Multi-year planning of LV networks with EVs accounting for customers, emissions and techno-economics aspects: A practical and scalable approach

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Abstract
The uptake of electric vehicles (EVs) is expected to trigger investments to adapt existing distribution networks, particularly in the low voltage (LV). To make adequate, holistic planning decisions over multiple years, the assessment of alternatives—such as reinforcements or the adoption of EV management strategies—must not only capture when the investments are needed but also the effects on customers and carbon emissions, all while accounting for uncertainties. This paper proposes a stochastic, practical, and scalable progressive multi-year planning methodology that considers technical, customer, economic and environmental aspects to make holistic planning decisions for existing LV networks to accommodate EVs. The proposed rule-based methodology contrasts the net present value and benefits of four planning alternatives: network reinforcements, EV charging point management, and their combinations. Uncertainties are catered for by adopting a Monte Carlo approach. Using two real UK LV networks and realistic time-series data, results demonstrate the importance of a holistic decision-making approach. From an economic perspective, EV management is better for voltage issues, and reinforcements for thermal problems. However, when customer effects are considered, the management can lead to unacceptable charging delays. Combinations, on the other hand, provide trade-offs between cost and the effects on customers or carbon emissions.

1 | INTRODUCTION
The need to decarbonize the transport sector combined with the falling prices of electric vehicles (EVs) are paving the way for the widespread adoption of the technology. For Distribution Network Operators (DNOs), the expected coincidence between EV charging and domestic demand raises concerns as it will increase evening peaks [1, 2]. This means that, in the coming decades, investments in existing distribution networks will be required to mitigate EV impacts such as thermal overloads and substantial voltage drops. However, as EV users are likely to charge at home, the corresponding infrastructure to which they are connected to, the residential low voltage (LV) networks (typically, comprised of one transformer and one or more LV feeders), is likely to need those investments first [2–4].

From a distribution expansion planning perspective, DNOs will, in practice, have to first forecast the horizon and corresponding EV uptake. Then, they will assess the ability of existing LV feeders to cope with the future EV demand via technical aspects such as asset utilization and voltage drops [5]. If technical problems are found, they will then identify suitable mitigation strategies to accommodate EVs over the corresponding planning horizon. Mitigation strategies can range from reinforcing the circuits, i.e. upgrading traditional assets (transformers/cables) [6–13], to implementing EV management strategies (i.e. smart grids) [14–21]. To ultimately decide between the traditional expansion planning alternative...
(i.e. reinforcements in the circuit) and the active distribution network planning alternative, DNOs will finally contrast the net present value (NPV) and other benefits (e.g. carbon emissions and customer effects) of each option [5].

While the above planning process seems straightforward, it is challenging for DNOs as they need to understand the costs of planning alternatives in a progressive, multi-year approach (i.e. the effects of planning decisions early in the horizon must be considered throughout) given that the uptake of new technologies evolves in time [5, 22]. Without being able to capture the timing of investments, it is not possible to estimate the corresponding NPV (or any other time-dependent metric). In addition, the increasing relevance of customer satisfaction as well as carbon emissions will push DNOs to assess potential solutions beyond their traditional techno-economic merits. Furthermore, the unbalanced nature of distribution networks, particularly at LV levels, requires the adoption of techniques that deploy three-phase power flows instead of simplified single-phase power flows. Finally, the uncertainties associated with the EVs need to be considered to avoid under or overestimations [2, 5, 22]. Capturing all these processes and aspects requires DNOs to adopt advanced planning approaches. However, given the number and diversity of LV networks in any given region, and the time-series nature of demand (including EV charging), such approaches need also to be practical and scalable.

A detailed review on the distribution network expansion planning problem is presented in [23]. Many works have dealt with the general expansion planning problem in medium voltage (MV) networks modelled as single-phase balanced circuits and no LV circuits (just lumped loads), e.g. [24–33]; ignoring the impacts and necessary investments in LV networks. Nonetheless, such a simplification of distribution networks allowed these works to produce multi-year formulations of the planning problem [24–33] (as also in [19–21]). However, to enable the use of dynamic or robust optimization techniques within multi-year frameworks, profiles for demand and other technologies (including EVs) are limited to resolutions (granularity) of one hour; which cannot adequately capture intra-hour impacts and/or control aspects. While these optimization techniques might be suitable for balanced MV networks, their application for three-phase LV networks has not been demonstrated. Furthermore, the size and diversity of LV networks (multiple feeders, dozens to hundreds of customers) might also create significant implementation challenges for DNOs.

There are multiple approaches that deal with the traditional expansion planning alternative in LV networks [7–13]. In [7, 8], the authors provide an approach to design brand new LV networks considering EVs and simplified (balanced) LV models. This, however, excludes existing LV networks and how the already deployed infrastructure should be adapted in time. On the other hand, some of the studies that attempt to address the planning needs of existing LV networks due to EVs, [9–11], do not consider network models. Instead, they estimate network reinforcements based on peak or diversified demand, neglecting the particularities of the circuits, impedances, customer voltages, power flows, etc., which can lead to under or overestimations. In [12], three-phase network models and hourly profiles are used to determine the network reinforcements needed to cope with a given EV penetration. Nonetheless, this study does not cater for the uncertainties associated with the demand and location of EVs and households. This limitation is addressed in [13] by carrying out a Monte Carlo-based analysis. However, all those works only focus on techno-economic aspects of single alternatives. Furthermore, they do not consider the multi-year nature of the planning problem of LV networks (similar to those in MV networks [24–33]).

In terms of EV management, there is a significant number of schemes available in the literature, for both LV (e.g. [14–18]) and medium voltage (MV) networks (e.g. [19–21]). The studies in [14–18], and similar ones, present optimization- or rule-based algorithms to mitigate thermal and voltage problems in LV networks. While the most recent studies [16–18] consider uncertainties (household demand and EV demand and location) and the effects on customers due to the management (in terms of electricity price or number of disconnections), none of the works in LV networks account for the multi-year nature of planning alternatives.

Beyond modelling aspects of the planning problem, existing works (in MV) do not contrast planning alternatives. Instead, the focus is on developing single alternatives (either reinforcements or management) to cope with the penetration of EVs (or other technologies). Without being able to contrast the cost and benefits of alternatives over the planning horizon, DNOs cannot make adequate decisions. Finally, most studies focus on techno-economic aspects, neglecting the increasing role that environmental and customer metrics (e.g. carbon emissions) have in network expansion planning [34].

To address the aforementioned gaps in the literature, this paper presents the following contributions:

(i) A practical and scalable, stochastic, progressive multi-year planning methodology that considers technical, customer, economic and environmental aspects to make holistic planning decisions for existing LV networks to accommodate EVs in the coming years. The approach is implementable by DNOs as it builds on existing power flow analysis tools, which is not affected by network size.

(ii) The proposed methodology contrasts the NPV and benefits of four planning alternatives: network reinforcements, EV charging point management and their combinations (i.e. switching from one alternative to another when needed) to explore potential trade-offs between cost and benefits.

(iii) It adopts a sequential Monte Carlo approach to capture uncertainties in the planning of LV networks due to demand and EV behaviour.

(iv) The application and benefits of the proposed approach are demonstrated using two real UK LV networks considering realistic, seasonal (1-min resolution) time-series data for the EV and household demands.
The remainder of the paper is structured as follows. Section 2 describes the scalable, stochastic, progressive multi-year planning methodology. Section 3 demonstrates the practicality of the methodology on two real UK LV networks using realistic, 1-min load and EV profiles for all aspects. Conclusions are finally drawn in Section 4.

2 | METHODOLOGY

This section presents the planning methodology that contrasts the NPV and benefits of four planning alternatives: network reinforcements, EV charging point management and their combinations. Three cost and benefit metrics are considered: charging delays, NPV, and carbon emissions. The flowchart shown in Figure 1 illustrates the different steps required by the methodology. In addition, Algorithm 1 shows the pseudocode of the proposed approach. As input data, it needs the planning horizon and expected EV uptake to define the corresponding EV penetration (i.e. number of houses with an EV) per year. Similarly, the uptake of distributed energy resources (DERs), such as solar photovoltaics, can also be defined to account for the corresponding interactions. It also requires the network data (e.g. transformer impedance, number of feeders, cable impedances, phase connections etc.), as well as the load, EV and DER profiles. To cater for demand, EV and DER changes throughout the year, profiles for winter, spring, autumn, and summer as well as for weekdays and weekends can be considered. To quantify the NPV and carbon emissions, capital and operational expenditure as well as emission factors are used. Finally, when a target such as maximum emissions or charging delays is specified, the combination of alternatives is investigated in which the target triggers the switch from one to another.

![Flowchart of the proposed planning methodology](image)

Algorithm 1: Expansion planning of existing LV networks with EVs

1. **Input**: Planning horizon, EV/DER uptake, LV network data, load/EV/DER profiles, costs, and emission factors.
2. **Output**: Statistical analysis of technical, economic, customer, and environmental metrics
3. **for each simulation** $i$ of Monte Carlo
   4. **for each simulation** $k$ of multi-year do
      5. **for each house** $h$ do
         6. load profile $h$ ← profile for type of days and seasons with load growth
         7. EV/DER profile $h$ ← profile and year of adoption
      8. end for
   9. BAU results ← time-series power flows over the horizon without planning alternatives
10. **for each planning alternative** $\delta$ do
11. results$_\delta$ ← time-series power flows over the horizon with planning alternative $\delta$
12. end for
13. assessment ← \{asset_utilization_level, \#customers_with_voltage_problem, NPV, charging_delay_index, emissions\}
14. end for
15. end for
16. end for

Uncertainties due to demand, EV, and DER behaviour are catered for by carrying out sequential Monte Carlo simulations [35]. For each simulation $i$, the multi-year progressive assessment for year $k$ is performed. From a modelling perspective, the multi-year approach means that the conditions for each simulation $i$ need to be consistent throughout the horizon. To achieve this, for each year $k$ in the horizon, the methodology defines the corresponding load profiles and the EV and DER penetration level to be assessed. Load profiles can be defined for the first year and then, if required, modified subsequently based on load growth\(^1\). For EVs and DERs, the allocation of profiles is done according to the EV and DER penetration estimated for year $k$, which accounts for the deployment curve of the country or area under assessment. EV and DER profiles allocated in the previous year remain fixed and the additional ones are randomly allocated.

From a planning perspective, the assessment of EV impacts and the implementation of each planning alternative in year $k$ is done progressively, i.e. considering the effects of planning

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\(^1\) If load growth is due to small behavioural/population changes, the demand profiles per household can be modified. However, if it is due to new houses/buildings, the LV network might require line upgrades or even new lines (a new topology). The latter is outside the scope of this paper.
decisions made earlier. The analyses are done performing time-series, three-phase power flows for the adopted seasons and day types as well as considering the procedures of each alternative (details in Section 2.2 and Section 2.3). If applicable, any infrastructure changes (e.g. new assets) from year \( k \) are considered for year \( k + 1 \) and subsequently. For each year \( k \) for simulation \( i \), the proposed methodology assesses the customer, economic and environmental aspects of each planning alternative, i.e. charging delays, NPV, and carbon emissions. This is done to determine, when alternatives are combined, if switching to the other alternative is necessary. If switching is needed in year \( k \), it is then implemented in year \( k + 1 \). The quantification approach is described in Section 2.4.

Once the last Monte Carlo simulation is reached, a statistical analysis is carried out to quantify the average (and standard deviation) charging delays, NPV and carbon emissions achieved by each alternative. Ultimately, it is in the hands of the DNO to select the most adequate planning alternative based on the metrics.

### 2.1 Thermal and voltage assessment

Prior to implementing a given planning alternative, DNOs must quantify the ability of existing feeders to cope with the demand of EVs. For each year \( k \), the technical impacts from EVs are assessed using the following metrics:

(i) **Asset utilization level:** Indicates the average maximum three-phase power (phase current) through the transformer (section of a cable) divided by its corresponding capacity.

(ii) **Percentage of customers with voltage problems:** Represents the ratio between the number of customers whose voltages at the connection point is below the statutory limit and the total number of customers in the LV network.

### 2.2 Network reinforcements

EV studies suggest that half of the LV networks are likely to face thermal problems due to large EV penetrations, with the other half facing voltage problems [2, 36].

Problems can be mitigated by reinforcing the circuits. While different reinforcement algorithms can be used in the proposed planning methodology (e.g. [6–13]), the one described in [37] is adopted due to its simplicity and effectiveness. The approach, which is based on UK DNO practices [6], replaces the assets for new ones with bigger capacity. This also reduces voltage problems given that bigger cables have lower impedances.

Figure 2 presents the adopted network reinforcement algorithm for year \( k \). The steps are as follows:

1. **Transformer Level (Thermal):** Its loading is checked. If it is overloaded, the asset is replaced by the next suitable one. The selection of the size must be defined according to the capacities available to the DNO. At the end of the horizon, only one replacement is considered.

2. **Feeder Level (Thermal):** The loading of each cable section in all feeders is checked. If there is a thermal problem in a given section of a cable, this is replaced by the next suitable size (capacity). The size selection must be defined according to the capacities available to the DNO. If same segment is replaced multiple times at the end of the horizon, this is considered only once.

3. **Three-phase four-wire power flow:** An unbalanced power flow is then run and voltages are checked. The replacement of cables for thermal issues may mitigate voltage problems.

4. **Feeder Level (Voltage):** For each (single-phase) customer connection point (e.g. black dots in Figure 3), the compliance with the statutory limits is checked. If there is a violation, the main path between the transformer and the customer with the worst voltage (e.g. blue dashed line) is identified (not necessarily the last customer). The main path is then divided in segments (e.g. 100m).

5. The first segment of the main path (e.g. red dotted line in Figure 3 from the substation to the customer) is replaced by a conductor with the next suitable size.

6. A power flow is run and voltages are checked.

7. If there are still voltage issues at the same customer point, the next segment is replaced (along the blue dashed line). This is repeated until issues are solved.

8. Solving voltage problems: Steps (i)–(iii) of step (4) above are repeated (for each customer with voltage problems) until all
customers are voltage compliant. If a segment is replaced multiple times, this is considered once.

2.3 | EV charging point management

Technical impacts caused by EVs can also be dealt with management strategies at their connection points. While different approaches can be used in the proposed planning methodology, the one introduced in [18], and trialed in 9 real UK LV networks as part of the industrial project “My Electric Avenue” (MEA) [38], is adopted to manage the EV charging points at households to mitigate the resulting thermal and voltage problems. Its implementation requires the following key infrastructure [18]: voltage sensors and actuators at the EV charging points, communication links, voltage and current sensors at the head of the feeders, and a programmable unit at the substation (e.g. a programmable logic controller, PLC) to host the control algorithm.

If needed for year \( k \), the strategy adopts at every control cycle, a hierarchical corrective approach (from feeder to transformer) and a hierarchical preventive approach (from transformer to feeder) to disconnect and reconnect (per phase) EV charging points, respectively. Since the control does not require the initial state of charge (SOC), the charging time (calculated by an internal counter) is used to determine the most suitable EVs to be managed (see [18] for full details of the control algorithm). As an improvement of the previously proposed control strategy, this work extends the original algorithm to cater for past errors with a proportional-integral controller; thus, resulting in a better performance of the control strategy (i.e. lower number of technical problems).

2.4 | Performance assessments

The methodology quantifies in every year \( k \) the three adopted independent metrics: charging delay index, NPV and carbon emissions. While it is possible to combine them (by monetizing or normalizing them), an adequate selection of weighting factors would be needed.

2.4.1 | Customer assessment

Understanding the impacts that planning alternatives have on customers with EVs is crucial to ensure those alternatives can be accepted. When the alternative is to reinforce the network, EV charging is uncontrolled and, therefore, there is no impact on customers; i.e. their charging times are not affected. However, when EV management strategies are in place, some EVs (or their charging point) will be controlled to avoid technical issues, resulting in longer charging times. While this effect could be quantified in terms of costs, this work uses charging delays as a proxy of customer satisfaction. More specifically, this work uses the charging delay index (CDI) proposed in [18]. The CDI of each EV, indexed by \( id \), in year \( k \), is estimated as follows:

\[
CDI^{id}_{k} = 100 \times \left( \frac{t^{id}_{1,k}}{t^{id}_{0,k}} - 1 \right)
\]

where \( t^{id}_{1,k} \) and \( t^{id}_{0,k} \) are the time with and without EV management, respectively. Note that a CDI = 0% means that the EV was not disconnected. A CDI = 100% means that charging the EV took double the time. A CDI > 100% means that the charging time with the EV management was more than twice the time without it. Given that each EV will have a different percentage of CDI, a scale and groups need to be made to understand the global effect of the alternative.

2.4.2 | Economic assessment

All capital expenditure (CAPEX, including installation or replacement of assets, i.e. transformer and cables) as well as the operational expenditure (OPEX, e.g. data management) resulting from the adoption of any planning alternative in year \( k \) are quantified.

The quantification of CAPEX depends on the assets needed to implement a planning alternative that mitigates the technical problems in each year (e.g. transformer and cables). For planning alternatives that involve the active management of EVs, the quantification of OPEX depends on whether the scheme is operational. Thus, the NPV in year \( k \), \( NPV_k \), is used as a metric of any CAPEX and OPEX as follows [32]:

\[
NPV_k = \frac{CAPEX_k + OPEX_k}{(1 + r)^k}
\]

where \( k \) is the year in the horizon when the investment is made, \( r \) is the discount rate, \( CAPEX_k \) is the capital expenditure made at the year \( k \), \( OPEX_k \) is the operational expenditure made at the year \( k \). To make decisions, DNOs will use the total NPV, calculated as the sum of all NPVs up to the end of the horizon \( N \).

2.4.3 | Environmental assessment

The environmental benefits of each planning alternative are quantified considering the cumulative grams of CO\(_2\) equivalent (gCO\(_2\)eq) for year \( k \). These are calculated using the carbon emission factors available for the life cycle assessment of the assets [39], as well as the emissions resulting from energy losses over the planning horizon (which can be significant [39]).

The emissions resulting from installing or replacing assets at year \( k \), \( CO_{2eq}^{asset}_{k} \), are calculated as follows:

\[
CO_{2eq}^{asset}_{k} = \sum_{x=1}^{M} \lambda_{k,x} \times EF_{k,x}
\]
where $M$ is the number of assets’ types indexed by $x$ (e.g. sensors and actuators at the EV charging points and sensors at the substation), $\lambda$ is the number of assets of the corresponding type $x$ at year $k$, and $EF_{k,x}$ is the emission factor of the corresponding asset type at year $k$. The emissions from assets are calculated from the year at which the asset is installed/replaced and accounted for until the end of the planning horizon. Emissions from unchanged assets are not accounted for as they will be the same for any alternative.

Following the deployment of a planning alternative, the $CO_{2eq}$ emissions resulting from the network operation are also accounted for by calculating the emissions from the energy losses (which depend on each country energy mix). These emissions, $CO_{2lust}\text{,}$ are quantified as follows:

$$CO_{2lust,k} = E_{lust,k} \times EF_{lust,k}$$  \hspace{1cm} (4)

where $E_{lust,k}$ is the energy losses at the year $k$, and $EF_{lust,k}$ is the emission factor from these losses at year $k$. Changes in the emission factor from losses need to be accounted for as the energy mix can vary in the horizon (e.g. due to load growth).

The total environmental benefits resulting from each planning alternative corresponds to the sum of the $CO_{2eq}$ emissions from assets and losses over the total horizon.

### 3 | CASE STUDY: REAL UK LV NETWORKS

Key to any planning methodology is to define the horizon of interest. To assess the effects from EVs across all penetrations, the horizon adopted in this work corresponds to that where all houses have an EV (100% penetration). For this purpose, the EV uptake rate from the “Two Degrees” scenario used in the Future Energy Systems report [40] produced by the system operator in the UK is adopted. Based on this report, the 100% EV penetration is reached by 2050, i.e. a horizon of 30 years (from 2020). Although this horizon will be used in the case study, a shorter and more practical one can also be adopted depending on the planning approaches of the DNO.

The rest of this section presents other data and considerations for the illustrative case study, as well as the results from implementing the proposed methodology.

#### 3.1 | Input data

This section presents the input data used in the assessment: the two UK LV Networks, domestic load and EV profiles, costs and emission factors. Although the case study focuses on EVs, other DER can also be incorporated.

#### 3.1.1 | UK LV networks

The study carried out in [36] found that in the UK, half of the residential LV networks are likely to face thermal problems due to large EV penetrations, with the other half facing voltage problems. Based on this, the methodology is implemented on two UK LV networks (supplied by one single transformer) with different density of customers and feeder lengths, thus resulting in different technical issues. The two residential, underground 400 V LV networks studied here are from the North West of England and are fully modelled using OpenDSS [41]. The topology and main characteristics (e.g. the length and main path...
average impedance) for LV Network 1 are shown in Figure 4 and Table 1, and for LV Network 2 in Figure 5 and Table 2.

These radially-operated LV feeders are three-phase with single-phase customer connection points. LV Network 1 consists of six feeders and 370 customers and, as it will be shown later, is constrained by thermal issues. LV Network 2 consists of five feeders and 428 customers and it faces voltage problems in long feeders. The networks are supplied by three-phase 11 kV/433 V 500 and 800 kVA single distribution transformers, respectively. The busbar voltage of the transformers is kept at approximately 424 V (line-to-line) to mimic UK DNO practices [42]. All the power flow simulations are executed using OpenDSS integrated with MATLAB [43] for the data analysis.

### 3.1.2 | Domestic load profiles

The 1-min resolution daily time-series load profiles of households are modelled using a tool presented in [44] – which considers the domestic behaviour of UK customers, the months, the type of day, the number of people at home, and the use of the appliances.

To mimic the stochastic behaviour of the load consumption per household, a pool of 1000 different load profiles was created for each season: winter (i.e. January), spring/autumn (both with similar electrical demand, i.e. April), and summer (i.e. July); as well as for each type of day (i.e. weekday/weekend). Each pool considers the proportion of houses with one, two, three and four or more people: 28%, 35%, 16% and 21%, respectively, based on the UK National Statistics [45]. Figure 6 illustrates the average demand for the 1000 load profiles for each specific season during weekdays.

For simplicity, domestic load growth is not considered in this case study. In practice, load growth can come with significant topological changes; large houses that become multiple smaller houses and/or new developments/buildings require new LV feeders and service lines. Capturing such complex topological evolution (that depends on the local geographical characteristics) is beyond the scope of this work.

### 3.1.3 | EV load profiles

To truly capture the EV charging demand in the LV network, EV load profiles must be created using country or regional level high-resolution data of the EV charging behaviour of users. Data of different EV brands, battery capacities, and EV charger demand will provide better estimations of the cost and benefits of the alternatives needed.

In this work, the EV daily time-series behaviour (1-min resolution) was created using the statistical analysis presented in [46]. The probability distribution functions of start charging time and charging duration are used to produce a pool of 1000 realistic EV profiles for weekdays and weekends. Given that seasonality has limited effect on the charging behaviour of EV users [46], the same pool is used along the year. Figure 6 also shows the average demand of the pool of 1000 profiles (weekdays). The EV charging process is assumed to be continuous, i.e. once it starts, it will not end until the battery stops withdrawing power (e.g. the EV is disconnected or fully charged). The EVs utilized in this work are similar to the commercially available Nissan LEAF (1st generation), i.e. the battery capacity is 24 kWh. Since EVs are assumed to be connected at home (single phase), the slow charging mode is considered, i.e. a constant charging rate of 3.6 kW. An inductive power factor of 0.98 is used [46].

### 3.1.4 | CAPEX, OPEX and carbon emission factors

Reinforcement alternatives consist primarily in replacing the transformer, the main cable and service cables. Their cost should also account for OPEX (mainly due to maintenance). The practical alternative adopted in this work uses information of costs (CAPEX + OPEX) from the DNO in the North West of England, which are shown in Table 3 [6].

The EV management considers CAPEX and OPEX. The costs were obtained from the MEA project [47]. Table 3 shows the actual assets’ costs (in 2015) as deployed in the project: the PLC device plus the monitors at the head of the feeders (PLC + Monitors), the voltage sensors and actuators at the EV charging points (also known as Intelligent Controlled Box, ICB), and signal repeaters installed along the feeders (one per feeder). This alternative also considers all OPEX associated with data management at the ICBs, which varies with the number of customers with the technology, and is needed every 5 years as suggested in the project [47].

In terms of the discount rates, these values are defined based on Ofgem (the UK regulator) [48]: 3.5% if the investment is within the next 30 years or 3.0% if later.

The carbon quantification for the traditional network reinforcement strategy assesses the carbon impact of replacing the

### TABLE 2 Main electrical characteristics of LV network 2

|     | F1    | F2    | F3    | F4    | F5    |
|-----|-------|-------|-------|-------|-------|
| # Customers | 23    | 15    | 106   | 135   | 149   |
| Length [m]  | 371.4 | 341.9 | 721.0 | 655.0 | 421.0 |
| R [Ω/km]    | 15.0  | 23.4  | 24.5  | 32.8  | 27.7  |
| X [Ω/km]    | 4.4   | 3.7   | 6.0   | 7.3   | 6.8   |

![FIGURE 6](image_url) Diversified demand for 1000 domestic and EV profiles (WD)
TABLE 3  CAPEX and OPEX used in the economic assessment

| Strategy          | Description        | Cost (£)     |
|-------------------|--------------------|--------------|
| Network reinforcement | Transformer      | 30,000 / unit |
|                   | Main cable        | 160 / m      |
|                   | Service cable     | 1200 / unit  |
|                   | OPEX              | 20% of total CAPEX / five years |
| EV management     | CAPEX: PLC + Monitors | 2000 / unit  |
|                   | CAPEX: ICBs + Comms | 300 / unit   |
|                   | CAPEX: Repeaters  | 50 / unit    |
|                   | OPEX              | 150 / customer / five years |

transformer, cable, and the resulting benefits from reducing energy losses (note that larger cables have smaller impedances and, thus, less energy losses). The emission factors of replacing the transformer and cable shown in Table 4 are taken from [39]. These values include not only joints and installation, but also a detailed assessment of civil, electrical, and structural engineering works.

The carbon emission factors associated with the assets deployed as part of the EV management are not available yet due to the prototype nature of this planning alternative. Therefore, electronic components available in the market that are similar (the manufacture line follows a comparable process) are considered. Table 4 details the original asset that is used in the EV management and the equivalent asset considered in this work, along with its corresponding emissions factor extracted from [49].

The conversion factor from energy losses to gCO₂eq is based on the data from 2017: 0.5016 kg CO₂eq / kWh [50].

4 | RESULTS

This section presents the results from implementing the proposed practical, stochastic, progressive multi-year planning methodology considering the input data mentioned above. The results are presented in terms of the average values and one standard deviation from a Monte Carlo analysis with 1000 simulations. To investigate the benefits from using combined alternatives to meet customer expectations, a maximum average CDI of 4 (a delay of twice the time) is considered as the trigger to switch from EV management to network reinforcement.

4.1 Timing of planning alternatives

The investigated planning alternatives have been designed to mitigate asset overloads and voltage drops (below the statutory limits) that might occur on LV networks due to EVs. Figures 7, 8 and Tables 5, 6 are presented here to show the penetrations at which the planning alternatives are needed to address each of the technical impacts.

The transformer utilization level (UL) of LV Network 1 is shown in Figure 7(a); thermal problems need to be solved for penetrations of 50% and above (see solid line “without planning”). In terms of feeder thermal overloads, the average feeder UL reaches 80% for a 100% EV penetration [Figure 8(a)]. Nonetheless, those feeders with many customers are likely to experience overloads at earlier penetrations (from 90%, see error bars). In terms of voltages at households, Table 5 highlights that no significant problems exist. Consequently, this network requires planning alternatives when a 50% EV penetration is reached, approximately by 2034, primarily to solve transformer overloads, followed by some cables.

For LV Network 2, Figure 7(b) shows that the transformer is overloaded from an EV penetration of 90%. However, due

TABLE 4  Carbon content of assets deployed in the alternatives

| Strategy       | Original asset       | Replaced asset       | Emissions factor   |
|----------------|----------------------|----------------------|--------------------|
| Network reinforcement | Transformer | --                   | 200 kg CO₂eq / unit |
|                 | Cable                | --                   | 75 kg CO₂eq / m    |
| EV management  | PLC + Monitors       | Dell Optiplex 780 ultra-small | 73.5 kg CO₂eq / unit |
|                 | ICBs + Comms         | Dell FX-100 Zero Client | 33.6 kg CO₂eq / unit |
|                 | Repeaters            | HP Mini 110 CA Netbook, 10” | 62.2 kg CO₂eq / unit |
### TABLE 5  Customers with voltage problems: LV network 1 (%)

| EV penetration | 60 | 70 | 80 | 90 | 100 |
|----------------|----|----|----|----|-----|
| Without planning | Avg. | 0.000 | 0.005 | 0.081 | 0.286 | 0.889 |
|                 | Std.  | 0.000 | 0.054 | 0.472 | 0.902 | 1.488 |
| EV management   | Avg. | 0.000 | 0.000 | 0.027 | 0.015 | 0.011 |
|                 | Std.  | 0.000 | 0.000 | 0.269 | 0.167 | 0.108 |
| Reinforcement  | Avg. | 0.000 | 0.000 | 0.000 | 0.049 | 0.124 |
|                 | Std.  | 0.000 | 0.000 | 0.000 | 0.279 | 0.426 |
| EV management → reinforcement | Avg. | 0.000 | 0.000 | 0.000 | 0.049 | 0.124 |
|                 | Std.  | 0.000 | 0.000 | 0.000 | 0.279 | 0.426 |

### TABLE 6  Customers with voltage problems: LV network 2 (%)

| EV penetration | 10  | 20  | 30  | 40  | 50  | 60  | 70  | 80  | 90  | 100 |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Without planning | Avg. | 0.002 | 0.026 | 0.124 | 0.364 | 0.794 | 1.435 | 2.474 | 4.140 | 5.841 | 7.470 |
|                 | Std.  | 0.023 | 0.181 | 0.392 | 0.673 | 1.057 | 1.366 | 1.743 | 2.363 | 2.582 | 2.826 |
| EV management   | Avg. | 0.000 | 0.001 | 0.079 | 0.222 | 0.544 | 0.965 | 1.577 | 1.935 | 2.042 | 1.993 |
|                 | Std.  | 0.000 | 0.018 | 0.294 | 0.515 | 0.749 | 0.979 | 1.031 | 0.887 | 0.983 | 0.773 |
| Reinforcement  | Avg. | 0.000 | 0.009 | 0.019 | 0.086 | 0.058 | 0.194 | 0.194 | 0.287 | 0.334 | 0.393 |
|                 | Std.  | 0.000 | 0.093 | 0.131 | 0.280 | 0.218 | 0.438 | 0.426 | 0.493 | 0.545 | 0.552 |

4.2 Customer assessment

The customer assessment is done only for alternatives that include the EV management strategy as reinforcements do not affect the EV charging time (i.e. \( \text{CDI} = 0 \)). In this work, the CDI is classified in ten groups from 0 to 9. The first group, CDI equal to 0, corresponds to zero additional time (the EV was not managed). From 1 to 9, each group corresponds to CDI values within ranges increasing in steps of 25% (e.g. 5 means up to 125% more).

Figure 9 reveals, particularly for EV penetrations higher than 50%, that LV Network 1 (a network constrained by the transformer) experiences more impacts on customers compared to LV Network 2 (a network constrained by voltages). This occurs primarily due to the magnitude of the technical problem, as well as the type of problem. For LV Network 1, high EV penetrations lead to higher transformer utilization, which requires all EVs across the network to be considered for management to
lower the asset utilization. For LV Network 2, on the other hand, high EV penetrations only affect the voltages of long feeders (which already started experiencing issues for lower penetrations), and thus, just a fraction of the EV population for this network needs to be considered for management.

Ultimately, the CDI is a metric to be used for decision making purposes. To illustrate its potential, Figure 9 shows the effects of considering a maximum average CDI = 4 (twice the original charging time). The EV management alone is acceptable in LV Network 1 for EV penetrations up to 70%. For higher penetrations, the switch to reinforcements is necessary. Since this is done to cover the whole new demand with new transformers and cables, the resulting CDI is zero (no management). The technical effects of this switch are shown in Figure 7(a), 8(a) and Table 5. As for LV Network 2, the switch to network reinforcement is not required as the maximum average CDI did not exceed Level 4.

4.3 Economic and carbon assessments

The total cost and carbon emissions are quantified from the year when deployment occurs for each planning alternative (2034 and 2022 for LV Network 1 and LV Network 2, respectively). An exchanged rate of £1 = US$ 1.26 is used here.

Figure 10(a) highlights for LV Network 1 that the EV management is more expensive than reinforcement (≈180% more); mitigating thermal issues at the transformer requires installing voltage sensors and actuators at all EV charging points, communication links in all feeders, and voltage and current sensors at the head of all the feeders. The reinforcement alternative, on the other hand, leads to ≈27% more aggregated emissions (assets plus operation) due to the larger transformer (from 500 to 750 kVA) and bigger cables (60% of the main cable of two feeders were changed). This is because for the same amount of demand, a larger transformer increases onload and no-load energy losses while bigger cables decrease losses. However, since the reinforcements allow for more EV demand, the losses also increase and, hence, the resulting emissions.

Regardless of the alternative, it was found that CO$_{2eq}$ emissions resulting from the daily operation of this LV network represent about 90% of the total emissions. This highlights that planning alternatives that reduce energy losses are likely to bring significant environmental benefits in countries where the generation portfolio involves fossil fuels. Finally, Figure 10(a) highlights that the combined approach (i.e. starting with the EV management and then switching to network reinforcement when the triggering condition is met – maximum CDI of 4) leads to higher costs and emissions as investments and installations were made initially to deploy the EV management and then the network reinforcements.

For LV Network 2, Figure 10(b) highlights that reinforcements are more expensive (23%) but result in lower emissions (about 8%) compared to the EV management alternative. This is because a significant part (≈87%) of the two longest feeders need to be upgraded to mitigate voltage issues. Even though reinforcements allow for more EV demand, in this case, voltage mitigation requires much larger cables (with capacity exceeding by far total demand) which, in turn, results in lower losses. For both alternatives, emissions due to energy losses represent nearly 88%. As mentioned before, the combination of EV management and network reinforcement is not applicable as the maximum average CDI did not exceed Level 4.

These contrasting results highlight the importance of holistic planning approaches to allow DNOs making informed decisions based on aspects beyond technical merits. Crucially, these results show that the combined used of EV management and reinforcements, one after the other, can provide a trade-off as it is more expensive but can improve customer experience.

4.4 Combined alternatives and CO$_{2eq}$ emissions

To investigate the benefits from using combined alternatives to meet a CO$_{2eq}$ emissions target, a maximum of 400 tonCO$_{2eq}$ is considered as the trigger to switch from reinforcements to EV management in LV Network 1.

Figure 11 highlights, for LV Network 1, that reinforcements are acceptable for EV penetrations up to 80%. Above this, the DNO will have to adopt the EV management approach to meet the CO$_{2eq}$ emission target despite being more expensive.
Switching to EV management requires only 234 m of main cable instead of 660 m and a new transformer. The need for fewer assets, results in lower embodied emissions. Furthermore, as mentioned previously, the management also results in lower losses than reinforcements (despite lower impedances, reinforcement allows for larger demand/current, hence more losses). Consequently, overall, the EV management results in lower emissions.

4.5 Effect of different CAPEX and OPEX reductions

The CAPEX and OPEX in the EV management are based upon the prototype developed in 2015 for the MEA project [38]. Mass production, particularly of ICBs, and more efficient data management processes are likely to reduce deployment costs. Figure 12 shows that, indeed, lowering the costs of the ICBs by 50% leads to a reduction in the total cost of about US$ 38k in LV Network 1. Similarly, it shows that a reduction of 50% in the OPEX lowers the total cost in US$37k. Although a 50% reduction in all CAPEX and OPEX (a total saving of US$ 75k) still makes the EV management more expensive than network reinforcements [US$ 57k, Figure 10(a)], this sensitivity analysis allows understanding the break-even point of each planning alternative. For LV Network 1, it was found that an overall 65% reduction is needed to make the EV management as attractive as network reinforcements.

5 CONCLUSION

This paper has proposed a practical, scalable, stochastic, progressive multi-year planning methodology that considers technical, customer, economic and environmental aspects for DNOs to make holistic planning decisions for existing LV networks to accommodate electric vehicles (EVs). Four alternatives were considered: network reinforcements, EV charging point management and their combinations. Customer and environmental aspects were embedded in the planning approach to trigger the switch between alternatives to deal with unacceptable customer impacts or climate targets set by governments in the fight of climate change. Uncertainties due to demand and EV behaviour were catered for by adopting a Monte Carlo approach with 1000 simulations. The methodology was applied to two residential LV networks from the North West of England considering realistic (1-min resolution) time-series data for all aspects of the assessment.

The proposed progressive multi-year approach was able to capture the timing of technical impacts, facilitating the effective deployment of planning alternatives throughout the horizon. The timing of investments was also captured, thus enabling the corresponding estimations of net present value (NPV), emission, and charging delays. This, in turn, made it possible to adequately and holistically compare the investigated planning alternatives for the studied horizon. In practice, this comparison process can eventually be used by planning engineers to make informed decisions.

Results demonstrate the importance of quantifying customer effects as the charging point management can lead to unacceptable charging delays. This impact, however, depends on the LV network and the penetration; a network constrained by asset overloads (in particular, the transformer) is likely to affect more EV users for high penetrations.

As for carbon emissions, energy losses were found to play a significant role, representing above 90% of the total emissions. This highlights that alternatives that reduce energy losses can bring significant environmental benefits in countries where the generation portfolio involves fossil fuels.

From an economic perspective, results suggest that when EVs cause voltage issues, the EV management is better as reinforcements in long feeders are avoided. To address thermal issues, however, reinforcements are more appropriate.

Combinations, on the other hand, provide a trade-off as they can help meet customer expectations or environmental targets but with higher cost (due to additional investments).

Finally, given that the proposed approach builds on power flow analysis tools, which are widely available to DNOs today, it can be implemented without significant complexity and for any LV network size.

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