Electric Vehicles Services in the Cornwall Local Energy Market enabled by Blockchain Smart Contracts

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Abstract

Electric vehicles (EVs) as a distributed energy resource represent a key opportunity to achieve emission reductions worldwide, although their large uncoordinated deployment could congest distribution networks generating load profiles leading to system failures. Flexible management systems to coordinate strategies between agents at different levels require high volumes of decentralized information exchanged to improve network assets utilisation and operational costs reduction. Incumbent technologies such as Smart Contracts (SCs) from Distributed Ledger Technologies (DLT) would enable these coordination approaches with near real-time resolution. Therefore, this study aims to evaluate and propose flexible charging strategies for high penetration levels of electric vehicles and renewable energies on already congested distribution networks. It considers the use of Smart Contracts as enablers of new decentralised coordination architectures among network agents. A multi-agent coordination through a Two-Part Tariff (TPT) to provide flexibility services in congested distribution power networks is stylised. Then, a market setting with large penetration of EVs from an aggregated portfolio has been individually modelled for the UK Local Energy Market of Cornwall to relieve local network congestion. Results illustrate that EVs coordination strategies are able to reduce network costs and manage congestion, allowing up to 6.5% more renewable energy to be delivered into the grid.

Keywords: Electric vehicles, distribution networks, flexibility, Smart Contracts

Nomenclature

Sets

T Set of hourly time periods, indexed by t

T^+ Subset of periods with DSO requests for upward regulation

T^- Subset of periods with DSO requests for downward regulation

N Set of buses of the distribution network, indexed by n

L Set of lines of the distribution network, indexed by l

TR Set of connections to transmission level of the distribution network, indexed by tr

I Set of generators, indexed by i

RE Subset of renewable energy generators

$DISP$ Subset of dispatchable generators

J Set of demands, indexed by j

EV Set of coordinated electric vehicles, indexed by ev

$EVUNC$ Set of uncoordinated electric vehicles, indexed by $evunc$

$rec\_bus_{l,n}$ Receiving bus n of line l

$send\_bus_{l,n}$ Sending bus n of line l

$gen\_bus_{i,n}$ Bus n to which generator i is connected

$dem\_bus_{j,n}$ Bus n to which demand j is connected

$tr\_bus_{tr,n}$ Bus n to which transmission tr is connected

$ev\_bus_{ev,n}$ Bus n to which electric vehicle ev is connected

$evunc\_bus_{evunc,n}$ Bus n to which uncoordinated set of EVs $evunc$ are connected

Parameters

η_{in} Charging efficiency (%)

η_{out} Discharging efficiency (%)

$\Pi^{curt}_{i,t}$ Generator i curtailment price at period t (£/MWh)

$\Pi^{flex}_{i,t}$ Electric vehicle ev flexibility price at period t (£/MWh)

$\Pi^{gen}_{i,t}$ Generator i bid price at period t (£/MWh)

$\Pi^{LS}_{j,t}$ Demand j load shedding price at period t (£/MWh)

$\Pi^{penlaty}$ Penalty price for G2V and V2G (£/MWh)

$\Pi^{trans}_{tr,t}$ Transmission tr price at period t (£/MWh)

B_l Susceptance for line l (p.u.)

$Cap^{renew}_{i,t}$ Generation capacity by renewable generator i at period t (MWh)

$D_{j,t}$ Demand consumption by j at period t (MWh)

E^{dep}_{ev} Battery level at departure time for ev (MWh)

E^{ini}_{ev} Battery level at arrival time for ev (MWh)

EV^{cnn}_{ev} Connected periods for ev

EV^{cntr}_{ev} Contracted periods for ev

EV^{data}_{ev} List of parameters for each ev

EV^{eff}_{ev} Power exchange efficiency for ev (%)

EV^{index}_{ev} EV index number for dataset

EV^{node}_{ev} Bus n to which ev is connected

EV^{plevel}_{ev} Power connection level for ev (MW)

$EV^{unc}_{evunc,t}$ Uncoordinated EVs load for subset $evunc$ at period t (MWh)

$Line\_cap_l$ Line capacity for line l (MWh)

$P^{DSO}_{n,t}$ DSO flexibility request signal at bus n and period t

$StocD$ Stochastic multiplier for inflexible demand

$StocG$ Stochastic multiplier for renewable generation

t^{arr}_{ev} Arrival time for ev

t^{dep}_{ev} Departure time for ev

TOU_t Time-Of-Use tariff for EVs at period t (£/MWh)

Variables

$\Pi_{Availability}$ SCs cost for EVs availability in flexibility services

$\Pi_{penalty}$ SCs non-compliance penalty to EVs

Π_{reward} SCs compliance rewards to EVs

$\theta_{n,t}$ Phase angle of bus n at period t

$E_{ev,t}$ Battery level of ev at period t (MWh)

$f_{l,t}$ Line l power flow at period t (MWh)

$P^{curt}_{i,t}$ Volume curtailed from generator i at period t (MWh)

$P^{disp}_{i,t}$ Volume from dispatchable generator i at period t (MWh)

$P^{in}_{ev,t}$ Volume charged (G2V) from ev at period t (MWh)

$P^{LS}_{j,t}$ Load shed volume from demand j at period t (MWh)

$P^{out}_{ev,t}$ Power discharged (V2G) from ev at period t (MWh)

$P^{trans}_{tr,t}$ Volume from transmission level tr at period t (MWh)

$Penalty^{G2V}_{n,t}$ Penalties computed for G2V at bus n and period t (MWh)

$Penalty^{V2G}_{n,t}$ Penalties computed for V2G at bus n and period t (MWh)

1. Introduction

1.1. Motivation

Meeting charging demands of large fleets of electric vehicles will raise electrical load significantly on already congested distribution networks, and may bring many challenges for power systems. Therefore, appropriate coordination of network agents in future flexibility markets becomes increasingly important to make systems more resilient in presence of intermittent renewable energy technologies. This study assesses a multi-agent coordination between electric vehicles, a central aggregator (Fleet Operator) and Distribution System Operator (DSO). A charging coordination model based on local flexibility markets for aggregators, to provide flexibility services at distribution network level is developed, inspired by projects such as Olivella-Rosell et al. (2018b), Olivella-Rosell et al. (2018a). The main contribution of this paper is the analysis of network Key Performance Indicators (KPIs), such as renewable energy curtailed, load shedding and congestion, among others, under the proposed coordination strategy based on Smart Contracts and a Two-Part Tariff. In this way, the research reported here complements previous work, such as Xiang et al. (2016), presenting an approach to coordinate fleets of EVs to respond to electricity grid operators' signals and distribute network risk among all the agents.

1.2. Flexibility market design

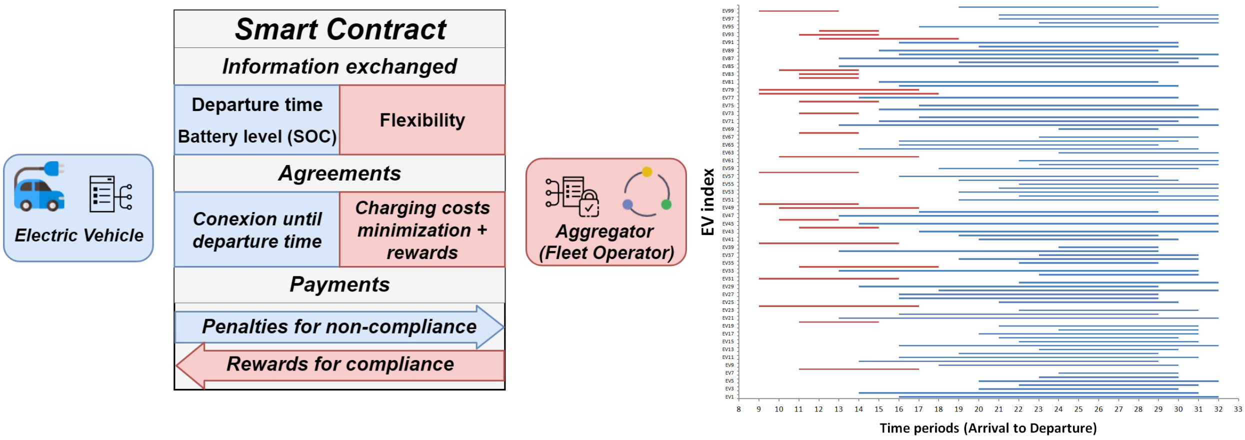
The inclusion of Distributed Energy Resources (DER) in distribution networks requires increasing flexibility along systems. The figure of an aggregator as a provider of flexibility through scheduling flexible devices is recently proposed as a local market facilitator Olivella-Rosell et al. (2018b). In addition, the DSO is not interested in controlling individual devices, and is not able to share grid parameters or status with other market participants Olivella-Rosell et al. (2016). However, the DSO is able to purchase flexibility by sending activation signals to the aggregator Olivella-Rosell et al. (2018a). It would be scheduled during day-ahead (DA) and activated in real-time (RT) markets. In the literature there are multiple approaches between electric vehicles and aggregators. Therefore, despite EVs driving patterns uncertainties, charging loads can be controlled and predicted to some extent. Consequently, flexible and interruptible charging can be used to improve grid reliability Xia et al. (2016). However, the concept increases system complexity due to the fact that EVs have more constraints than stationary systems Wei et al. (2016).

1.3. Two-Part Tariff (TPT)

Flexible markets require a specific economical framework to be implemented. Therefore, Two-Part Tariffs (TPT) are well suited to deal with different levels of risks, as studied in Laur, A., Nieto-Martin, J., Bunn, D., Vicente-Pastor (2019). They consist of a non-refundable reservation price in the DA (forecast period) and an activation price in RT. In addition, the use of TPTs alongside renewable energies integration is able to increase network social surplus, as concluded in Munoz-Alvarez & Tong (2017). Therefore, the implementation of this approach could be beneficial for a local energy market, as the DSO would be able to improve network KPIs through flexibility activation signals.

1.4. Smart Contracts (SCs)

Recently, some studies focus on the decentralisation of decision-making. Decentralised or transactive control is a structure that enables the interaction of agents through an economic signal, with the objective of optimizing resource allocation Hu et al. (2016a). Consequently, it requires explicit responses from individual EVs. An EVs transactive control was compared with a centralised control achieving a good performance in Hu et al. (2017). In addition, it was also implemented through price signals in DA and RT in Liu et al. (2018b). A hierarchical EVs management system is able to ensure the safe operation of the network by DSO and optimise vehicles charging by a fleet operator (FO), as was concluded in Hu et al. (2015).



(a)

(b) Connected periods of EVs by location: Workplace (red), homeplace (blue).

Figure 1: Smart Contracts: a) Structure EV - aggregator, b) Information received by the aggregator.

All of these studies motive the inclusion of Smart Contracts as enablers of new architectures through decentralised control mechanisms. However, this approach has not been widely studied yet. Coordination between EVs and aggregator would be intensive, particularly on the centralised fleet manager side Kok & Widergren (2016). Previous research considered theoretic contracts as enablers of EVs and aggregators coordination Xiang et al. (2016). Therefore, Smart Contracts, defined as "specific code executed on top of the Blockchain to facilitate, execute and enforce an agreement between untrusted parties without the involvement of a trusted third party" Alharby & van Moorsel (2017), are proposed to cope with the aforementioned issues. Moreover, these technologies are used to implement Peer-to-Peer (P2P) transactions Wang et al. (2018). Results in Kang et al. (2017) and Liu et al. (2018a), highlight that EVs P2P improve network social welfare and reduce power fluctuation levels. Previous work on Demand Side Response (DSR) programs with rewards and penalties implemented on SCs was successfully developed Pop et al. (2018), and maximization of social welfare in a microgrid was achieved by Munsing et al. (2017). Figure 1a illustrates the main structure of the proposed SCs. Information exchanged would inform the fleet aggregator about EVs schedules by periods and locations along the network, as it is shown in Figure 1b. Therefore, flexible scheduling of EVs charging, to meet DSO activation signals would be performed based on this information.

1.5. Payments scheme proposal

The scheme proposed considers SCs rewards (-) and penalties (+) as variations of EVs charging costs. TPT penalties for non-compliance volumes related to DSO activation signals are computed by the DSO to the aggregator. Therefore, aggregators' business model would be based on maximising payments from DSO, while minimising penalties. In order to be profitable, SCs rewards have to be lower than reserve and activation payments.

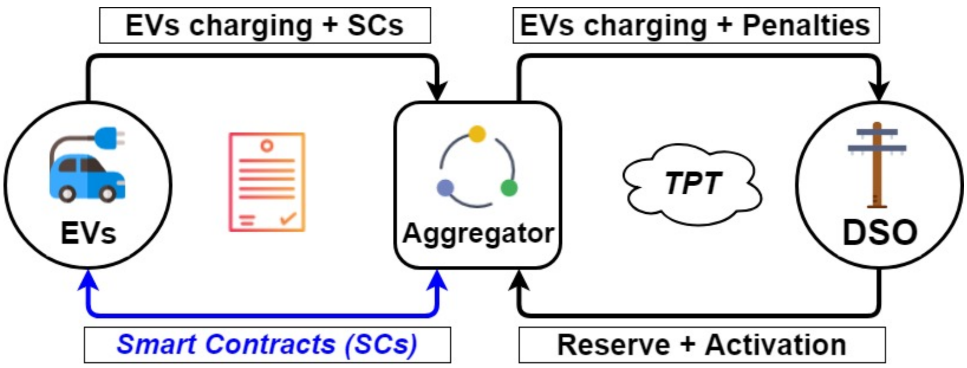


Figure 2: Payments coordination scheme with Smart Contracts integration.

In conclusion, motivated by the requirements of this new business environment, the technical challenges and the multidimensionality of this problem, we propose a solution framework in which our contribution is three-fold:

- Implementation of a two-stage stochastic algorithm to stylise the TPT scheme from the DSO economic dispatch point of view. Development of a case study to assess the evolution of network KPIs, from a benchmark scenario to various EVs penetration-coordination scenarios.

- Stylise how the aggregator would schedule EVs to meet DSO activation signals under the TPT shcheme. Illustration of Grid-to-Vehicle/Vehicle-to-Grid(G2V/V2G) performances as well as penalties for non-compliance.

- Propose a formulation for the future implementation of SCs under the coordination scheme considered.

The rest of this paper is organised as follows: Section 2 covers the methodology and mathematical models developed from DSO and aggregator points of view. In section 3, we show and discuss the results of the case study, of the benchmark comparison, behavioural sensitivity analysis and future implementation of SCs. Finally, conclusions are summarised in section 4.

2. Methodology

Models from DSO and aggregator perspectives are implemented to stylise the whole structure of the system proposed. Electric vehicles 2030, 2040 and 2050 deployment scenarios are considered according to National Grid 2018 Future Energy Scenarios (FES) for the UK National Grid (2018). Analysis of the impacts of electric vehicles for each scenario compares coordinated and uncoordinated charging strategies at distribution level. Uncoordinated charging considers EVs as inflexible loads, while coordinated charging allows load shifting from peak to off-peak periods and V2G Hu et al. (2016a).

2.1. Monte Carlo Simulation (MCS)

Monte Carlo methods are widely used to make probabilistic analyses based on random sampling. In this study Monte Carlo Simulations (MCS) are used to simulate EVs driving patterns that generate batteries requirements. Hence, individual daily distance travelled (IDDT) by a vehicle is obtained following a Gamma distribution, which represents a reliable assumption for the context of electric vehicles Plötz et al. (2014), Lin et al. (2012). In addition, two charging locations are considered: Workplace (L2 & L3 charging levels) and homeplace (L1 & L2) California Energy Commission (2018). Moreover, energy battery of electric vehicles at arrival time is obtained following a linear relation based on number of km travelled and EV consumption, also a minimum of 20% State-of-Charge (SOC) battery level at arrival time is assumed. MCS are run in Visual Basic for Application (VBA) and introduced in the model as battery parameters/requirements for arrival/departure time respectively.

2.2. DSO economic dispatch model

In a local energy market, the DSO assumes System Operation role in order to match supply and demand. Hence, an optimization problem of maximizing social welfare on the network over a 24 hours period is implemented, which amounts to minimize generation costs, while respecting network constraints. The problem is traditionally known as economic dispatch.

$$Minimize: \sum_{t}\Bigg(\sum_{i}(\Pi^{gen}_{i,t}\cdot P^{disp}_{i,t}+\Pi^{curt}_{i,t}\cdot P^{curt}_{i,t}) \quad (1)$$

$$+\sum_{tr}(\Pi^{trans}_{tr,t}\cdot P^{trans}_{tr,t})+\sum_{j}(\Pi^{LS}_{j,t}\cdot P^{LS}_{j,t})+\sum_{ev}(\Pi^{flex}_{ev,t}\cdot(P^{out}_{ev,t}+0.05\cdot P^{in}_{ev,t})\Bigg)$$

Equation 1 represents the objective function. The optimization considers: dispatchable generators such as CHP ($P^{disp}_{i,t}$), volumes purchased from transmission level ($P^{trans}_{tr,t}$), renewable energy curtailment ($P^{curt}_{i,t}$), demand load shedding ($P^{LS}_{j,t}$) and charging/discharging EVs batteries as flexibility services ($P^{in}_{ev,t}, P^{out}_{ev,t}$). A 5% of flexibility costs is arbitrarily allocated for scheduling EVs charging, as price optimization is out of the scope in this first stage of research.

$$\begin{aligned} \sum_{l \in rec\_bus} f_{l,t} &- \sum_{l \in send\_bus} f_{l,t} + \sum_{i \in gen\_bus} (P^{disp}_{i,t} + StocG \cdot Cap^{renew}_{i,t} - P^{curt}_{i,t}) \\ &+ \sum_{tr \in tr\_bus} P^{trans}_{tr,t} - \sum_{j \in dem\_bus} (StocD \cdot D_{j,t} - P^{LS}_{j,t}) \\ &+ \sum_{ev \in ev\_b} (P^{out}_{ev,t} - P^{in}_{ev,t}) - \sum_{evunc \in evu\_b} EV^{unc}_{evunc,t} = 0 \quad \forall n,t \end{aligned} \tag{2}$$

Equation 2 represents the flow balance at each node and period. Inflexible load from uncoordinated EVs is introduced ($EV^{unc}_{evunc,t}$). The EVs charging/discharging rates are represented on Equation 3. Specific data for each electric vehicle is introduced in the model through a list parameter called EV^{data}_{ev} on Equation 4, the list of parameters include: EV index number, connection node, arrival time, departure time, initial battery level, expected final battery level, charging power level and efficiency.

$$E_{ev,t} = E_{ev,t-1} + P^{in}_{ev,t} \cdot \eta_{in} - \frac{P^{out}_{ev,t}}{\eta_{out}} \quad \forall ev,t \tag{3}$$

$$EV^{data}_{ev} = \left[EV^{index}_{ev}, EV^{node}_{ev}, t^{arr}_{ev}, t^{dep}_{ev}, E^{ini}_{ev}, E^{fin}_{ev}, EV^{plevel}_{ev}, EV^{eff}_{ev}\right] \tag{4}$$

Equations 5 and 6 account for the relation between flow at each line and phase angle by node, they are the only network constraints for the lossless model.

$$f_{l,t} = B_l \cdot (\theta^{rec}_{n,t} - \theta^{send}_{n,t}) \quad \forall l,t \tag{5}$$

$$\theta^{slack}_{n,t} = 0 \quad \forall t \tag{6}$$

Constraints limits are represented from Equation 7 to 14.

$$P^{curt}_{i,t} \leq Cap^{renew}_{i,t} \quad \forall i,t \tag{7}$$

$$P^{disp}_{i,t} \leq Cap^{renew}_{i,t} \quad \forall i,t \tag{8}$$

$$P^{LS}_{j,t} \leq D_{j,t} \quad \forall j,t \tag{9}$$

$$-\Pi \leq \theta_{n,t} \leq \Pi \quad \forall n,t \tag{10}$$

$$-Line\_Cap_l \leq f_{l,t} \leq Line\_Cap_l \ \forall l,t \tag{11}$$

$$\underline{P_{ev,t}} \leq P^{in}_{ev,t} \leq \overline{P_{ev,t}} \quad \forall ev,t \tag{12}$$

$$\underline{P_{ev,t}} \leq P^{out}_{ev,t} \leq \overline{P_{ev,t}} \quad \forall ev,t \tag{13}$$

$$\underline{E_{ev,t}} \leq E_{ev,t} \leq \overline{E_{ev,t}} \quad \forall ev,t \tag{14}$$

On the other hand, deterministic models are built with fixed parameters, whereas realistic problems normally include some uncertain parameters that follow a probability distribution that is widely known or can be estimated Juul et al. (2015). Therefore, to tackle intermittent renewable energy generation and inflexible demand forecasts, a two stage stochastic programming has been implemented through two random variables ($StocG, StocD$), as stochastic multipliers. On these kind of formulations, decision maker takes a decision on stage 1 and tries to minimize the expected costs of the consequences of that decision on stage 2. In this way, it is possible to create a scenario tree on the General Algebraic Modeling System (GAMS) so that a Deterministic Equivalent (DE) of the stochastic model is built. As a consequence, uncertainty is managed based on the array of possibilities and the model is solved for each scenario. Three possibilities are considered for StocG values: low (0.9 at P=0.3), medium (1 at P=0.6) and high (1.1 at P=0.3). Two possibilities are considered for StocD: medium (1 at P=0.6) and high (1.1 at P=0.4). Finally, the objective function expected value is weighted by each scenario probability. This approach is traditionally adopted for electric power networks decision making under uncertainty Conejo et al. (2016). The problem is solved through the EMP framework in GAMS and its stochastic scenario dictionary.

Algorithm 1: DSO economic dispatch with EVs flexible schedules

Inputs : $\left[Cap^{renew}_{i,t},\ D_{j,t},\ B_l,\ Line\_Cap_l,\ EV^{data}_{ev},\ EV^{unc}_{evunc,t}\right]$

Outputs: An optimal power network portfolio:

$\left[P^{disp}_{i,t}, P^{curt}_{i,t}, P^{trans}_{tr,t}, P^{LS}_{j,t}, P^{out}_{ev,t}, P^{in}_{ev,t}\right]$

Result: DSO economic dispatch := min(Network generation costs)

Run for each node ($n \in N$) and period ($t \in T$)

for *StocG and StocD for each stochastic scenario* **do**
- **while** *network is not balanced* **do**
  - **for** *each supplier ($i \in DISP$) and ($tr \in TR$)* **do**
    - $P^{disp}_{i,t}$:= Power from dispatchable generators
    - $P^{trans}_{tr,t}$:= Power from transmission level
  - **for** *each renewable supplier ($i \in RE$)* **do**
    - $P^{curt}_{i,t}$:= Power curtailed from renewable energy source
  - **for** *each demand ($j \in J$)* **do**
    - $P^{LS}_{j,t}$:= Load shedding from inflexible demand
  - **for** *each $ev \in EV$* **do**
    - **while** $E_{ev,t} \neq E^{fin}_{ev}$ *at period* $t^{dep}_{ev} \in EV^{data}_{ev}$ **do**
      - **if** *($t > t^{arr}_{ev}$ and $t \leq t^{dep}_{ev}$ $\forall t \in T$)* **then** Power schedules:
        - $P^{out}_{ev,t}$(V2G) := Discharge battery/Upward regulation
        - $P^{in}_{ev,t}$(G2V) := Charge battry/Downward regulation
      - **else**
        - EV not connected (G2V/V2G not allowed)

Iterate and evaluate **Outputs** until optimal **Result**

This model aims to obtain improvements on different network KPIs based on the use of flexibility volumes purchased to the aggregator. Therefore, DSO model outputs represent the optimal power portfolio for a distribution network with high levels of renewable energy technologies and the use of electric vehicles flexibility services from an aggregator. Algorithm 1 metacode stylises the procedure for the DSO economic dispatch.

2.3. Aggregator model

Aggregator of electric vehicles model looks to stylise the actions taken by this fleet operator (FO), aligned with the proposed business model. It is built as a validation model to illustrate the coordination approach. Therefore, it not only has to meet the vehicles requirements previously agreed on the Smart Contracts, but also schedule the fleet to meet flexibility activation signals sent from the DSO in Real-Time (RT). The objective function accounts for minimizing aggregators' penalties ($Penalty_{n,t}^{G2V}$, $Penalty_{n,t}^{V2G}$) and EVs charging costs. In order to perform flexible charging of EVs, a specific Time-of-Use (TOU) tariff is considered based on already special EVs tariffs emerging in the market SRP (2018).

$$Minimize: \sum_{t} \left(\Pi^{pnlt} \cdot \sum_{n} (Penalty_{n,t}^{V2G} + Penalty_{n,t}^{G2V}) + \sum_{ev} (P_{ev,t}^{in} \cdot TOU_{t}) \right) \tag{15}$$

$$P_{n,t}^{DSO} = \sum_{ev} (P_{ev,t}^{out} - P_{ev,t}^{in}) + Penalty_{n,t}^{V2G} \qquad \forall n, t \in T^{+} \tag{16}$$

$$(-P_{n,t}^{DSO}) \leq \sum_{ev} (P_{ev,t}^{in} - P_{ev,t}^{out}) + Penalty_{n,t}^{G2V} \quad \forall n, t \in T^{-} \tag{17}$$

Therefore, the main constraints are the EVs power schedules (Equations 3, 4, 12, 13 and 14) to meet DSO flexibility signals ($P_{n,t}^{DSO}$), for both upward and downward regulation periods at each node of the network, represented by Equations 16 and 17. Algorithm 2 shows the method to schedule EVs charging to meet DSO requests. Note that the aggregator is not able to discharge more energy into the grid than DSO requests during upward regulation periods. In this model, network constraints are not considered as it represents the aggregators' response to DSO flexibility signals.

Algorithm 2: Aggregators' fleet schedules to meet DSO flexibility request

Inputs : $\left[EV_{ev}^{data}, TOU_t, P_{n,t}^{DSO} \right]$

Outputs: Optimal fleet schedules:

$\left[P_{ev,t}^{out}, P_{ev,t}^{in}, Penalty_{n,t}^{V2G}, Penalty_{n,t}^{G2V} \right]$

Result: Aggregator cost minimization := min(EVs charging, DSO penalties)

Run for each node ($n \in N$) and period ($t \in T$)

```
while DSO flexibility request not met do
    for each ev ∈ EV do
        while E_{ev,t} ≠ E_{ev}^{fin} at period t_{ev}^{dep} ∈ EV_{ev}^{data} do
            if (t > t_{ev}^{arr} and t ≤ t_{ev}^{dep}   ∀t ∈ T) then Power schedules:
                P_{ev,t}^{out}(V2G) := Discharge battery/Upward regulation
                P_{ev,t}^{in}(G2V) := Charge battry/Downward regulation
            else
                EV not connected (G2V/V2G not allowed)
    if P_{n,t}^{DSO} ≠ Σ_{ev}(P_{ev,t}^{out} − P_{ev,t}^{in}) at t ∈ T^+ then
        Compute Penalty_{n,t}^{V2G}
    if (−P_{n,t}^{DSO}) > Σ_{ev}(P_{ev,t}^{in} − P_{ev,t}^{out}) at t ∈ T^− then
        Compute Penalty_{n,t}^{G2V}
```

Iterate and evaluate **Outputs** until optimal **Result**

3. Numerical studies

3.1. Case study definition

The presented methodology has been implemented for the UK Local Energy Market of Cornwall as a case study analysis. A 7-bus and 9-lines distribution network is studied in the central area of the region, where congestion is the highest. Generators include renewable energy sources such as wind and solar, and dispatchable sources like CHP. Figure 3 illustrates the network considered. Network data is aggregated to 33 kV and 132 kV levels, which capacities are 15 and 49 MW respectively, and susceptances of 1 p.u. Conejo et al. (2016).

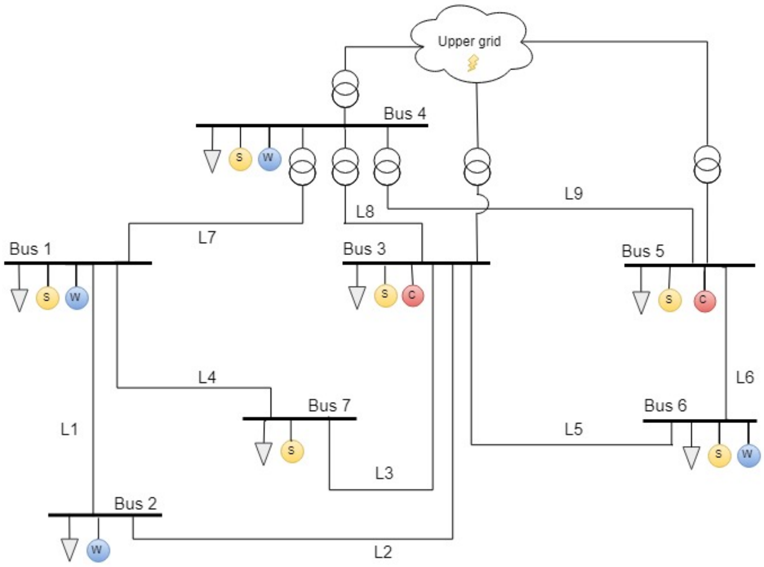


Figure 3: Stylised section of the Central Cornwall area for case study.

National Grid electric vehicles scenarios for the UK are scaled and allocated to the buses of main cities according to vehicle/population ratio. Motorway power stations are considered connected to transmission level, and are out of the scope of this study. Electric vehicles scenarios analysed are based on penetration (nº of EVs) - coordination (nº of flexible EVs) levels, as it is shown in Table 1. Only private Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs) are considered and connected to buses 1, 2, 4 and 5. Therefore, Toyota Prius and Nissan Leaf specifications for PHEV and BEV are respectively stylised Prius (2017), Nissan (2018).

Table 1: Electric vehicles scenarios considered for DSO model.

Penetration levels	**Total EVs**	**Coordination levels [% of Total EVs]**	**Uncoordinated EVs**
Scenario 2030	26840	0%, 35%, 65%, 95%	*Complementary to coordination*
Scenario 2040	51240		
Scenario 2050	95160		

In addition, a benchmark model without electric vehicles is simulated as a starting point for the results analysis. Otherwise, integration of SCs on the models are considered as acknowledgement of arrival and departure times of EVs, and their parameters, by the aggregator. In this way, flexible charging schedules can be predicted, and services to the DSO can be offered to improve network KPIs.

3.2. *Results and discussion*

This section presents a general analysis of the coordination scheme proposed. Firstly, the evolution of various network KPIs are presented and discussed. Secondly, behaviour between agents is illustrated through a sensitivity analysis of DSO flexibility activation signals and EVs schedules. Finally, a future formulation to model SCs for EVs is proposed as a next step of research.

3.2.1. *Network KPIs evolution*

Figure 4 represents network KPIs evolution by penetration-coordination scenario. Electric vehicles uncoordinated deployment increase network costs regardless of the penetration scenario. New loads entering on the system force energy to be purchased from transmission level at a higher price, or perform load shedding in order to balance supply and demand. Therefore, if not well managed, uncoordinated charging is able to reduce network social surplus Wafa et al. (2017).

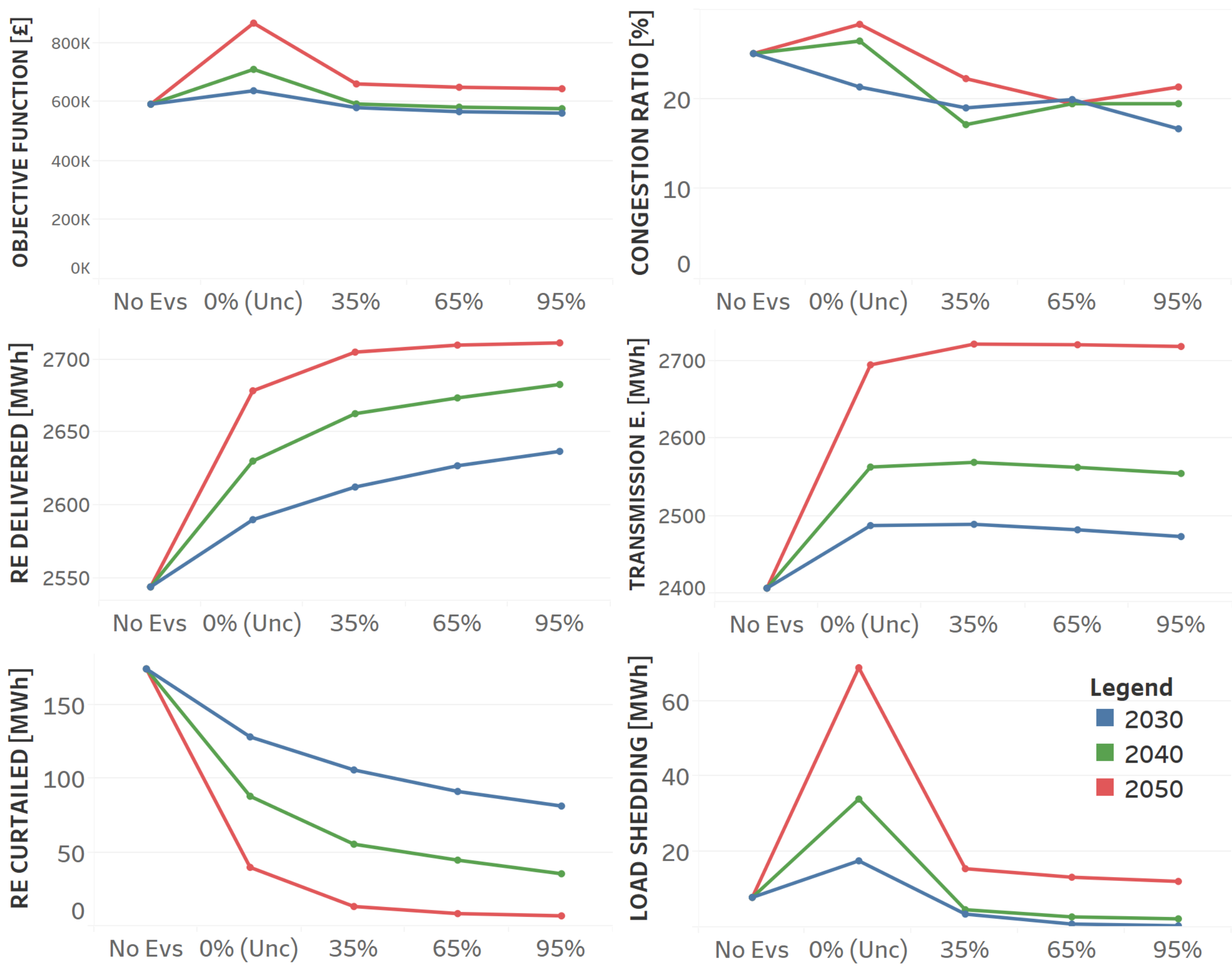


Figure 4: Network KPIs evolution by penetration - coordination scenario.

On the other hand, our simulated scenarios for 35, 65 and 95% coordination not only validates results reached on Xiang et al. (2016), but determine that there is a linear trend between network costs and the number of controlled EVs. This highlights that coordination of EVs minimizes costs associated with their loads, as they allow up to 6.5% more renewable energy to be delivered into the grid. These results are consistent with a 7.9% curtailment reduction achieved by Zhou et al. (2014), although their research was totally focused on curtailment reduction. However, even with a linear reduction, the 2050 penetration scenario generates higher costs than the benchmark model, showing that high penetration levels still increase these costs, and an in depth analysis on this issue needs to be performed. It can be explained as charging/discharging performances bring about higher utilisation rates of each battery and some EVs need to be charged more than once during their connected periods Yao et al. (2017).

Results highlight how uncoordinated deployment generates a significant curtailment reduction by increasing demand on nodes, where previously renewable energy could not be delivered. Meyer & Wang (2018) analyses the similarities of renewable energy plants and EVs charging stations in order to integrate them together. Consequently, this indicates that a strategic location of future EVs charging stations could be used to reduce curtailment on distribution networks with high penetration levels of renewable energies. Our results show that charging stations connected to the same node of wind and solar power plants could reduce curtailment up to 77% with an uncoordinated deployment of EVs. Then, by applying coordination strategies extra reduction can be achieved. Hence, areas with high levels of renewable energy curtailed could be benefited from large penetration levels of EVs. In addition, location of charging stations based on network topology and penetration – coordination scenarios should be studied in depth to obtain consistent recommendations about how to develop future electric vehicles infrastructure.

On the contrary, load shedding levels increase drastically with the uncoordinated deployment of EVs. As well as in the objective function, coordination strategies on scenarios 2030 and 2040 are able to reduce load shedding under benchmark values (No EVs). These results are consistent with recent studies that use EVs to reduce household load shedding Shemami et al. (2017), although they consider EVs as private house back up and not as a whole network management system. However, 2050 scenario maintains lower levels than uncoordinated, but higher than benchmark. This reinforces the theory that coordination strategies are effective to manage EVs uncoordinated deployment, but high penetration levels would still affect the network, as shown on results from 2040 and 2050 scenarios. Therefore, a very high EVs penetration scenario would force the implementation of high load shedding levels, even with the best coordination strategy. This concept is highly linked to congestion over network lines. Load shedding represents a last resource to balance the grid due to network congestion or excess of demand Elango (2011a), Elango (2011b). Specifically in this study, load shedding is produced during periods of low renewable energy in the system and high congestion ratios.

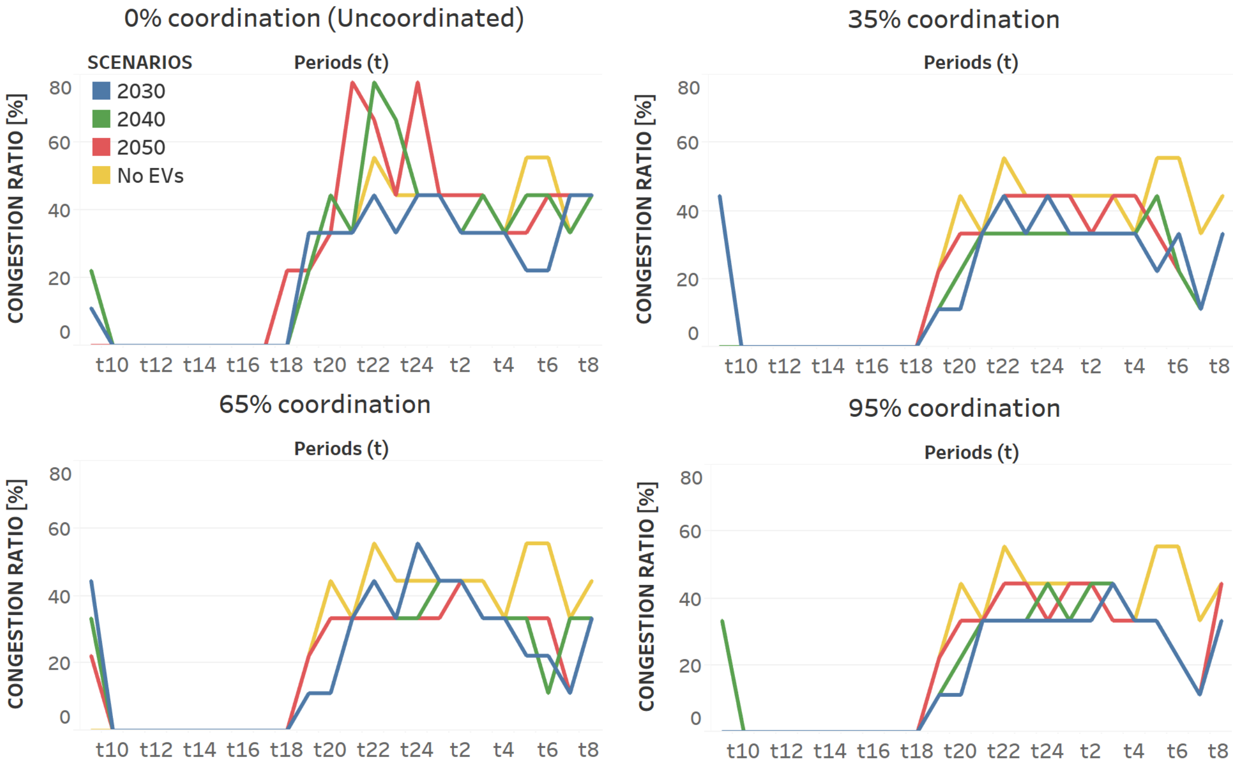


Figure 5: Congestion ratios per period aggregated by coordination levels.

Figure 5 illustrates how congestion appears during periods of electricity purchased from transmission level, at low renewables generation (18-8h). High penetration levels of uncoordinated EVs (2040 and 2050) produce periods of up to 80% congestion on the network. Nevertheless, coordination strategies keep congestion under benchmark scenario levels.

In this study, EVs schedules are based on aggregators' commitment with the Two-Part Tariff (TPT) (reserve and activation). This differs from previously proposed EVs market price-based control methods Hu et al. (2016b), Liu et al. (2018c), since the aggregator knows the actual connected periods of EVs, and is able to control the fleet according to DSO requests. Figure 6 shows electric vehicles flexibility reserve capacity purchased by the DSO at each node, during the DA market. In this case, 2050 penetration scenario is chosen to illustrate the variations of volumes for different levels of coordination. Note that V2G is not purchased during abundant renewable generation periods, because it would increase curtailment.

This research contemplates a combination of DA schedules of a forecasted fleet (aggregator), and flexibility activation signals to improve network KPIs in RT. As a consequence, the possibility to activate flexibility reserves in RT manages the uncertainty of both EVs and renewable generators.

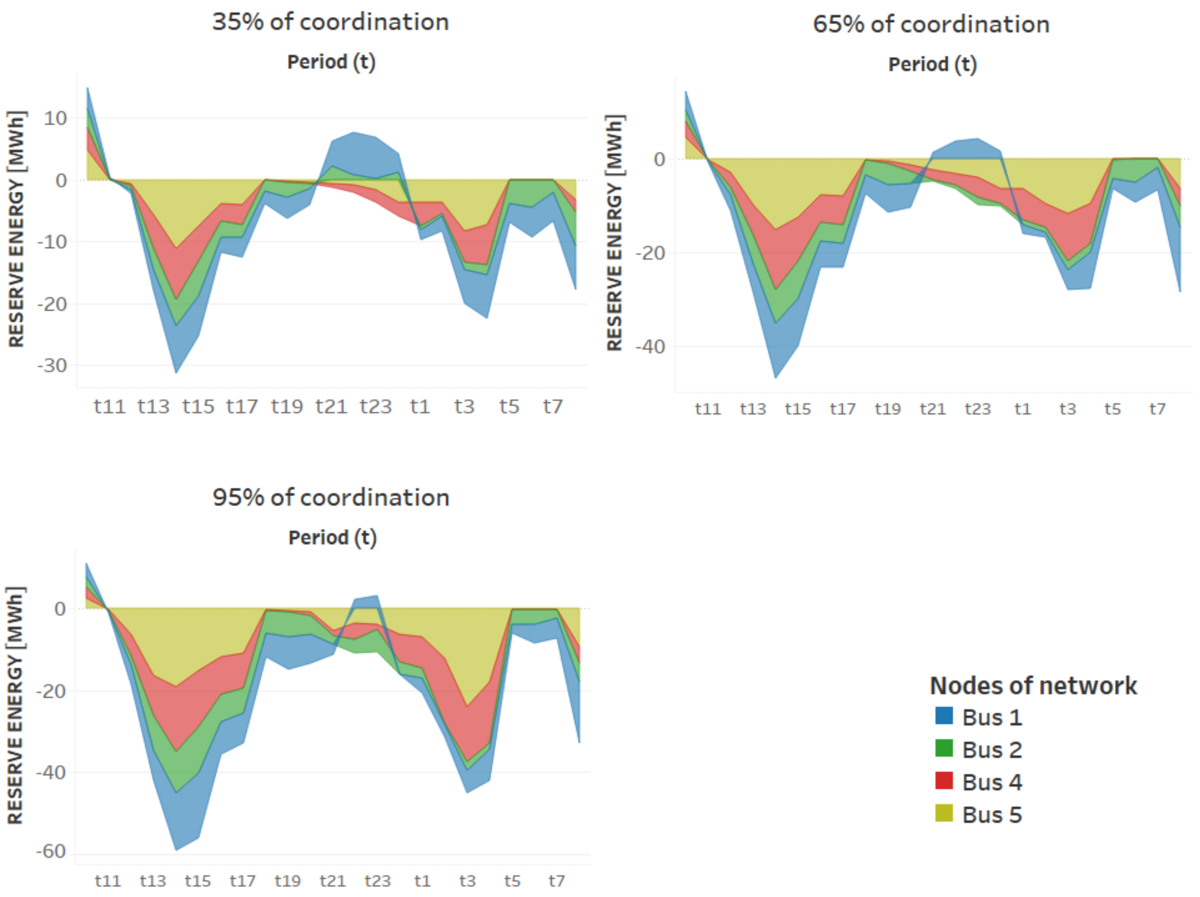


Figure 6: Flexibility reserve capacity purchased during DA per node. 2050 scenario.

3.2.2. Sensitivity analysis of coordination strategy

The aggregator model is built as a validation model in order to stylise and explain how the TPT would work from the FO perspective. As a consequence, it is not focused on scenarios to compare penetration - coordination, but to check how the EVs are scheduled by the aggregator in order to meet DSO flexibility activation signal during Real-Time (RT). Therefore, a sensitivity analysis is developed to check if the fleet is able to perform large G2V/V2G requests, and illustrate computed penalties.

The scenario 2050 with 35% of coordination is simulated as a validation from DSO model. Reserve capacities from Figure 6 are activated at 100% for V2G and 80% for G2V in Real-Time (RT). Therefore, Figure 7 illustrates the results for this scenario. DSO requests signals are sent to every node the aggregator has flexible EVs connected (Bus 1, 2, 4, 5). As can be seen, the aggregator has enough capacity to meet DSO request signals with EVs schedules, and no penalties are computed. Note that EVs are not allowed to perform more V2G than DSO requests, as they are acting as a generator. However, G2V performances can exceed the request if EVs need to be charged at those periods. It is validated that EVs can be scheduled according to a flexibility signal in order to provide services to a distributed network if there is enough volume to meet EVs requirements.

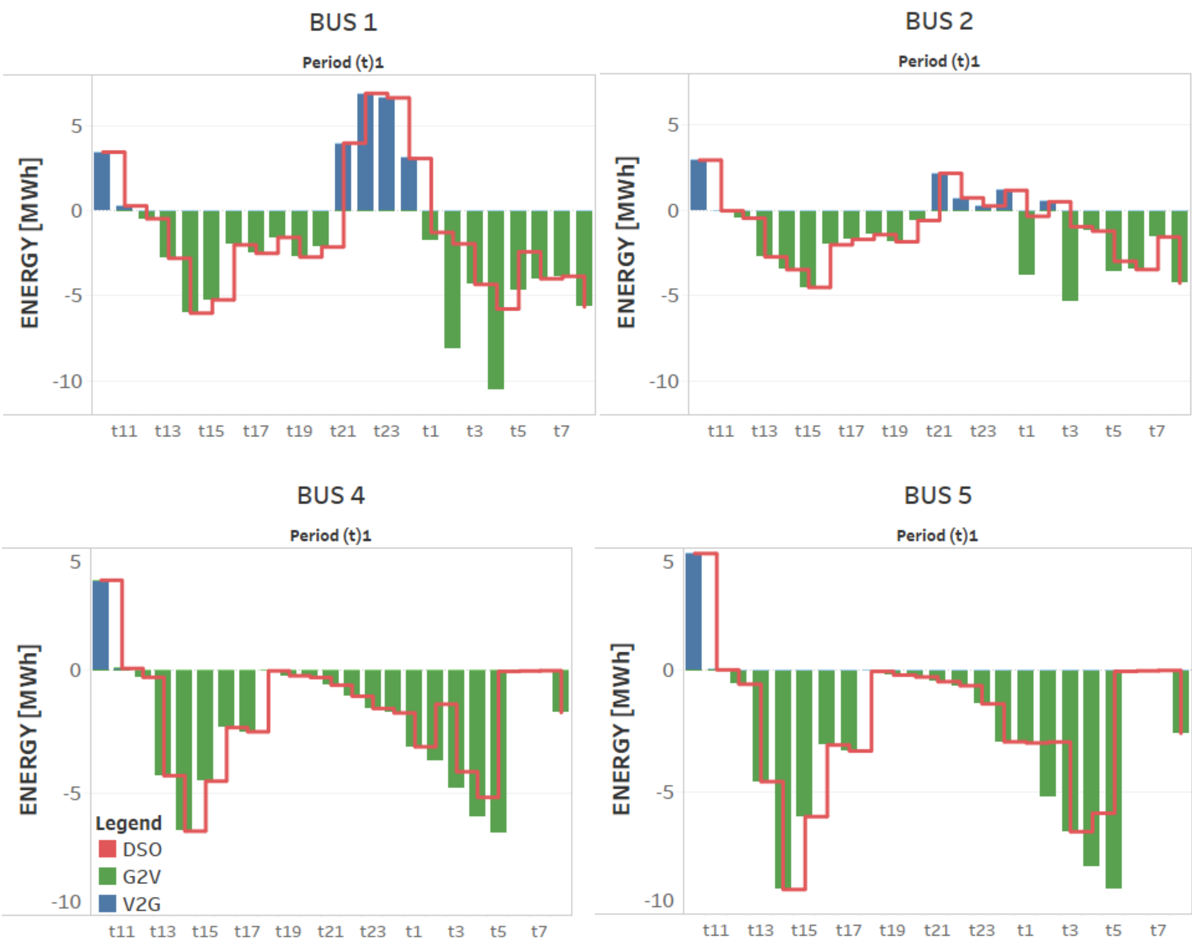


Figure 7: EVs schedules to meet DSO activation signal (red) for all connected buses.

On the other hand, in order to check the coordination approach for an extreme case, the following flexibility reserve and activation signals are proposed. A very large request by the DSO is introduced on the model to stylise a scenario in which the aggregator does not have enough capacity to meet both DSO and EVs requirements. Figure 8 illustrates the TPT mechanism, both from DSO and aggregator perspectives in this situation. During RT, the DSO is able to activate a flexibility signal (red), up to DA reserve levels (grey).

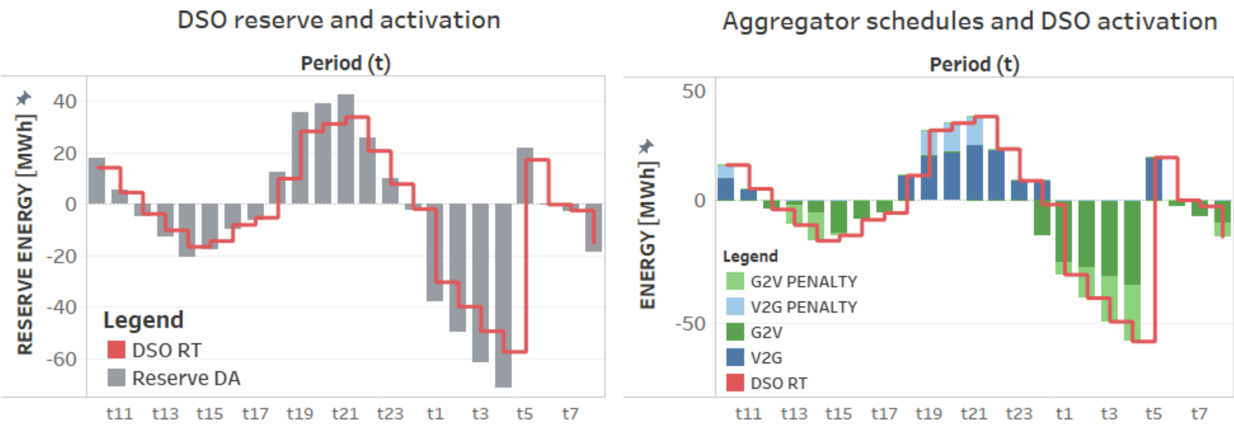


Figure 8: Example of TPT mechanism in bus 4: DSO (left) and Aggregator/EVs (right).

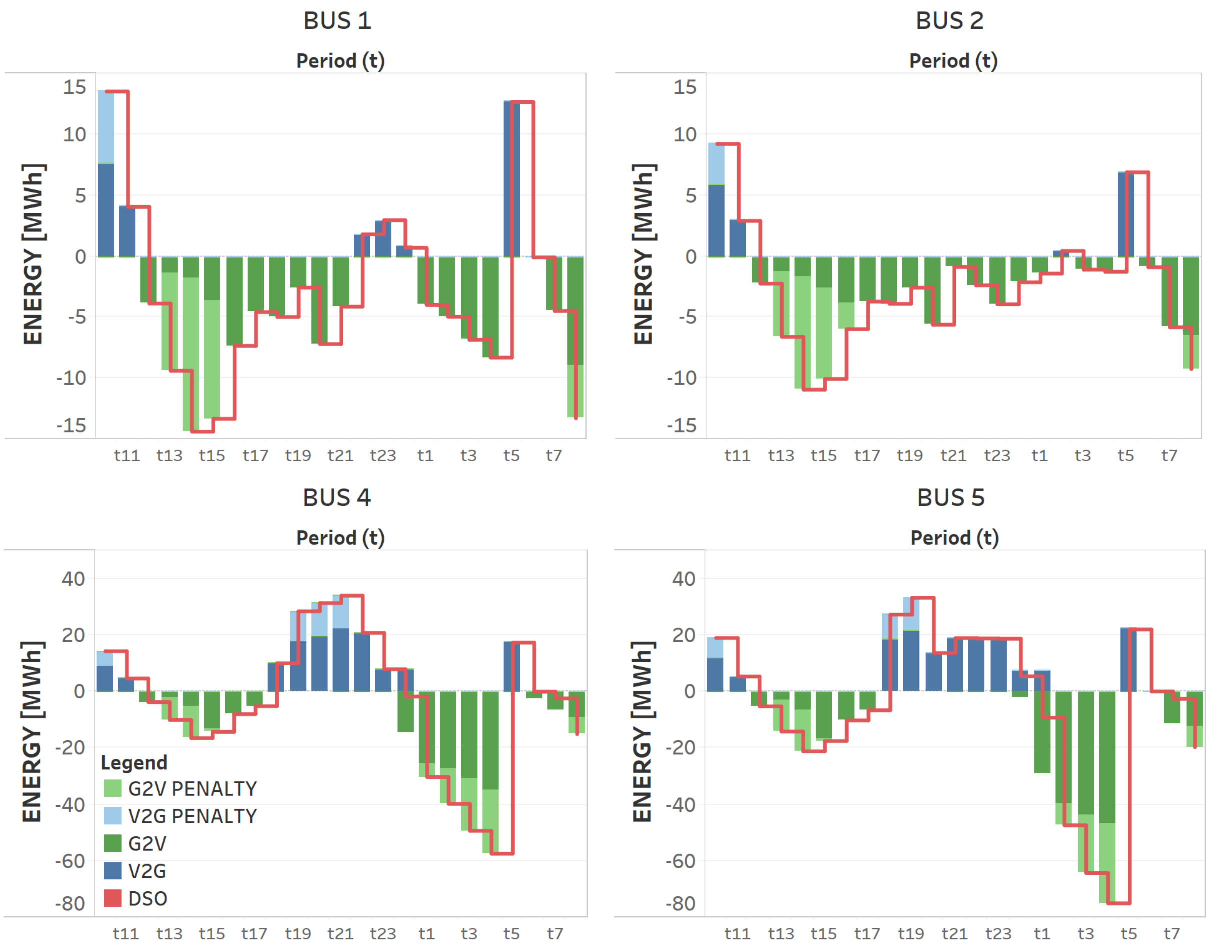


Figure 9: EVs schedules to meet DSO flexibility signals for all connected buses.

Figure 9 validates how the aggregator is able to schedule flexible EVs to meet DSO activation signals for multiple nodes of the network, at some periods. Very high DSO requests (red) are introduced to stylise the coordination performance during RT. G2V and V2G penalties are computed when there is not enough capacity to meet DSO requests and EVs requirements (Smart Contracts) at the same time. Note that EVs fleet perform G2V and V2G at the same time during periods t_{23} and t_1 (Buses 4 & 5), this means some of the vehicles are discharging their batteries to charge other vehicles at the same node. As can be seen, different requests signals are sent to every single node the aggregator has flexible EVs connected. This scenario exemplifies what would happen if the aggregator fails on its EVs forecasts during DA and sells more capacity than the fleet can offer during RT.

3.2.3. Smart Contracts implementation

In order to establish the values for SCs, a multi-aggregator flexibility market model needs to be performed, it is the next step to be implemented as a continuation of this research. The structure proposed in this research lead us to a future formulation similar to Equation 18. Total SCs costs should be calculated considering EVs availability participation (Π_{Av}), power restriction (P_{ev}^{rest}) (power connection or battery capacity) and periods ($t_{ev}^{cnn}, t_{ev}^{cntr}$) (connected and contracted).

$$SCs = \Pi_{Av} \cdot P_{ev}^{rest} \cdot (t_{ev}^{cnn} + t_{ev}^{cntr} \cdot (\Pi_{rew} - \Pi_{penal})) \tag{18}$$

The presented formulation has not been found among the literature. Therefore, this proposition represents a novel contribution to the field, and further research related to price optimization can be performed as a next stage.

4. Conclusion

Transition from centralised to decentralised energy markets requires innovative coordination strategies. In this way, under high penetration of DER, energy systems would become more resilient. This research evaluates the contribution of multi-agents coordination for EVs aggregators, using Smart Contracts and a TPT, to provide flexibility services in congested distribution power networks. A novel coordination scheme for EVs, a central aggregator and the DSO has been formulated. It addresses the challenges of large fleets of EVs and high penetration levels of renewable energy technologies on already congested distribution networks. The nature of DER requires decentralised mechanisms integrated under an economic framework. Consequently, Smart Contracts, as a new technology, are considered as enablers of intensive communication systems between EVs and FO.

Two models have been developed. One to analyse a set of network KPIs and determine the impacts or benefits of different levels of penetration - coordination levels of EVs, under the proposed coordination scheme. The second one serves as an illustration on how the coordination mechanism would operate. These models informed our research objectives:

- Electric vehicles flexible services are able to improve network KPIs, reducing network costs and managing congestion for high penetration levels, allowing up to 6.5% more renewable energy to be delivered into the grid. In addition, a strategic location of future EVs charging stations could be used to reduce curtailment on distribution networks with high penetration levels of renewable energies.

- The coordination scheme proposed allows to transfer penalties from DSO to the aggregator through the TPT, and from the aggregator to the EVs through the SCs. Consequently, flexibility activation signals reduce uncertainties and distribute network risk among all the agents. Otherwise, profitability of the scheme proposed would lead to novel business models for transport aggregators.

- Finally, a first formulation of Smart Contracts for electric vehicles is proposed. However, its implementation and price optimization within the TPT can be investigated in further research.

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