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Optimal Autonomous Electric Vehicle Charging Algorithm for Minimising Battery Degradation

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Abstract. The large-scale adoption of electric vehicles (EVs) requires controlled integration into the power system to avoid security and stability issues. While centralised charging strategies offer theoretically optimal solutions, they require extensive data and communication infrastructure, limiting user flexibility. Conversely, collaborative algorithms enhance decentralisation but face challenges related to data privacy, real-time communication, and implementation complexity.

To address the urgent need for effective charging strategies, this paper proposes an autonomous charging algorithm that minimises charging costs while considering battery degradation. Autonomous approaches serve as a transitional solution towards collaborative algorithms, enabling immediate deployment while maintaining control benefits. Two case studies are conducted: one accounting for battery degradation and another neglecting it. The results highlight the importance of incorporating degradation into charging strategies to enhance battery lifespan and ensure a more sustainable EV integration.

Key words. Electric vehicle, charging algorithm, optimal charging, autonomous charging algorithm and battery degradation.

1. Introduction

In the context of the energy transition, where renewable energy sources, distributed generation, and smart grids are playing an increasingly significant role in the power system, electric vehicles (EVs) emerge as key enablers of this transition. However, the growing adoption of this technology and its uncontrolled large-scale integration into the grid may lead to various security and stability issues [1].

In this regard, a controlled integration of EVs is required through charging management strategies that satisfy all stakeholders. However, to extend battery lifespan, these strategies must consider the degradation induced in the batteries by the charging process [2].

Although numerous charging standards and modes exist [3-5], current EV charging stations are mostly passive elements with predefined operations that do not consider other components of the grid. Presently, charging stations lack information on grid topology, the number of connected chargers, their consumption, distributed renewable generation, and energy storage systems, among other factors.

In the near future, a large-scale deployment of charging stations is expected. To prevent adverse effects on the grid, these stations must be managed as active system elements.

So far, the few controlled charging strategies that have been implemented, have been centralised ones. While this centralised approach theoretically achieves a more optimal global solution, it requires extensive data and a complex communication infrastructure. Additionally, it limits the decision-making ability of end users. Moreover, as the number of active elements increases, implementing such a centralised approach will become increasingly challenging [6-8].

Collaborative algorithms, on the other hand, can achieve individual objectives without compromising global goals. However, they rely on real-time communication systems, are more vulnerable to data privacy attacks, and often require pre-defined charging data. Furthermore, these communications are typically conducted via power line communication (PLC) technology, which can introduce disturbances into the grid. Although collaborative algorithms are expected to become the standard in the future, they are not yet mature enough for immediate deployment [9-12].

In the short and medium term, charging algorithms must be sufficiently developed to enable immediate implementation. Due to the urgent need for control strategies, autonomous algorithms must be developed as a transitional solution towards collaborative algorithms. These autonomous approaches should combine the benefits of controlled charging while allowing for rapid deployment. Additionally, they should be relatively easy to implement and integrate, providing an effective solution for the imminent large-scale adoption of EVs into the power system [13-16].

Therefore, this paper presents an autonomous charging strategy that minimises charging costs while considering battery degradation. Two case studies are conducted using the same algorithm: (a) considering degradation and (b) disregarding degradation. This comparison allows for an assessment of the impact of degradation in the battery lifespan.

2. Mathematical formulation

In this section, the mathematical formulation of the algorithms will be explained [17].

A. Charging powers

The charging power of the EV number (i) in the period (t) is given in (2-1). Where $V_{i,t}^{grid}$ denotes the grid voltage of the EV number (i) in the period (t), $I_{i,t}^{VE}$ denotes the charging current of the EV number (i) in the period (t), $\mathcal{T}$ denotes the total time of the charging process, in other words, the sum of all the periods to be evaluated. And N_{VE} denotes the total number of EVs to be charged.

$$P_{i,t}^{VE} = \sqrt{3} \cdot V_{i,t}^{grid} \cdot I_{i,t}^{VE}, \forall t \in \mathcal{T}, \forall i \in N_{VE} \quad (2\text{-}1)$$

EVs can be connected to either an individual or a collective charging point (CP). In the latter case, multiple EVs share the same CP. Similarly, each consumption point (CPt) may have one or more consumption loads, may (or may not) include distributed generation (DG), and may (or may not) have one or more charging points.

Consequently, the total consumption at a CP is defined as the sum of all connected consumption loads ($P_{j,t}^{cons}$) plus the total charging power of all EVs connected to that CPt, minus the local generation at that CP ($P_{j,t}^{PV}$). This is evaluated for each period, as shown in (2-2).

$$P_{j,t}^{CP} = P_{j,t}^{cons} - P_{j,t}^{PV} + \sum_{i=1}^{N_{VE,j}} P_{i,t}^{VE}, \forall t \in \mathcal{T}, \forall j \in N_{cons,k} \quad (2\text{-}2)$$

The power of a given feeder in a specific period ($P_{k,t}^{feed}$) is defined as the sum of the demands from all consumption points connected to that feeder during the same evaluation period, plus the losses generated by these demands in the feeder's lines ($P_{k,t}^{loss,feed}$). This expression is presented in (2-3), while the expression for the losses is shown in (2-4). Where $N_{cons,k}$ refers to the number of consumption points on feeder k, N_{feed} represents the total number of feeders.

$$P_{k,t}^{feed} = P_{k,t}^{loss,feed} + \sum_{j=1}^{N_{cons,k}} P_{j,t}^{CP}, \forall t \in \mathcal{T}, \forall k \in N_{feed} \quad (2\text{-}3)$$

$$P_{k,t}^{perd,feed} = f\left(\sum_{j=1}^{N_{cons,k}} P_{j,t}^{CP}\right), \forall t \in \mathcal{T}, \forall k \in N_{feed} \quad (2\text{-}4)$$

B. Battery degradation

The battery degradation cannot be calculated for each (t), but rather for each charging cycle, that is, for each $(\mathcal{T})$. This is due to the significant impact that the Depth of Discharge (DoD) has on degradation.

To better understand the expression for battery degradation, the variables that make up this expression will first be explained.

The voltage of the battery of EV (i) at a given moment $(V_{i,t}^{B})$ is a function of the state of charge (SOC) of the battery at that same instant, as shown in (2-5).

$$V_{i,t}^{B} = f\left(SoC_{i,t}^{B}\right), \forall t \in \mathcal{T}, \forall i \in N_{VE} \quad (2\text{-}5)$$

The battery current of EV i in period t ($I_{i,t}^{B}$) is calculated by performing a power balance. That is, the power drawn by EV i from the grid, adjusted by the efficiency of its charger ($\eta_{i,t}$), is equal to the power absorbed by the battery. This balance is shown in (2-6).

$$I_{i,t}^{B} = \frac{P_{i,t}^{VE} \cdot \eta_{i,t}}{V_{i,t}^{B}}, \forall t \in \mathcal{T}, \forall i \in N_{VE} \quad (2\text{-}6)$$

Since the instantaneous current cannot be used for the degradation calculation, the average charging current is determined ($I_{i,\mathcal{T}}^{B}$). This current is calculated between the arrival time (t_i^{arr}) and the hour before the departure time (t_i^{dep}), as it is assumed that the EV is not charging at the departure time.

It is important to highlight that, for this algorithm to be applied, it must be assumed that the Aggregator has access to user charging requirements (arrival and departure times, energy demands, etc.) or that its prediction is sufficiently accurate. See (2-7).

$$I_{i,\mathcal{T}}^{B} = \frac{\sum_{t_i^{arr}}^{t_i^{dep}-1} I_{i,t}^{B}}{t_i^{dep} - t_i^{arr}}, \forall i \in N_{VE} \quad (2\text{-}7)$$

To calculate the DoD, it is necessary to know in advance the SoC at which EV *i* arrives at the charging point (SoC_i^{arr}) and the target state of charge at the end of the charging process (SoC_i^{dep}). Consequently, the expression for DoD is given as shown in (2-8).

$$DoD_{i,\mathcal{T}}^{B} = SoC_i^{dep} - SoC_i^{arr}, \forall i \in N_{VE} \quad (2\text{-}8)$$

Based on this, the degradation ($\gamma_{i,\mathcal{T}}^{B}$) is defined as a function of the average charging current, the average charging temperature ($T_{i,\mathcal{T}}^{B}$), and the DoD to be charged, as shown in (2-9).

$$\gamma_{i,\mathcal{T}}^{B} = f\left(I_{i,\mathcal{T}}^{B}, T_{i,\mathcal{T}}^{B}, DoD_{i,\mathcal{T}}^{B}\right), \forall i \in N_{VE}, \forall \mathcal{T} \in N_{\mathcal{T}} \quad (2\text{-}9)$$

C. Economic analysis

The total charging cost must consider two aspects: the price of electricity and the lost value of the battery due to degradation induced during the charging process.

The total electricity cost of charging is calculated as the sum of all hourly electricity costs between the arrival and departure times, i.e., during the charging period. This hourly cost is determined by the product of the energy consumed in each period (calculated as the power multiplied by the duration of the period) and the price set by the Aggregator for that EV at that moment. This is shown in (2-10). Where

$\psi_{i,t}^{EV}$ refers to the price at which EV i purchases electricity in period t or, in the case of an Aggregator, the price at which the Aggregator sells electricity to the EV.

$$\sum_{t_i^{llegada}}^{t_i^{salida}-1} \psi_{i,t}^{EV} \cdot P_{i,t}^{EV} \cdot \Delta t, \forall i \in N_{VE} \tag{2-10}$$

Regarding the degradation cost, it is important to highlight the use of the battery's effective price. The EV battery is purchased at a price of $\psi_i^{B,pur}$ and is considered to have reached its End of Life (EoL) for traction purposes once it reaches 80% of its nominal capacity. However, the battery can still be used for other applications and could be sold at a price of $\psi_i^{B,sell}$. Consequently, the effective battery price ($\psi_i^{B,efec}$) is calculated as in (*2-11*).

$$\psi_i^{B,efec} = \psi_i^{B,pur} - \psi_i^{B,sell} \tag{2-11}$$

Consequently, the battery value lost during charging is given by the product of the degradation induced by that charging cycle and the effective battery price, as shown in (2-12).

$$\gamma_{i,\mathcal{T}}^{B} \cdot \psi_i^{B,efec}, \forall i \in N_{VE}, \forall \mathcal{T} \in N_{\mathcal{T}} \tag{2-12}$$

3. Algorithms

Two optimisation algorithms are analysed. On the one hand, the effect battery degradation is not considered in the target function. On the other hand, the optimisation algorithm takes battery aging into account.

A. Without considering the degradation of the batteries

From now on, this algorithm will be referred as Algorithm A. This algorithm minimises the charging cost of each EV.

$$\min_{I_{i,t}^{VE}} \left\{ \sum_{t_i^{llegada}}^{t_i^{salida}-1} \psi_{i,t}^{VE} \cdot P_{i,t}^{VE} \cdot \Delta t \right\}, \forall i \in N_{VE}, \forall t \in \mathcal{T} \tag{3-1}$$

$$s.a. \quad \left| \sum_{t_i^{llegada}}^{t_i^{salida}-1} \left[P_{i,t}^{VE} \cdot \eta_{i,t} \cdot \Delta t \right] = E_i^{charge} \right.$$

This optimisation is subject to the condition that the energy delivered to the battery equals the energy required to charge EV i (E_i^{charg}).

B. Considering the degradation of the batteries

From now on, this algorithm will be referred as Algorithm B. This algorithm minimises the charging cost of each EV while taking into account the battery degradation. In other words, it minimises the total charging cost.

$$\min_{I_{i,t}^{VE}} \left\{ \sum_{t_i^{llegada}}^{t_i^{salida}-1} \psi_{i,t}^{VE} \cdot P_{i,t}^{VE} \cdot \Delta t + \gamma_{i,\mathcal{T}}^{B} \cdot \psi_i^{B,efec} \right\}, \forall i \in N_{VE}, \forall \mathcal{T} \in N_{\mathcal{T}} \tag{3-2}$$

$$s.a. \quad \left| \sum_{t_i^{llegada}}^{t_i^{salida}-1} \left[P_{i,t}^{VE} \cdot \eta_{i,t} \cdot \Delta t \right] = E_i^{carga} \right.$$

The expression (3-2) consists of two terms: a) the total electricity cost of charging, as shown in (2-10) and b) the battery cost lost during charging, as shown in (2-12).

4. Electrical grid and EV fleet

The validation of the algorithms is performed through simulation using the software tools MATLAB R2023a and DIgSILENT PowerFactory 2023 SP3. The algorithms are implemented in the first one, while the load flow calculations are executed in the second one. This approach allows the analysis of the impact of battery degradation on the final charging cost of the EV. For the battery degradation, model from reference [17] has been taken.

A. Electrical grid

The low-voltage (LV) network used for the load flow simulations consists of a 20/0.4 kV Dyn11 transformer with a rated power of 0.63 MVA, from which four feeders originate. The characteristics of these feeders are detailed in Table 4-1 and Fig. 4-1 shows the feeders, the industrial loads (in green), the residential loads and the CPs (in red).

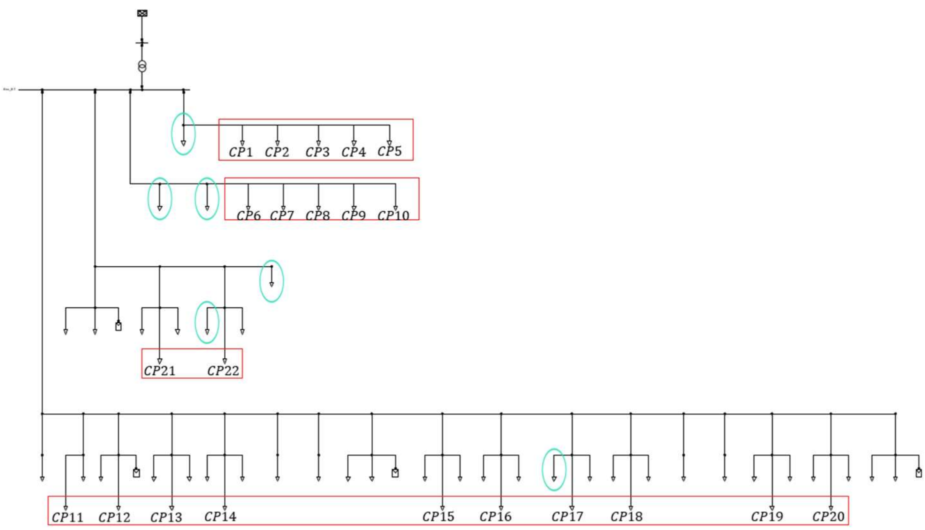

Fig. 4-1. Feeders and load and CP distribution.

Table 4-1. Feeder characteristics.

Loads	Industrial / commercial [number-power]	Residential [number - power]	PV generation [number - power]
Feeder 1	1 – 61.55 kW	-	-
Feeder 2	2 – 141.57 kW	-	-
Feeder 3	2 – 135.41 kW	5 – 16.25 kW	1 – 3.1 kW
Feeder 4	1 – 77 kW	26 – 83.6 kW	3 – 11.3 kW

According to the base load (the load profile without taking the EV charging into account), Fig. 4-2 shows the transformer's base load and Fig. 4-3 the ones of the feeders, both for 48 h.

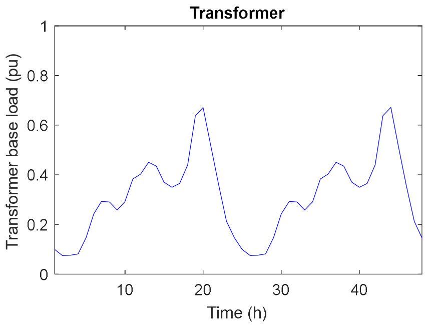

Fig. 4-2. Transformer's base load.

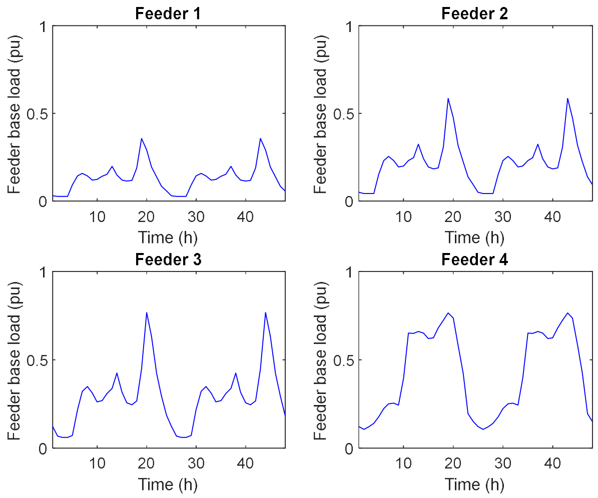

Fig. 4-3. Feeders' base load.

B. EV fleet

Table 4-2 shows the different EV models and their characteristics used for the simulations [18]. In total, 200 EV were simulated.

Table 4-2. EV models and their characteristics.

EV model	Quantity	Battery capacity [kWh]	Charger max. power [kW]	Charger efficiency
Chevrolet Bolt EV	34	60	7,2	0,84
Nissan Leaf 3	13	24	3,3	0,885
Nissan Leaf 6	13	40	6,6	0,895
Peugeot e-208 11	54	60	11	0,9
Peugeot e-208 7	34	60	7,2	0,89
Tesla S 11	5	85	11	0,87
Volkswagen e-Golf	47	36	7,2	0,945

The vehicles are randomly distributed among 22 CPs, and for each EV, the arrival time, departure time, and required charging energy are known. These values were generated using a Truncated Normal Distribution, represented in (4-1), with parameters detailed in Table 4-3.

$$f(x;\mu,\sigma,a,b)=\frac{1}{\sigma}\cdot\frac{\varphi\left(\frac{x-\mu}{\sigma}\right)}{\Phi\left(\frac{b-\mu}{\sigma}\right)-\Phi\left(\frac{a-\mu}{\sigma}\right)} \tag{4-1}$$

Where:

- μ: mean value.
- σ: standard deviation.
- a: minimum value of x.
- b: maximum value of x.
- φ: probability density function.
- Φ: distribution function of the normal distribution.
- $-\infty < a < b < +\infty$.
- $a \leq x \leq b$.

Table 4-3. EV charging data.

	μ	σ	a	b
Arrival time	17 h	2 h	15 h	21 h
Departure time	9 h	1,25 h	6 h	13 h
SoC at the arrival	60%	15%	10%	80%
Desired SoC	87,5%	5%	80%	95%

5. Study cases

The study cases must validate the developed charging strategies and allow a comparison between them. In this regard, the following scenarios are designed for the feeders:

- **Feeder 1:** This feeder has a low base load and a small number of EVs. The objective is to analyse the economic impact of considering battery degradation when optimising the charging process.
- **Feeder 2:** This feeder has a low base load but a high number of EVs. The goal is to assess the importance of accounting for battery degradation in charging optimisation algorithms.
- **Feeder 3:** This feeder also has a low base load but features a peak load.
- **Feeder 4:** Similar to Feeder 3 but with a wider peak in the base load and fewer EVs.

Regarding the charging algorithms, the two algorithms described in Section 3 have been considered. In this sense, two cases can be distinguished:

- **Case A:** simulation performed using the Algorithm A.
- **Case B:** simulation performed using the Algorithm B.

For both cases, the used electricity price is shown in Fig. 5-1.

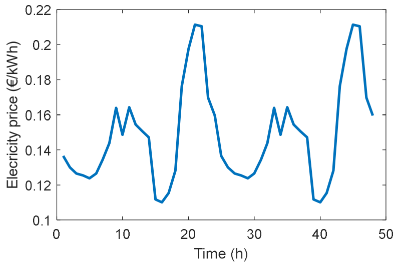

Fig. 5-1. Electricity price.

6. Results and discussion

On the one hand, Fig. 6-1 and Fig. 6-2 show the base load (dashed black) of the transformer and the feeders, as well as the simulation results of Case A (green) and Case B (blue). On the other hand, Fig. 6-3 shows the total charging cost and Fig. 6-4 shows the charging cost per feeder.

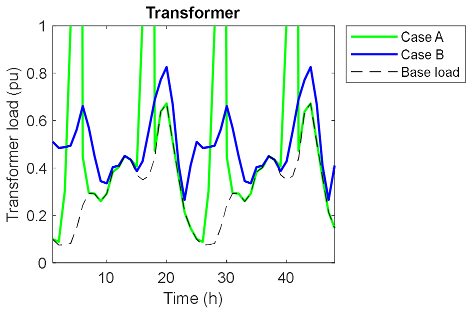

Fig. 6-1. Transformer´s load.

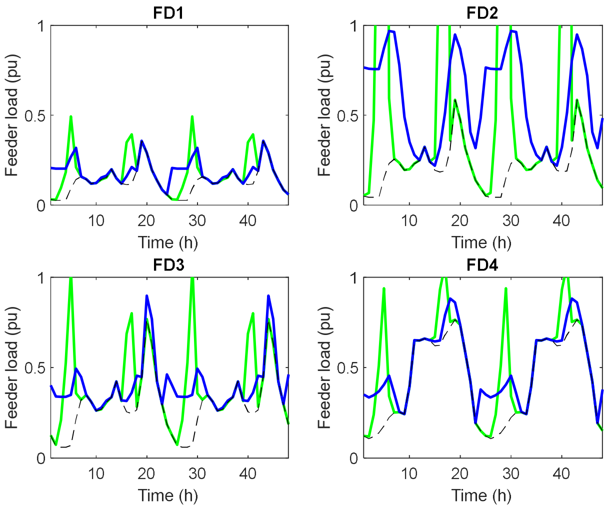

Fig. 6-2. Feeders' load.

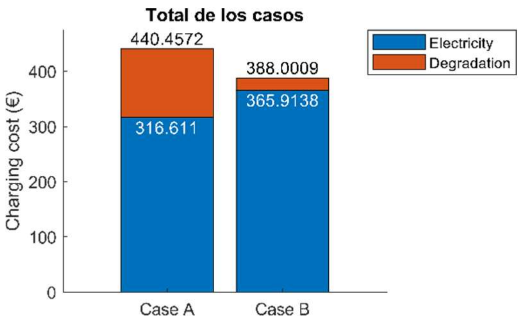

Fig. 6-3. Total charging cost.

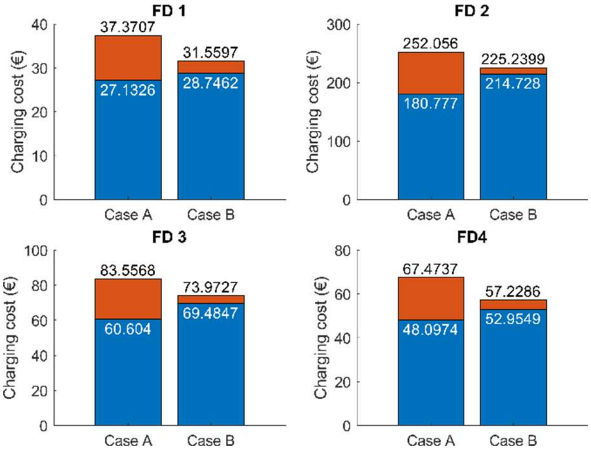

Fig. 6-4. Charging cost per feeder.

From Fig. 6-1 and Fig. 6-2, it can be observed that in Case A, the optimisation algorithm does not consider battery degradation. As a result, EV charging is concentrated during periods when electricity prices are lowest. This occurs because the algorithm aims to minimise charging costs. However, this leads to high current peaks during those hours, as all EVs charge simultaneously, causing both transformer and feeder saturation.

In contrast, in Case B, degradation is taken into account, preventing excessive current peaks. This happens because high current peaks accelerate battery degradation (considered as capacity loss and internal resistance increment). This peaks, increase the overall charging cost. Therefore, the algorithm penalises such peaks, distributing the charging more evenly.

Similarly, from Fig. 6-3 and Fig. 6-4, it can be seen that although electricity prices are lower in Case A, the total charging cost is lower in Case B, making it the more cost-effective option overall.

Table 6-1 and Table 6-2 show the electricity component of the charging cost and the degradation component of the charging cost, respectively.

Table 6-1. Electricity cost per feeder and case in €/kWh.

	Case A	Case B
FD 1	0,11907	0,126724
FD 2	0,119917	0,144398
FD 3	0,120025	0,139257
FD 4	0,11957	0,133336

Table 6-2. Degradation cost per feeder and case in €/EV.

	Case A	Case B
FD 1	0,568784	0,156306
FD 2	0,642153	0,0947019
FD 3	0,573819	0,112201
FD 4	0,625039	0,13786

7. Conclusions

A charging algorithm for EVs has been presented and tested in two scenarios. In one scenario, the optimisation algorithm did not consider battery degradation, while in the other, it did. To demonstrate its effectiveness, various scenarios were designed for each feeder, and seven different EV models were used.

Analysing the results, it can be concluded that considering battery degradation in the optimisation algorithm is crucial. Although electricity prices are lower when degradation is not accounted for, the overall charging cost is lower when it is included. Moreover, when degradation is ignored, EV charging is concentrated during the cheapest electricity periods, which can lead to feeder and transformer saturation.

8. Acknowledgement

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