frac{\kappa_v}{100}\right| \frac{\chi_{ntv}^{\mathrm{EV^+\text{-}dis}}}{e_v^{\mathrm{bat\text{-}cap}}} c_v^{\mathrm{bat}} \Bigg\}, \quad (1)$$

subject to:

$$\sum_{i\in I} P_{nti} + P_{nt}^{\mathrm{W}} + \sum_{v\in V}\eta_v^{\mathrm{dis}} P_{ntv}^{\mathrm{EV^+\text{-}dis}} + L_{nt}^{\mathrm{C}} - P_{nt}^{\mathrm{GC}} = L_{nt} + \sum_{v\in V} P_{ntv}^{\mathrm{EV^+\text{-}chg}} + \sum_{v\in V}\left[N_v^{\mathrm{EV}} - N_v^{\mathrm{EV^+}}\right] d_{ntv}^{\mathrm{EV^-}}, \quad \forall n,\forall t, \quad (2)$$

$$\sum_{i\in I^{\mathrm{SPR}}} R_{nti}^{\mathrm{U}} + \sum_{v\in V} R_{ntv}^{\mathrm{U\text{-}EV^+\text{-}chg}} + \sum_{v\in V}\eta_v^{\mathrm{dis}} R_{ntv}^{\mathrm{U\text{-}EV^+\text{-}dis}} \geq \mathrm{RR}_{nt}^{\mathrm{U}}, \quad \forall n,\forall t, \quad (3)$$

$$\sum_{i\in I^{\mathrm{SPR}}} R_{nti}^{\mathrm{D}} + \sum_{v\in V} R_{ntv}^{\mathrm{D\text{-}EV^+\text{-}chg}} + \sum_{v\in V}\eta_v^{\mathrm{dis}} R_{ntv}^{\mathrm{D\text{-}EV^+\text{-}dis}} \geq \mathrm{RR}_{nt}^{\mathrm{D}}, \quad \forall n,\forall t, \quad (4)$$

$$\sum_{n\in N}\sum_{t\in T}\sum_{i\in I}\Phi_n \mathrm{EMI}_{nti}^{\mathrm{CO_2}} \leq \mathrm{SEI}\cdot\sum_{n\in N}\sum_{t\in T}\Phi_n\Bigg\{\sum_{i\in I} P_{nti} + P_{nt}^{\mathrm{W}} + \sum_{v\in V}\eta_v^{\mathrm{dis}} P_{ntv}^{\mathrm{EV^+\text{-}dis}}\Bigg\}, \quad (5)$$

$$H_{nti} \geq \mathrm{NLH}_{il}^{0} U_{nti} + \mathrm{HR}_{il}^{\mathrm{inc}} P_{nti}, \quad \forall n,\forall t,\forall i, \quad (6)$$

$$\mathrm{EMI}_{nti}^{\mathrm{CO_2}} = \mathrm{EF}_i^{\mathrm{CO_2}}\Big[\mathrm{H}_i^{\mathrm{SU}} S_{nti}^{\mathrm{U}} + H_{nti} + \mathrm{H}_i^{\mathrm{SD}} S_{nti}^{\mathrm{D}}\Big]\cdot\Big(1-\mathrm{ER}_i^{\mathrm{CCS}}\Big), \quad \forall n,\forall t,\forall i \quad (7)$$

$$U_{nti} p_i^{\min} \leq P_{nti} \leq U_{nti} p_i^{\mathrm{Max}}, \quad \forall n,\forall t,\forall i, \quad (8)$$

$$P_{nti} - P_{n(t-1)i} \leq \left[U_{nti} - S_{nti}^{\mathrm{U}}\right]\tau\Delta_i^{\mathrm{U}} - S_{nti}^{\mathrm{D}} p_i^{\min} + S_{nti}^{\mathrm{U}}\max\left\{p_i^{\min},\tau\Delta_i^{\mathrm{U}}\right\}, \quad \forall n,\forall t,\forall i, \quad (9)$$

$$P_{n(t-1)i} - P_{nti} \leq \left[U_{nti} - S_{nti}^{\mathrm{U}}\right]\tau\Delta_i^{\mathrm{D}} - S_{nti}^{\mathrm{U}} p_i^{\min} + S_{nti}^{\mathrm{D}}\max\left\{p_i^{\min},\tau\Delta_i^{\mathrm{D}}\right\}, \quad \forall n,\forall t,\forall i, \quad (10)$$

$$U_{nti} \geq \sum_{\hat{t}=t-(\mathrm{MT}_i^{\mathrm{U}}/\tau)+1}^{t} S_{n\hat{t}i}^{\mathrm{U}}, \quad \forall n,\forall t,\forall i, \quad (11)$$

$$N_i^I - U_{nti} \geq \sum_{\hat{t}=t-(\mathrm{MT}_i^{\mathrm{D}}/\tau)+1}^{t} S_{n\hat{t}i}^{\mathrm{D}}, \quad \forall n,\forall t,\forall i, \quad (12)$$

$$R_{nti}^{\mathrm{U}} \leq \min\left\{U_{nti} p_i^{\mathrm{Max}} - P_{nti}, U_{nti}\mathrm{R}_i^{\mathrm{Max\text{-}U}}\right\}, \quad \forall n,\forall t,\forall i\in I^{\mathrm{SPR}}, \quad (13)$$

$$R_{nti}^{\mathrm{D}} \leq \min\left\{P_{nti} - U_{nti} p_i^{\min}, U_{nti}\mathrm{R}_i^{\mathrm{Max\text{-}D}}\right\}, \quad \forall n,\forall t,\forall\, i\in I^{\mathrm{SPR}}, \quad (14)$$

$$U_{nti} = U_{n(t-1)i} + S_{nti}^{\mathrm{U}} - S_{nti}^{\mathrm{D}}, \quad \forall n,\forall t,\forall i, \quad (15)$$

$$U_{nti} \leq N_i^I, \quad \forall n,\forall t,\forall i\in I\smallsetminus I^{\mathrm{MR}}, \quad (16)$$

$$U_{nti} = N_i^I, \quad \forall n,\forall t,\forall i\in I^{\mathrm{MR}}, \quad (17)$$

$$P_{nt}^{\mathrm{W}} + P_{nt}^{\mathrm{WC}} = P_{nt}^{\mathrm{W\text{-}pwr}}, \quad \forall n,\forall t, \quad (18)$$

$$E_{ntv}^{\mathrm{EV^+}} = \eta_v^{\mathrm{elec}} E_{n(t-1)v}^{\mathrm{EV^+}} + \left(\eta_v^{\mathrm{chg}} P_{ntv}^{\mathrm{EV^+\text{-}chg}} - P_{ntv}^{\mathrm{EV^+\text{-}dis}}\right)\tau - N_v^{\mathrm{EV^+}} e_{ntv}^{\mathrm{tr}}, \quad \forall n,\forall t,\forall v, \quad (19)$$

$$N_v^{\mathrm{EV^+}} e_v^{\mathrm{bat\text{-}min}} \leq E_{ntv}^{\mathrm{EV^+}} \leq N_v^{\mathrm{EV^+}} e_v^{\mathrm{bat\text{-}Max}}, \quad \forall n,\forall t,\forall v, \quad (20)$$

$$\chi_{ntv}^{\mathrm{EV^+\text{-}dis}} = \max\left\{0, E_{n(t-1)v}^{\mathrm{EV^+}} - E_{ntv}^{\mathrm{EV^+}}\right\}, \quad \forall n,\forall t,\forall v, \quad (21)$$

$$P_{ntv}^{\mathrm{EV^+\text{-}chg}} \leq \left\{\begin{array}{ll} \frac{N_v^{\mathrm{EV^+}} p_v^{\mathrm{chg\text{-}Max}}}{\eta_v^{\mathrm{chg}}}, & \forall t\in T_v^{\mathrm{gc}} \\ 0, & \forall t\in T\smallsetminus T_v^{\mathrm{gc}} \end{array}\right\}, \quad \forall n,\forall v, \quad (22)$$

$$P_{ntv}^{\mathrm{EV^+\text{-}dis}} \leq \left\{\begin{array}{ll} N_v^{\mathrm{EV^+}} p_v^{\mathrm{dis\text{-}Max}}, & \forall t\in T_v^{\mathrm{gc}} \\ 0, & \forall t\in T\smallsetminus T_v^{\mathrm{gc}} \end{array}\right\}, \quad \forall n,\forall v, \quad (23)$$

$$R_{ntv}^{\mathrm{U\text{-}EV^+\text{-}chg}} \leq P_{ntv}^{\mathrm{EV^+\text{-}chg}}, \quad \forall n,\forall t\in T_v^{\mathrm{gc}},\forall v, \quad (24)$$

$$R_{ntv}^{\mathrm{U\text{-}EV^+\text{-}dis}} \leq N_v^{\mathrm{EV^+}} p_v^{\mathrm{dis\text{-}Max}} - P_{ntv}^{\mathrm{EV^+\text{-}dis}}, \quad \forall n,\forall t\in T_v^{\mathrm{gc}},\forall v, \quad (25)$$

$$R_{ntv}^{\mathrm{U\text{-}EV^+\text{-}dis}} \leq \frac{\left(\eta_v^{\mathrm{elec}} E_{n(t-1)v}^{\mathrm{EV^+}} - N_v^{\mathrm{EV^+}} e_v^{\mathrm{bat\text{-}min}}\right)}{\tau} - P_{ntv}^{\mathrm{EV^+\text{-}dis}}, \quad \forall n,\forall t\in T_v^{\mathrm{gc}},\forall v, \quad (26)$$

$$R_{ntv}^{\mathrm{D\text{-}EV^+\text{-}chg}} \leq \frac{N_v^{\mathrm{EV^+}} p_v^{\mathrm{chg\text{-}Max}}}{\eta_v^{\mathrm{chg}}} - P_{ntv}^{\mathrm{EV^+\text{-}chg}}, \quad \forall n,\forall t\in T_v^{\mathrm{gc}},\forall v, \quad (27)$$

$$R_{ntv}^{\text{D-EV}^+\text{-chg}} \le \frac{\left(N_v^{\text{EV}^+} e_v^{\text{bat-Max}} - \eta_v^{\text{elec}} E_{n(t-1)v}^{\text{EV}^+}\right)}{\tau \eta_v^{\text{chg}}} - P_{ntv}^{\text{EV}^+\text{-chg}}, \quad \forall n, \forall t \in T_v^{\text{gc}}, \forall v, \quad (28)$$

$$R_{ntv}^{\text{D-EV}^+\text{-dis}} \le P_{ntv}^{\text{EV}^+\text{-dis}}, \quad \forall n, \forall t \in T_v^{\text{gc}}, \forall v, \quad (29)$$

$$E_{ntv}^{\text{EV}^+} = N_v^{\text{EV}^+} e_v^{\text{ed}}, \quad \forall n, \forall t \in T^{\text{ed}}, \forall v, \quad (30)$$

$$N_i^I \le N_i^{I\text{-Max}}, \quad \forall i, \quad (31)$$

$$N_v^{\text{EV}^+} \le N_v^{\text{EV}}, \quad \forall v, \quad (32)$$

$$\Omega^{\text{DV}} = \left\{N_i^{\text{I}}, U_{nti}, S_{nti}^{\text{U}}, S_{nti}^{\text{D}}, N_v^{\text{EV}^+}\right\} \in \mathbb{Z}_{\ge 0}, \quad \forall n, \forall t, \forall i, \forall v, \quad (33)$$

$$\Omega^{\text{CV}} = \Big\{P_{nti}, F_{nti}, \text{EMI}_{nti}^{\text{CO}_2}, R_{nti}^{\text{U}}, R_{nti}^{\text{D}}, R_{ntv}^{\text{U-EV}^+-\text{chg}}, R_{ntv}^{\text{U-EV}^+-\text{dis}}, R_{ntv}^{\text{D-EV}^+-\text{chg}}, R_{ntv}^{\text{D-EV}^+-\text{dis}}, \chi_{ntv}^{\text{EV}^+-\text{dis}}, E_{ntv}^{\text{EV}^+}, P_{ntv}^{\text{EV}^+\text{-chg}}, P_{ntv}^{\text{EV}^+\text{-dis}}, P_{nt}^{\text{GC}}, L_{nt}^{\text{C}}, P_{nt}^{\text{W}}, P_{nt}^{\text{WC}}\Big\} \in \mathbb{R}_{\ge 0}, \quad \forall n, \forall t, \forall i, \forall v. \quad (34)$$

The objective function (1) is the total system cost that includes: (a) the conventional generation investment cost (1$^{\text{st}}$ term); (b) the conventional generation operating cost, which is given by the summation of start-up, O&M, fuel, $CO_2$ and shut-down costs (2$^{\text{nd}}$ to 6$^{\text{th}}$ term respectively); (c) the load, conventional generation and wind generation curtailment costs (7$^{\text{th}}$ to 9$^{\text{th}}$ term respectively); (d) the EV flexibility investment cost, which corresponds to the metering, control and communication infrastructure costs required to enable and coordinate flexible EV operation (10$^{\text{th}}$ term); and, (e) the cost associated with the degradation of the EV batteries due to V2G (11$^{\text{th}}$ term). Constraints (2) to (5) are system-wide and correspond to the demand-supply balance equations, upward and downward spinning reserve requirements, and the $CO_2$ emissions restriction respectively.

The operational constraints of conventional generation are given by equations (6) to (17). Constraints (6) correspond to the piecewise linear heat consumption function. The $CO_2$ emissions are expressed by equalities (7). Constraints (8) express the minimum stable and maximum power output limits, while constraints (9) and (10) establish limits for upward and downward ramping capabilities respectively. The minimum up and down times are enforced by constraints (11) and (12) respectively. Constraints (13) and (14) establish limits for the upward and downward spinning reserve provision. Equalities (15) correspond to the unit commitment status equations, while constraints (16) and (17) correspond to unit commitment restrictions of non-must-run and must-run generation technologies respectively. The power balance of wind generation is enforced by equalities (18).

The operational constraints of smart-charging/discharging EV are given by equations (19) to (30). Constraints (19) express the energy balance in the EV battery considering the charging losses of the battery and the grid connection's power electronics, the self-discharging energy losses of the battery, the power discharge due to V2G, and the EV users' traveling energy requirements. The energy level of the EV battery is bounded by the maximum depth of discharge and maximum state of charge of the battery, which are enforced by constraints (20). The energy drawn from the EV battery when V2G capability is exercised is expressed by equalities (21). Constraints (22) and (23) express the maximum charging/discharging power rate of the EV battery and the grid connection's power electronics, and the inability of the EV to charge/discharge their batteries when they are not plugged into the grid respectively. The upward and downward spinning reserve provision of EV are limited by constraints (24) to (26), and (27) to (29), respectively. The energy neutrality constraints (30) establish that the EV battery's energy level at the end of each day must be equal to a common pre-defined level; these constraints express the assumption that the energy requirements of flexible EV can only be redistributed on an intraday basis.

Constraints (31) and (32) limit the investment in conventional generation and EV flexibility. The former constraints establish an upper bound for the number of generation units of each technology type to be installed in order to confine the problem's solution space. The latter constraints, on the other hand, ensure that the number of flexible EV of each type is bounded by the total number of EV of the respective type.

The model uses integer instead of binary decision variables for the generation investment and commitment decisions (33), following a similar methodology to the one proposed in [20]. The use of integer variables makes the inclusion of unit commitment constraints into the GEP problem tractable because it allows clustering generation units by technology types, avoiding the use of binary variables to decide on both the investment and the on/off commitment status of a set of candidate generation units. This translates into a massive reduction of the problem in terms of the number of decision variables and constraints, as well as in the required computational time, as quantitatively explored in Section III-C. The model employs a similar clustering technique for flexible EV. The total electrical power demand and V2G injection, as well as the battery energy level of all flexible EV of the same type–instead of the respective quantities of a single flexible EV–are defined as decision variables, in order to avoid non-linear terms (products of number of flexible EV of each type times the power demand/injection or the spinning reserve provision of a single EV of the respective type) in the objective function (1) and system-wide constraints (2) to (5). This is also a key feature of the proposed model, which greatly improves the computational performance of the model, as quantitatively explored in Section III-C.

## III. Case Studies

### A. Scenarios Definition and Input Data

The examined case studies involve the application of the proposed model in the context of the UK, considering different

Table I
COST AND TECHNICAL PARAMETERS OF GENERATION SIDE

| Generation Technology | $\mathrm{FC}_i$ (£/kW-yr) | $\pi_i^{\mathrm{O\&M}}$ (£/MWh) | $\pi_i^{\mathrm{fuel}}$ (£/MBTU) | $\pi_i^{\mathrm{SU(a)}}$ (k£/SU) | $K_i$ (MW) | $\mathrm{NLH}_{il}^{0}$ (MTBU/h) | $\mathrm{HR}_{il}^{\mathrm{inc}}$ (MBTU/MWh) | $\mathrm{H}_i^{\mathrm{SU}}$ (MBTU/SU) | $\mathrm{EF}_i^{\mathrm{CO_2}}$ ($\mathrm{tCO_2}$/MBTU) | $\mathrm{ER}_i^{\mathrm{CCS}}$ (pu) |
|---|---|---|---|---|---|---|---|---|---|---|
| Nuclear | 503 | 2.00 | 0.41 | N/A | 1,500 | 4,756 | 10.4 | N/A | 0.0000 | 0.0 |
| Coal large | 290 | 2.40 | 4.47 | 26.53 | 525 | 266 | 8.8 | 2,102 | 0.0965 | 0.0 |
| Coal small | 333 | 2.40 | 4.47 | 12.64 | 250 | 138 | 9.6 | 1,001 | 0.0965 | 0.0 |
| Coal-CCS | 336 | 3.80 | 4.47 | 15.67 | 650 | 330 | 12.0 | 2,602 | 0.0965 | 0.9 |
| CCGT large | 86 | 2.20 | 7.02 | 22.54 | 750 | 759 | 6.4 | 1,105 | 0.0531 | 0.0 |
| CCGT small | 107 | 2.20 | 7.02 | 10.52 | 350 | 409 | 7.1 | 516 | 0.0531 | 0.0 |
| CCGT-CCS | 171 | 3.20 | 7.02 | 9.75 | 380 | 525 | 7.5 | 582 | 0.0531 | 0.9 |
| OCGT | 69 | 5.85 | 7.02 | 4.80 | 150 | 137 | 9.7 | 134 | 0.0531 | 0.0 |
| Oil | 147 | 6.31 | 15.81 | 0.14 | 50 | 33 | 11.0 | 0 | 0.0871 | 0.0 |
| **Generation Technology** | $p_i^{\mathrm{min}}$ (MW) | $p_i^{\mathrm{Max}}$ (MW) | $\Delta_i^{\mathrm{U}}$ (MW/h) | $\Delta_i^{\mathrm{D}}$ (MW/h) | $\mathrm{MT}_i^{\mathrm{U}}$ (h) | $\mathrm{MT}_i^{\mathrm{D}}$ (h) | $\mathrm{R}_i^{\mathrm{Max\text{-}U}}$ (MW/h) | $\mathrm{R}_i^{\mathrm{Max\text{-}D}}$ (MW/h) | $I^{\mathrm{MR}}$ | $I^{\mathrm{SPR}}$ |
| Nuclear | 1,200 | 1,500 | 150 | 150 | N/A | N/A | 0 | 0 | ✓ | |
| Coal large | 263 | 525 | 158 | 158 | 24 | 12 | 26 | 26 | | ✓ |
| Coal small | 125 | 250 | 75 | 75 | 24 | 12 | 13 | 13 | | ✓ |
| Coal-CCS | 325 | 650 | 195 | 195 | 24 | 12 | 33 | 33 | | ✓ |
| CCGT large | 225 | 750 | 750 | 750 | 6 | 12 | 128 | 128 | | ✓ |
| CCGT small | 105 | 350 | 350 | 350 | 6 | 12 | 60 | 60 | | ✓ |
| CCGT-CCS | 114 | 380 | 380 | 380 | 6 | 12 | 65 | 65 | | ✓ |
| OCGT | 38 | 150 | 150 | 150 | 0 | 0 | 150 | 150 | | ✓ |
| Oil | 13 | 50 | 50 | 50 | 0 | 0 | 50 | 50 | | ✓ |

[a]Shut-down costs are assumed to be negligible.

scenarios for EV penetration (10%, 50% and 100%) and wind generation capacity (10GW, 30GW and 50GW) levels.[1] According to the authors' best knowledge, there are no studies in the literature comprehensively quantifying the value of EV flexibility enabling costs, i.e. $\mathrm{FC}_v^{\mathrm{EV}^+}$. For this reason, we have decided to follow a sensitivity analysis approach in the case studies, investigating the impact of different values of $\mathrm{FC}_v^{\mathrm{EV}^+}$; specifically, the set of values used in this sensitivity analysis is $\{0, 50, 100, 200, 400, 800, 1600, 3200, 6400\}$ [£/EV-yr].

Five typical weeks representing the four seasons plus an extreme winter week are used in the case studies. The load demand profile was generated using historical data obtained from UK National Grid Electricity Transmission (NGET) website [21]. The employed wind generation profile was produced based on the model developed in [22], and has a load factor of 30%. The conventional generation portfolio includes nuclear, coal, gas and oil technologies, whose economic and technical parameters are presented in Table I [23]–[25].

Data regarding the UK vehicle fleet size and average driving patterns was extracted from [26] and [27]. Based on this data, each EV is assumed to carry out two journeys per day, and a set of different types of EV was produced, each defined by the combination of the start time, end time, and electrical energy requirements of each of its two daily journeys. Two different scenarios regarding the place of charging are investigated. Under the first one, referred to as "home charging" scenario hereinafter and deemed as the most plausible one in the literature [28], EV are assumed connected to the grid during the period between the end of their second journey and the start of their first journey next day. Under the second one, referred to as "home+work charging" scenario hereinafter, EV are assumed connected to the grid whenever they are parked.

[1]*EV penetration level* is defined as the percentage of UK light to medium-sized vehicles that are assumed to be electric, and *wind generation capacity level* as the amount of wind generation capacity installed in the system.

The values of the rest of EV parameters have been assumed identical for the different EV types and are shown in Table II. The remaining parameters used in the case studies are summarized in Table III.

Table II
EV BATTERY PARAMETERS

| Parameters | Value | Units | Parameter | Value | Units |
|---|---|---|---|---|---|
| $e_v^{\text{bat-cap}}$ | 15 | kWh | $\eta_v^{\text{elec}}$ | 100 | % |
| $e_v^{\text{bat-min}}$ | 3 | kWh | $\eta_v^{\text{chg}}$ | 93 | % |
| $e_v^{\text{bat-Max}}$ | 15 | kWh | $\eta_v^{\text{dis}}$ | 93 | % |
| $e_v^{ed}$ | 7.5 | kWh | $\kappa_v$ | 0.0154 | % |
| $p_v^{\text{chg-Max}}$ | 3 | kWh | $c_v^{\text{bat}}$ | 350 | £/kWh |
| $p_v^{\text{dis-Max}}$ | 3 | kWh | | | |

Table III
GENERAL PARAMETERS

| Parameter | Value | Units | Parameter | Value | Units |
|---|---|---|---|---|---|
| $\tau$ | 1 | h | $\pi^{\mathrm{CO_2}}$ | 76 | £/$\mathrm{tCO_2}$ |
| $\Phi_{(\text{average-Winter})}$ | 16.75 | # | $\pi^{\mathrm{LC}}$ | 10 | k£/MWh |
| $\Phi_{(\text{extreme-Winter})}$ | 0.25 | # | $\pi^{\mathrm{GC}}$ | 1,000 | k£/MWh |
| $\Phi_{(\text{average-Spring})}$ | 9 | # | SEI | 50 | $\mathrm{gCO_2}$/kWh |
| $\Phi_{(\text{average-Summer})}$ | 13 | # | $\mathrm{RR}_{nt}^{\mathrm{U\ (b)}}$ | $3.5\sigma_{nt}^{\text{WFE-4h}}$ | MW/h |
| $\Phi_{(\text{average-Autumn})}$ | 13 | # | $\sigma_{nt}^{\text{WFE-4h}}$ | $7\%P_{nt}^{\text{W-pwr}}$ | MW |
| $\max\{L_{nt}\}$ | 60.84 | GW | $N_i^{I\text{-Max}}$ | 500 | # |

[b]Upward and downward spinning reserve requirements are assumed to be equal.

## B. Impact of EV Flexibility

We firstly investigate the home charging scenario, i.e. when EV are charged while being parked at home, assuming that V2G capability is not available. When EV flexibility can be deployed without cost, i.e. when $\mathrm{FC}_v^{\mathrm{EV}^+}$ is equal to £0/EV-yr, all EV in the system become flexible as shown in the fourth row of Fig. 2. As this cost increases, the proportion of flexible EV is decreased. Beyond a flexibility enabling cost of £3,200/EV-yr, deployment of EV flexibility is not economically justifiable in any of the examined scenarios. On the other hand, a significant deployment of flexible EV (more that 10% of the total EV population) would require a flexibility cost lower than £400/EV-yr.

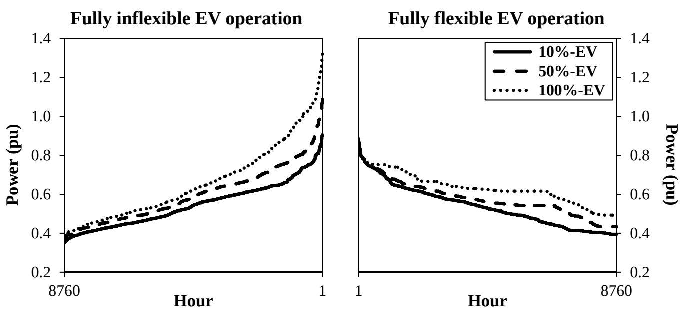



Fig. 1. Load duration curves comparison under home charging scenario and 30GW wind generation capacity.

Given the assumed home charging scenario, in combination with the fact that most users return home during evening hours (17:00-20:00), inflexible EV demand coincides with the non-EV system demand peak. This results in increased peak demand levels as shown in Fig. 1, where a comparison of the normalized net-of-wind load duration curves[2] is made for fully inflexible and fully flexible EV operation ($\mathrm{FC}_v^{\mathrm{EV}^+}$ equal to 6,400 and £0/EV-yr respectively).

The larger peak demand levels under inflexible EV operation result into larger requirements for mid-merit and peaking generation, i.e. CCGT and OCGT, and into reduced requirements for baseload generation, i.e. nuclear, as it becomes a less cost-effective option given the increased net-demand variability. The reduction of nuclear generation capacity translates into larger shares of CCGT-CCS, required to satisfy the $CO_2$ emissions constraint. This is shown in the top row of Fig. 2, where the optimal generation mix composition is depicted for different values of $\mathrm{FC}_v^{\mathrm{EV}^+}$, and different EV penetration (left column) and wind generation capacity levels (right column). The ratio of baseload generation is also reduced as the installed wind capacity increases, since more flexible generation is required to absorb the increased variability introduced by wind generation and provide the higher reserve requirements. Given that mid-merit and peaking generation are characterized by higher operational and lower investment costs, increased inflexible EV penetrations and wind generation capacity levels yield systems of larger operation cost proportions, as shown in the second row of Fig. 2.

On the other hand, under flexible EV operation EV demand is optimally rescheduled towards off-peak hours, which allows reducing peak demand levels and significantly flattening net-demand, as shown in Fig. 1. The reduced net-demand variability translates into larger requirements for nuclear generation with respect to inflexible EV operation, reduced requirements for mid-merit and peaking generation, and subsequently into systems of higher investment cost proportions, as shown in the second row of Fig. 2. Additionally, larger shares of nuclear generation allow satisfying the $CO_2$ emissions constraint without requiring CCS enabled generation, and even more, allow reducing $CO_2$ emissions below the system-wide limit of 50 [$gCO_2$/kWh], which is binding in the inflexible EV operation scenario, as shown in the bottom row of Fig. 2. These effects are enhanced as the enabling cost of EV flexibility decreases, since a higher number of flexible EV are cost-effectively integrated into the system, and thus a more significant flattening of net-demand is achieved.

The third row of Fig. 2 illustrates the total system cost reduction (saving), when the option of EV flexibility deployment is available for different values of $\mathrm{FC}_v^{\mathrm{EV}^+}$, with respect to a case where this option is not available (all EV are inflexible). As the enabling cost of EV flexibility decreases, the number of flexible EV is increased as shown in the fourth row of Fig. 2, and therefore the net-value of EV in terms of total costs saving is enhanced.

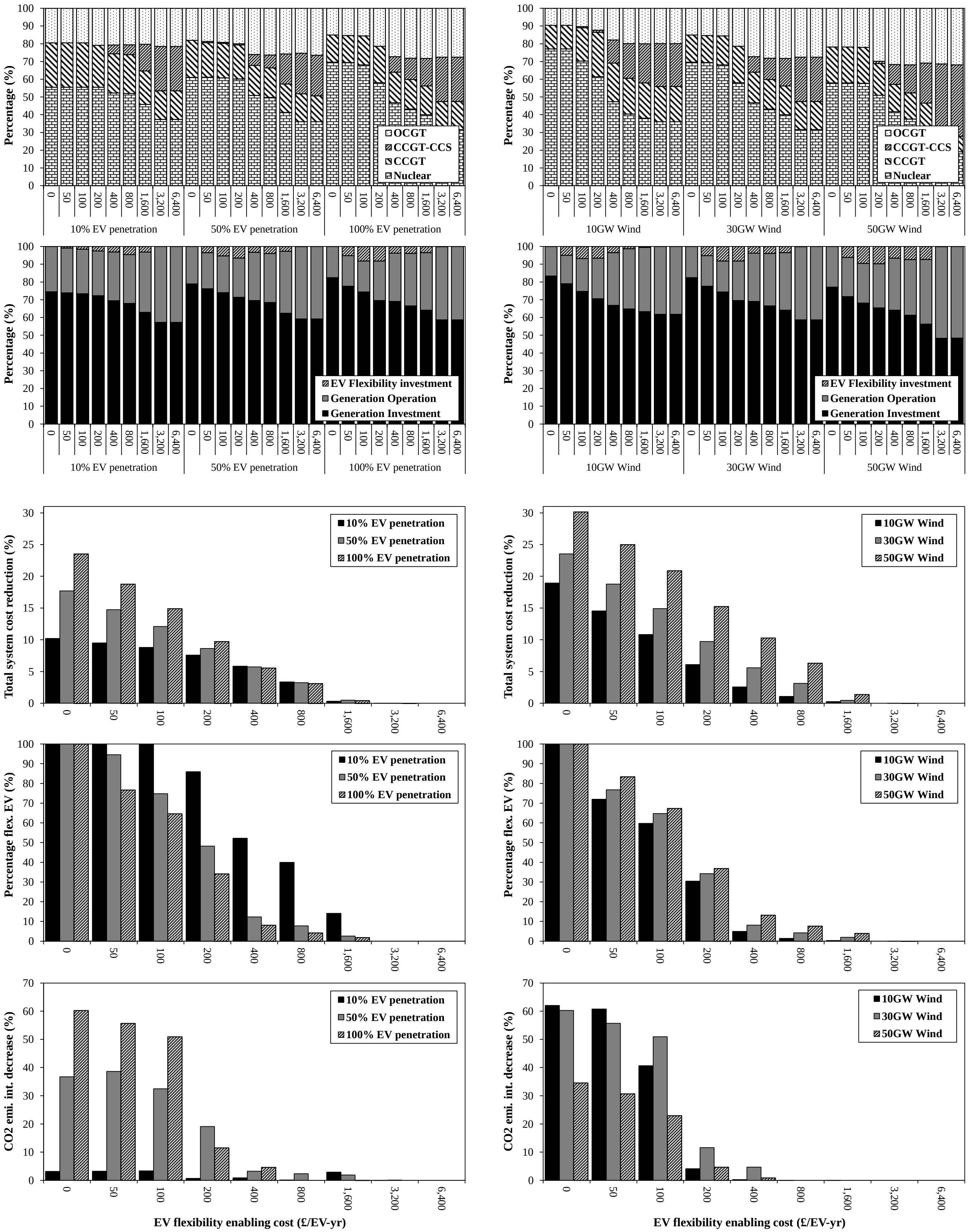
From an environmental perspective, larger shares of flexible EV allow increasing the share of inflexible carbon-free baseload generation and, at the same time, improve the integration of wind generation, which results into significant reductions of $CO_2$ emissions as shown in the bottom row of Fig. 2. These two effects highlight the relevance of flexible demand for the efficient integration of renewables, and also for the achievement of future carbon emissions reduction targets.

For the same value of $\mathrm{FC}_v^{\mathrm{EV}^+}$, the value of EV flexibility is higher as the wind penetration increases. This is justified by the fact that the increased variability introduced by wind generation enhances the value of EV flexibility in absorbing such variability, and avoiding the alternative employment of flexible yet more expensive mid-merit and peaking generation. Furthermore, for $\mathrm{FC}_v^{\mathrm{EV}^+}$ up to about £400/EV-yr, the value of EV flexibility increases with an increasing EV penetration, as the economic implications of inflexible EV operation– in terms of employment of peaking generation with high operational costs–are aggravated. These two effects highlight the increased potential of flexible demand in a future with wide de-carbonization of demand and power generation.

Interesting conclusions are also drawn by analyzing the types of EV that are selected by the optimization model to become flexible. For the sake of this analysis, the different EV are categorized according to: a) the time they get plugged into the grid (after the end of their second journey); and b) the daily distance of their journeys (two categories are considered, i.e. EV with short and long journeys, which group the EV with daily traveled distances smaller and larger than 30 kilometers respectively). Tables IV and V present the minimum value of $\mathrm{FC}_v^{\mathrm{EV}^+}$, for which flexibility is not deployed in each of the previously defined categories (none of the EV of the respective category is selected to become flexible) in a scenario with 100% EV penetration and 50GW of wind generation capacity.

Table IV demonstrates that the threshold value of $\mathrm{FC}_v^{\mathrm{EV}^+}$ is very large for EV that are plugged-in at peak demand times (18:00-20:00) and gradually decreases as we move to plug-in times away from this peak period. This result reveals

[2]Non-EV system demand minus wind power dispatched plus EV power demand, normalized by the peak non-EV system demand, i.e. $\max\{L_{nt}\}$.




(a) 30GW wind generation / 10%, 50% and 100% EV penetration.

(b) 100% EV penetration / 10GW, 30GW and 50GW wind generation.

Fig. 2. Optimal conventional generation mix composition (*top row*), total system cost composition (*second row*), total system cost reduction with respect to the fully inflexible EV operation scenario (*third row*), percentage of flexible EV (*fourth row*), and $CO_2$ emissions intensity reduction with respect to the fully inflexible EV operation scenario (*bottom row*).

the increased value of flexibility deployment in EV whose plug-in time coincides with peak demand, as their inflexible operation would aggravate the economic implications of peaks. Furthermore, the value of flexibility deployment is higher for EV with larger traveling distances as shown in Table V, since their total electric energy requirements are higher, and therefore they offer a higher amount of redistributable energy to the system when they become flexible.

Table IV
FLEXIBILITY DEPLOYMENT THRESHOLD WRT PLUG-IN TIME

| Plug-in time | $\mathrm{FC}_v^{\mathrm{EV}^+}$ (£/EV-yr) | Plug-in time | $\mathrm{FC}_v^{\mathrm{EV}^+}$ (£/EV-yr) |
|---|---|---|---|
| 10:00 | 100 | 17:00 | 800 |
| 11:00 | 100 | 18:00 | 1,600 |
| 12:00 | 100 | 19:00 | 3,200 |
| 13:00 | 200 | 20:00 | 3,200 |
| 14:00 | 200 | 21:00 | 200 |
| 15:00 | 200 | 22:00 | 50 |
| 16:00 | 400 | 23:00 | 50 |

Table V
FLEXIBILITY DEPLOYMENT THRESHOLD WRT JOURNEYS' LENGTH

| Journeys' length | $\mathrm{FC}_v^{\mathrm{EV}^+}$ (£/EV-yr) |
|---|---|
| Short | 800 |
| Long | 1,600 |

Finally, the impact of the charging place and the V2G capability is analyzed, considering a scenario with 100% EV penetration and 30GW of wind generation capacity. When EV are allowed to charge both at home and work, the peak demand levels under inflexible EV operation are significantly reduced, as part of the required energy is acquired during the off-peak hours that the EV are parked at the work place (Fig. 3). As a result, the value of EV flexibility is lower than in the home charging scenario, as shown in the top plot of Fig. 4. With V2G capability available, as shown in the top plot of Fig. 4, the value of flexible EV operation is increased despite the additional degradation cost, as flexible EV can inject power into the grid during peak demand periods and provide increased volumes of spinning reserve, resulting in a reduction of the required peaking generation capacity. This additional value comes despite the fact that a smaller number of EV become flexible, as shown in the bottom plot of Fig. 4, since the benefits brought by each flexible EV are enhanced.

### *C. Computational Performance of Proposed Model*

The proposed optimization model has been implemented using FICO$^{\mathrm{TM}}$ Xpress [19], and all the simulations presented in this paper have been carried out on a Windows-based desktop computer, with a 3.33GHz Intel(R) Xeon(R) processor and 12GB of RAM.

The computational performance of the proposed model was tested against an equivalent formulation without clustering generation units, i.e. a formulation that uses binary variables for generation investment and unit commitment decisions.

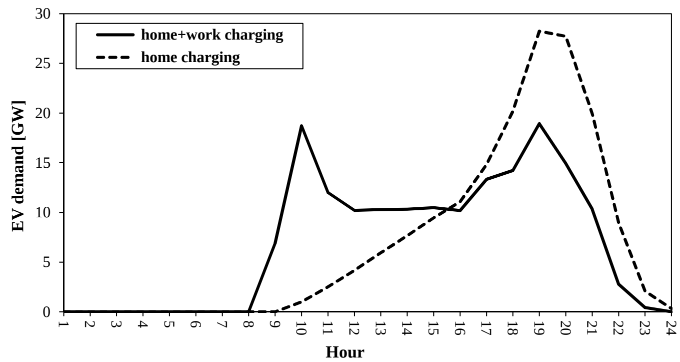



Fig. 3. EV demand profiles under inflexible operation.

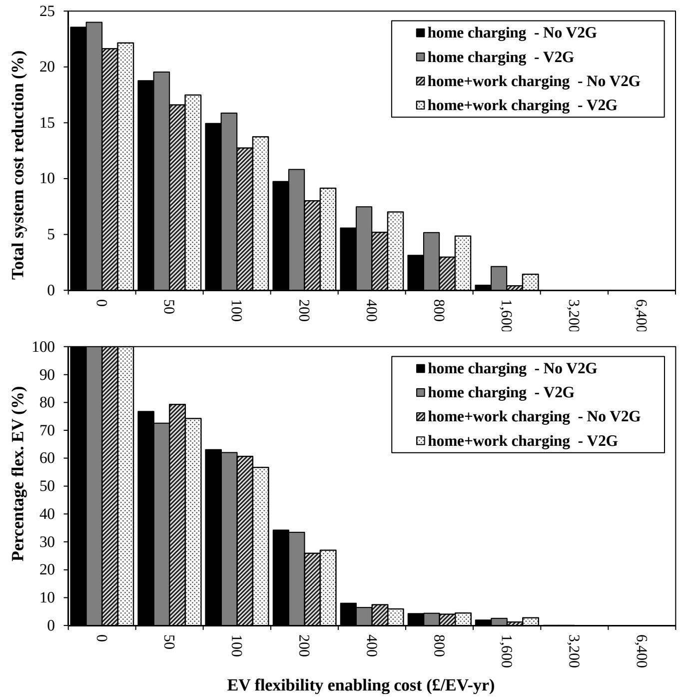



Fig. 4. Total system cost reduction with respect to the fully inflexible EV operation scenario (*top*) and percentage of flexible EV (*bottom*).

Investment decision variables have been initially bounded to 500 units per generation technology in the integer formulation, which translates into a full set of 4,500 candidate generation units for the binary model (Binary–4500 in Table VI). The latter was not manageable by the desktop computer due to the RAM memory limitation, so in another test, the size of the set of candidate generation units in the binary formulation was reduced to 536 units (Binary–536 in Table VI), based on the optimal solution of the integer model.

Table VI shows a comparison between the binary (with and without the candidate units set reduction) and integer formulations in terms of the number of generation-related discrete decision variables and constraints, the solution time, and the optimal value of the objective function, obtained after running the above models for 100% EV penetration, 30GW wind generation capacity, $\mathrm{FC}_v^{\mathrm{EV}^+}$ equal to £200/EV-yr, home charging and V2G capability available. Even with a reduced set of candidate generation units, the binary model involves a very large number of decision variables and constraints, exhibiting a prohibitive computational requirement for practical applications. With the integer formulation, the numbers of decision variables and constraints, as well as the required computational time, are dramatically reduced without compromising the model's results accuracy, as indicated by the small difference between the optimal values of the objective function in Table VI.

The integer model was also tested without the proposed EV clustering technique, resulting in a non-linear MIP problem (Section II-B), which failed to converge after $6 \cdot 10^5$ s.

## IV. Conclusions

A novel planning model is proposed in this paper which allows co-optimizing investment and operation costs of conventional generation assets and demand flexibility in the form of smart-charging EV with and without V2G capability. Along with the full set of different generation technologies' technical characteristics, the capability of optimally scheduling EV demand and V2G injections–according to a detailed model of their users' traveling requirements and batteries/grid connections' technical properties–is considered. In contrast to previous works, the enabling costs for introducing and coordinating such flexibility–associated with the relevant metering, control and communication infrastructure–and those related to the degradation of the EV battery due to V2G are accounted for, and the optimal number of flexible EV is determined along with the optimal portfolio of generation assets.

The developed model is formulated as a large-scale mixed-integer linear optimization problem. Clustering of generation units (following the approach proposed in [20]) and EV (adopting a new approach) of similar characteristics limits the computational requirements of the model, by reducing the number of decision variables and constraints, and avoiding non-linearities.

Case studies in the context of the UK demonstrate that EV flexibility significantly flattens net-demand by reducing peak demand levels and absorbing the variability introduced by wind generation, and subsequently impacts the optimal generation mix by allowing the cost-effective integration of a larger proportion of baseload generation. The value of EV flexibility in terms of total system cost saving is shown to increase with an increasing electrification of the transport sector and increasing wind generation capacity levels, highlighting the enhanced potential of flexible demand in a future with wide decarbonization of demand and power generation. Furthermore, the results illustrate the dependency of the optimal number of flexible EV and the net-value of EV flexibility on the cost of the enabling infrastructure, the place of charging and the deployment of V2G capability. Finally, the value of EV flexibility is shown to depend on the traveling patterns of EV users, with EV plugged into the grid during demand peak periods and EV with larger traveling distances yielding higher system benefits when becoming flexible.

Future work will incorporate other promising flexible demand technologies into the model, such as electric heat pumps and deferrable domestic appliances, and will compare their impacts on system planning under different values of their enabling costs. Although this paper addresses the planning problem from the perspective of a central planner seeking to minimize total system cost, in the existing market-based environment, investment and operating decisions of generation and demand participants are taken in a decentralized fashion, according to the individual participants' profit-maximizing objectives. The derivation of suitable market mechanisms for the realization of the cost-minimizing solution in a deregulated environment is thus an essential area of future work. As part of this work, suitable incentives should be developed for consumers with favorable demand patterns, as the ones identified in this paper.

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Table VI
BINARY VERSUS INTEGER GEP MODELS COMPARISON[(b)]

| Model formulation | Discrete variables *Investment* | Discrete variables *Operation* | Generation constraints | Solution time (ks) | Objective function (M£) |
|---|---|---|---|---|---|
| Binary–4500 | 4,603 | 11,344,603 | 55,914,000 | – | – |
| Binary–536 | 639 | 1,351,359 | 6,726,432 | 368.75 | 28334.152 |
| Integer | 112 | 22,792 | 111,828 | 2.93 | 28348.119 |

[b]MIP gap tolerance set at 0.2% for all case studies.


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