Nonlinear Online Optimization for Vehicle-Home-Grid Integration including Household Load Prediction and Battery Degradation

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I. INTRODUCTION

The rapid growth of electric vehicles (EVs) is reshaping transportation and energy systems, significantly increasing global electricity demand. With bidirectional technologies, concepts such as vehicle-to-grid (V2G) and vehicle-to-home (V2H) are emerging, enabling EVs to act as energy nodes that support grid services and enhance home energy management [2]. Despite its potential, V2G and V2H face concerns over battery degradation and vehicle availability. Research has addressed energy management for V2G and V2H mainly through offline optimization [3], [4], assuming full knowledge of future data and often neglecting or simplifying battery aging models. Recent online optimization efforts [5], [6] improve adaptability but still rely on simplified degradation representations and do not comprehensively integrate V2G, V2H, battery dynamics, and household uncertainties.

To address the identified gaps, this work proposes a nonlinear online optimization algorithm, aiming to minimize user costs through dynamic energy trading. Considering a single user owning both an EV and a house, the algorithm operates online by processing data as it arrives. A hybrid long short-term memory (LSTM) neural network predicts household load to improve real-time energy allocation, while a detailed battery model captures both calendar and cycle aging. This approach enables sustainable and cost-effective energy management for EV owners in real-world scenarios.

II. METHODOLOGY

The vehicle-home-grid integration considered, shown in Fig. 1, involves three actors: an EV, a house, and the power grid. The EV can supply energy to both the grid (V2G) and the house (V2H), while grid-to-vehicle (G2V) covers EV charging. The house can also receive energy directly from the grid through grid-to-home (G2H).

A. Vehicle-Home-Grid Control

While the EV is parked, an optimization problem is formulated to minimize the user cost for energy trading and battery degradation:

$$\min \sum_t EC_t + BC_t + s_t, \tag{1}$$

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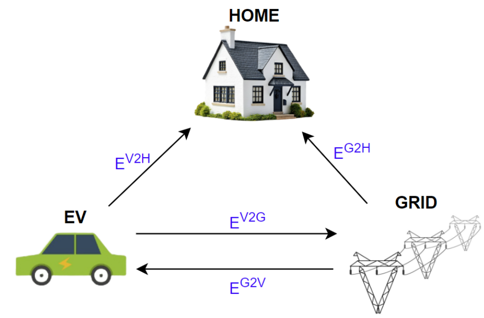

Fig. 1. Vehicle-home-grid interaction of the proposed algorithm. The arrows indicate the allowable energy flows for V2H, V2G, G2V and G2H.

where t represents time, s_t is a slack variable for a soft constraint related to the EV's SoC at the pickup time, and EC_t and BC_t denote the energy and battery costs, respectively.

EC_t and BC_t can be calculated by

$$EC_t = (E_t^{G2V} + E_t^{G2H}) \cdot p_t - E_t^{V2G} \cdot \gamma \cdot p_t, \tag{2}$$

$$BC_t = NV \cdot \frac{BD_t(\%)}{100\% - EoL(\%)}, \tag{3}$$

where the energy flows are expressed in kWh, and p_t is the day-ahead energy price, expressed in €/kWh. Energy costs arise from purchasing energy from the grid for G2V and G2H, minus the profits from selling energy to the grid (V2G). γ is the price ratio, representing the ratio between the selling price and the buying price of energy. If $\gamma = 1$, it means the buying and selling prices are equal. In (3), BD_t is the battery degradation in percentage of the initial battery capacity, EoL is the battery capacity at the end of life, and NV is the net value of the battery.

The optimization problem in (1) is subject to constraints that ensure the non-negativity of energy flows, respect the limits imposed by the EV charger, and maintain the battery state of charge (SoC) within operational bounds. A soft constraint guarantees the desired SoC level at pickup times.

B. Battery Model

An empirical model for lithium-iron-phosphate batteries is employed to describe the degradation characteristics, including both calendar and cycle aging [7]. The calendar aging is a function of temperature, SoC and time in hours. The cycle aging is a function of temperature, energy throughput, current and SoC. The total battery degradation BD_t, defined as the capacity loss in percentage, is computed as sum of calendar and cycle aging at each time step by

$$BD_t = BD_t^{cal} + BD_t^{cyc}. \tag{4}$$

All the details of the model, including the parameters, their derivation, and detailed formulas, can be found in [7].

C. Household Load Prediction and Management

In real-world scenarios, future household load is highly uncertain due to weather conditions and user behavior. To address this, a real-time household load predictor based on a hybrid long short-term memory (LSTM) neural network is developed. The hybrid LSTM approach is adopted from [8] to incorporate additional features that influence energy consumption, providing the model with more contextual information and improved prediction accuracy.

The hybrid LSTM predicts the household load one hour ahead. Four features are extracted from a chosen dataset: *f1)* the previous 24 hours of energy consumption, forming the input sequence for the LSTM; *f2)* day of the year; *f3)* day of the week; *f4)* hour of the day. The features $f2$, $f3$, $f4$ are fed into a dense neural network.

The architecture used has been extensively studied in [8]. Since our output is limited to a single hour of prediction, to predict multiple hours, we use the neural network recursively, where the output of each prediction becomes the input for the next.

III. RESULTS AND DISCUSSION

Simulations were conducted for two distinct scenarios to evaluate user costs in the vehicle-home-grid integration:

- ***A.*** Vehicle-home-grid integration, as formulated in (1).
- ***B.*** Unidirectional smart charging (benchmark): This scenario seeks to minimize costs, including battery degradation, without employing V2G and V2H technologies.

With the price ratio $\gamma = 1$, meaning the price for purchasing and selling energy is identical, Table I summarizes the user costs for the two scenarios. Here, the user's final cost (FC) is calculated as the sum of the energy cost (EC) and battery cost (BC).

TABLE I

USER COSTS AND BATTERY DEGRADATION FOR SCENARIOS $\boldsymbol{A}$ AND $\boldsymbol{B}$.

	FC [€]	EC [€]	BC [€]	BD [%]	BD^{cal} [%]	BD^{cyc} [%]
A	-1070.21	-1739.38	669.17	5.42	2.26	3.16
B	1976.60	1549.12	427.48	3.46	2.72	0.75

By comparing scenarios $\boldsymbol{A}$ and $\boldsymbol{B}$, it can be observed that the vehicle-home-grid integration provides a substantial economic advantage of €3046.81 annually for the user in the final cost. Specifically, scenario $\boldsymbol{A}$ degrades the battery by 1.96% more but reduces the energy costs by €3288.50 compared to scenario *B*.

The results above assume a price ratio $\gamma = 1$, but different values of γ may significantly affect the final cost FC due to changes in the energy cost EC. Fig. 2 shows the final cost FC for scenarios $\boldsymbol{A}$ and $\boldsymbol{B}$ across a range of γ values from 0 to 1.

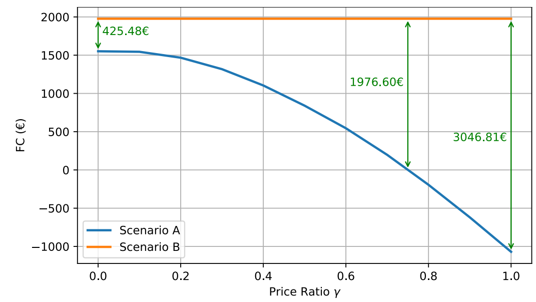

Fig. 2. FC for scenario $\boldsymbol{A}$ and $\boldsymbol{B}$ varying the price ratio γ.

In scenario $\boldsymbol{B}$, the cost curve remains constant due to unidirectional charging. In scenario $\boldsymbol{A}$, as γ decreases, FC increases since the reduced price difference between buying and selling makes V2G less profitable. At $\gamma = 0.75$, $FC = 0$, eliminating electricity-related costs. When $\gamma = 0$, V2G is no longer performed as it offers no benefit; however, V2H continues, contributing to self-consumption, still yielding savings over scenario $\boldsymbol{B}$.

Overall, these results demonstrate that vehicle-home-grid integration consistently offers benefits: even in the worst-case scenario, the user saves around €425 annually.

IV. CONCLUSION

This work demonstrates that vehicle-home-grid integration with nonlinear online optimization and hybrid LSTM load prediction offers substantial economic benefits compared to traditional smart charging. Simulations show up to €3046.81 annual savings, despite slightly higher battery degradation. Even under unfavorable conditions, V2H alone ensures consistent cost reductions. Additional sensitivity analyses confirm that the proposed method remains advantageous across different energy price scenarios, battery sizes, and household loads, highlighting its real-world applicability.

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