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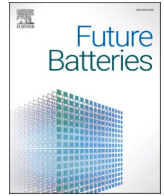
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Health-aware V2G scheduling: A multi-modal transformer optimization framework

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ABSTRACT

Vehicle-to-Grid (V2G) systems offer radical capabilities to grid stability and integrate renewable energy, but are not being utilized due to shortsighted scheduling and non-consideration of long-term battery health, and poor modeling of uncertainties in user behavior, grid behavior, and degradation. To eliminate such barriers, this paper will suggest a Multi-Mode Transformer-Based Optimization Framework. Our framework incorporates three predictors, each proposed under the Transformer framework, of user behavior, grid prices, and battery State-of-Health (SOH) to predict these variables unlike conventional models like LSTM, GRU, and ARIMA, which are proven to be robust through the use of empirical data. These forecasts are used to run a multi-objective optimization engine, which is incorporated in a receding horizon Model Predictive Control (MPC) scheme. The key of the innovations is the iterative degradation sensitive refinement mechanism. This supports a closed-loop feedback design which would be able to smoothly incorporate state-of-health degradation predictions into the optimization process. On-the-road experiments demonstrate high-performance attaining 1.8 times reduced battery depreciation and 8 %age cumulative revenues of a 100 EV fleet in 12 months. The framework provides sustainable high-fidelity solution which matches grid service contribution with battery capacity in the face of uncertainty.

Symbol	Description	Unit
Indices and Sets		
t, k	Time step indices	–
H	Prediction horizon	–
T	Set of time steps in the horizon $[t, t + H]$	–
Optimization Variables		
P_{tH}^{V2G*}	V2G power dispatch at time k (+ Discharging, – Charging)	kW
SoC_k	Battery State-of-Charge at time k	%
T_k	Battery cell temperature at time k	K or °C
I_k	Battery current at time k	A
Cost Function Parameters		
J	Total objective function value	\$
J_{econ}	Economic utility (Revenue)	\$
J_{deg}	Battery degradation cost	\$

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Symbol	Description	Unit
ω_1, ω_2	Weighting coefficients for revenue and degradation	–
λ_{ke}	Forecasted Locational Marginal Price (LMP)	\$/kWh
λ_{kr}	Forecasted Regulation Market Price	\$/kW
C_{rep}	Battery pack replacement cost	\$/kWh
$\Delta Q_{loss,k}$	Incremental capacity loss at time k	%
Battery & Physical Parameters		
Q_{nom}	Nominal battery capacity	kWh
V_{nom}	Nominal battery voltage	V
η_c, η_d	Charging and Discharging efficiency	–
P_{min}, P_{max}	Minimum and Maximum power limits	kW
SoC_{min}, SoC_{max}	Minimum and Maximum State-of-Charge limits	%

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Symbol	Description	Unit
R_{int}	Internal battery resistance	Ω
mC_p	Battery thermal mass (mass $\times$ specific heat)	J/K
hA	Heat transfer coefficient $\times$ Area	W/K
T_{amb}	Ambient temperature	K
Degradation Model		
B	Pre-exponential factor	–
E_a	Activation energy	J/mol
R	Universal gas constant	J/ (mol·K)
I_{krms}	Root-mean-square current	A
z, p	Stress exponents for current and DoD	–
Transformer & Forecasting		
$E_{trip,pred}$	Predicted trip energy consumption	kWh
t_{dept}	Predicted departure time	h
d_{modeld}	Transformer embedding dimension	–
Q, K, V	Query, Key, and Value matrices	–

Introductions

The increased and increasing energy needs across the globe and the environmental issues have brought forth the pressing necessity of having efficient and sustainable energy systems. Electric vehicles as a component of the smart grid architecture in Vehicle-to-Grid (V2G) technology play a key role in this type of smart grid: they are a disruptive factor in the existing transportation applications [1]. Outside of their use as energy consumers, V2G systems allow electric cars to release power to the electric grid and thus generate a two-way flow of energy. As a result, electric vehicles may be used as distributed energy sources and provide service to the reduction of peak loads, frequency regulation, and integrating renewable energy sources. Through such potential, energy infrastructures will be able to become more resilient and sustainable, with a stronger grid stability, efficiency, and penetration of intermittent renewable sources [2].

Although this is a promise, there are a number of challenges that are limiting the widespread adoption of V2G. One of the main shortcomings of existing V2G scheduling schemes is the fact that they are too focused on short-term monetary benefits. This usually results in failure to maintain good health of the battery in the long-term and rapid depreciation. This shortsightedness can lead to a premature degradation of batteries, which negatively affects the viability of this approach and the positive effect on the environment of V2G [3]. To make matters worse is high level of uncertainty that is marked by V2G operations. The driving patterns of users are random, power market rates are not constant, and the process of battery degradation is based on non-linear and complex influence on the temperature, Depth of Discharge (DoD), and C-rate. Existing models find it difficult to model and manage these multi-modal uncertainties on a regular basis [4].

The literature has examined various optimization techniques, such as sophisticated Model Predictive Control (MPC) technique to rule-of-thumb techniques. Most of them though informative fail to combine grid requirements, user convenience and battery health into an integrated framework. Of the latter some focus more on economic dispatch and simplify the description of degradation, and others prioritize battery maintenance instead of responsiveness to grid signals or market opportunities [5,6]. This incoherent attention underscores the challenge of coming up with a holistic system that can forecast multi-modal dynamics of behavior and intelligently trade off V2G behavior in dynamic uncertain conditions [7].

The latest development of deep learning, especially Transformer networks, is a potential avenue to take. Transformers are also superior at capturing untangled temporal associations and utilizing multi-modal data across the fields of time-series prediction, computer vision and natural language processing [8]. Their self-attention processes obtain long-range dependencies and attribute the right importance to various elements of sequential data, thus being very appropriate to V2G

operations [9]. However, their use in a holistic V2G optimization particularly in multi-modal forecasting and health-sensitive scheduling through iterative refinement is not very common. The current usages of deep learning can be rather limited to specific elements, including load or price predictions, with no consideration of these forecasts as part of a multi-objective optimization problem that explicitly considers battery health [10].

The key contributions of this work are threefold:

1. **Multi-Mode Transformer-Based Forecasting System** We develop three purpose-specific Transformer-based encoders, each possessing its unique and mutually dependent V2G operational parameters:
 - **User Behavior Forecast:** This model it predicts the user centric parameters which include trip energy demand and departure / arrival times. The convenience that users will have by quantifying weekly and seasonal mobility patterns entrenches this aspect within V2G scheduling making it a vital part of adoption.
 - **Grid Price Forecast:** The encapsulated encoder produces the accurate forecast of dynamical electricity market indicators, including locational marginal prices (LMP) and frequency regulation prices. It is a predictive time series model of price trends by taking advantage of the property of the Transformer to capture nonlinear, long-term dependencies, and thus allows the predictor to exploit the market opportunities.
 - **Battery State-of-Health (SOH) Forecast:** This is a new model that uses Transformer-based Surrogate in order to forecast incremental capacity degradation. It predicts degradation dynamics directly based on operational information unlike empirical formulations (Eq. 4), which utilize constant parameters, and can therefore provide realistic and more flexible SOH prediction under different V2G stresses.
2. **Health Aware Multi-Objective Optimization Problem.** We develop V2G scheduling as a MPC receding-horizon problem. It has a multi-objective cost functional (Eq. 1) that directly expresses a trade off between the economic utility of energy arbitrage and regulation services and monetized battery-degradation costs. The optimization is subject to an extensive usage of constraints:
 - **Battery State -of- Charge Dynamics (Eqs. 7–9):** Rule out unsafe and inadvisable operation.
 - **Power and Energy Limit (Eqs. 10–11):** Reduce over stressing the components of the vehicle and the grid.
 - **User Mobility Limit (Eq. 12):** Assure the adequate power of the next determined trip, which is a vital user issue.
 - **Thermal Dynamic Constraint (Eqs. 13–15)** Control the temperature of batteries which is a significant cause of degradation. These constraints have been integrated to produce operationally and economically viable schedules.
3. The feedback between the optimizer and the State-of-Health (SOH) forecasting model is also one of the main features of our architecture (Eq. 34). The starting schedules are considered against degradation effect and projected losses in capacity the output of which are recirculated to the optimizer. This process continues until convergence to create schedules that make good co-optimization of power dispatch and battery health. The large-scale simulations through real-world data prove that this structure has strong results in comparison to the traditional baselines in predictive accuracy, revenue generation, and battery preservation. As a result, the given strategy provides a powerful, comprehensive solution to the sustainable inclusion of the Electric Vehicles into the smart grid. In the following sections, the mathematical formulation, experimental methodology and overall findings of the study are outlined.

Literature review

The growing imperative of sustainable energy has made electric vehicles (EVs) vital participants of future smart grid, in particular, Vehicle-to-Grid (V2G) technology. V2G systems enhance grid stability, allow assimilation of renewable energy sources, and provide the necessary ancillary services, including demand response, due to the ability to provide bi-directional power transmission. This chapter presents a more or less general overview of the available literature related to V2G optimization, the predictive methods and approaches, battery degradation modeling, as well as the integration of deep-learning algorithms.

V2G optimization and control strategies

Early V2G optimization strategies were based on deterministic model based on prediction or past data to schedule [11]. These approaches usually applied linear, mixed-integer linear (MILP) or dynamic programming to optimize the cost of EV owners or grid revenue [12]. Indicatively, the economic potential of V2G frequency regulation [13], a concept originally defined by Kempton and Tomic, was established. Also, studies propose the use of remote, local or hierarchical control schemes and the latter can usually be used with large fleets [14]. Deterministic approaches, however, are not very effective in dealing with the high degree of uncertainty in real-world conditions of V2G [15], which requires stochastic and resilient optimization methods [16]. Stochastic programming requires the use of probabilistic parameters, the prices or demand of electricity, in order to develop schedules that are effective in multiple situations [17]. On the other hand, robust optimization is concerned with worst-case uncertainties to make sure the work is feasible and it performs [18]. Model Predictive Control (MPC) has become especially useful to V2G, providing the option of real-time adjustments through receding horizon optimization [19]. The complexity of constraints is a feature that is suitable to MPC in terms of handling State-of-Charge (SoC) of the battery together with power limits and grid signals in parallel [20].

Battery degradation modeling in V2G

The V2G coordination scope to focus on security and the specific grid services [21], proposed a blockchain-based model to establish reliable scheduling and clear energy commerce between EVs and the grid. On the same note, new capacity-reservation schemes have been suggested to harness V2G operations to be applied specifically in the distribution system load deviation alleviation measures [22]. At the forecasting end, there is turnover where pure accuracy is no longer the concern, and value-oriented data-driven solutions are currently under investigation to directly correlate prediction loss functions with V2G scheduling goals [23]. Optimization V2G Advanced V2G optimization approaches model battery degradation semi-empirically or using physics based degradation models [24,25]. They are generally associated with capacity fade or resistance rise with operating factors Depth of Discharge (DoD), C-rate, temperature and number of cycles [26,27]. Surveys conducted by Han et al. and Uddin et al. counted the costs of degradation using these stress factors, thus providing the opportunity to use optimization strategies to expressly trade off generation of revenue and battery health. Nevertheless, those models are usually based on some pre-determined parameters, and they might not provide the complete picture of complex and non-linear degradation patterns under the conditions of dynamic V2G [28,29]. As a result, it is still vital to create models that can be predictive and also allow the computational efficiency to be achieved at real times [30].

Uncertainty management and forecasting in V2G

V2G scheduling depends on properly forecasting the uncertain

parameters [31]. These uncertainties are mostly categorized under three:

- **Uncertainty of User Behavior:** The future driving requirements, the desired State-of-Charge (SoC) and times required to connect to the vehicle must be predicted to guarantee the convenience of the user and the availability of the vehicle [32]. The classical methods involve using statistical models like Markov chains or to follow rules [33].
- **Grid and Market Uncertainty:** The changes in the prices of electricity (LMP), the cost of regulation, and the renewable energy production also affect the economic feasibility of V2G greatly [34]. Time-series forecasting methods that are commonly employed are ARIMA, Exponential Smoothing, and Gaussian Processes [35].
- **Battery Degradation Uncertainty:** It is unclear how to predict battery health in future [36] and in uncertain V2G operations, which may typically need probabilistic extensions of empirical models [37].

The latest developments with Artificial Intelligence (AI) and Machine Learning (ML) can provide better forecasting. Recurrent Neural Networks (RNNs), Long Short-term Memory (LSTM), and Gated Recurrent Units (GRUs) deep learning models exhibit better results in the analysis of the temporal dynamics involved in V2G [38,39]. Using huge amounts of data, these models forecast electricity prices, load demand, and behavior of users at elevated accuracy when compared with traditional statistical techniques [40].

Deep learning and transformer networks in smart grids

A time-series forecasting model based on self-attention Transformer networks, which were originally developed on natural language processing, have fundamentally changed time-series forecasting [41]. Unlike the sequential processing that is inherent to RNNs and LSTMs, the given mechanism allows Transformers to give input sequences variable weights, thus, effectively representing long-range dependencies and complex patterns [42]. Their ability to work with multi-modal data simultaneously makes them significantly adaptable to the integrated smart-grid-forecasting [43]. Transformers have therefore been utilized in the prediction of electricity loads, renewable and fault detection [44]. However, their application in a vehicle-to-grid (V2G)-wide optimisation, in which multi-modal forecasts (user, grid, state of health) are integrated directly into a multi-objective model-predictive control (MPC) to schedule health-aware is also a nascent field of application [45,46]. The literature lacks serious consideration of the iterative feedback inherent in sustained V2G management [48] and focuses instead on single forecasting problems or simplified optimisation problems [47]. This paper aims to fill this gap by utilizing the high-level Transformers to develop a holistic, health-conscious V2G optimisation system [49,50].

Methodology

Core V2G scheduling optimization problem

The V2G scheduling challenge is framed as a receding horizon model predictive control (MPC) problem. In this paradigm, at each discrete time step t , an optimal power trajectory $P_{t,H}^{V2G*}$ is calculated for a future horizon H . However, only the immediate command, P_t^{V2G*} , is executed, enabling continuous adaptation to evolving conditions.

Multi-objective cost function

The main goal of the optimisation is to find a control sequence that optimises an aggregate utility, J . This role balances set-off of economic benefits and financial expenses of battery degradation.

$$J = \max_{P_k^{V2G}} (\omega_1 J_{\text{econ}} + \omega_2 J_{\text{deg}}) \quad (1)$$

In this case, ω_1 and ω_2 are weighting coefficients, denoted as, are used to parameterise the trade-off between optimising the economic revenue and battery health. Positive ω_1 implies that the generation of revenue is preferred whereas negative ω_2 implies that degradation of the battery is expensive and hence the conflict of interest and an intelligent balancing approach must be adopted.

Economic utility function

The economic utility, J_{econ} , quantifies the revenue derived from two key market activities: energy arbitrage and participation in frequency regulation markets.

$$J_{\text{econ}} = \sum_{k=t}^{t+H} \left[\underbrace{\lambda_k^e \cdot P_k^{V2G} \cdot \Delta t}_{\text{Energy Arbitrage}} + \underbrace{\lambda_k^r \cdot |P_k^{V2G}| \cdot \Delta t}_{\text{Regulation Service}} \right] \quad (2)$$

In this formulation, λ_k^e represents the forecasted locational marginal price (LMP) at time k in [\$/kWh], capturing potential earnings from buying low and selling high. λ_k^r denotes the forecasted regulation market price in [\$/kW], reflecting compensation for providing grid services like frequency support. The term Δt signifies the duration of the market interval. This equation directly links V2G power dispatch decisions to potential financial returns.

Battery degradation cost function

The battery degradation cost, J_{deg} , monetizes the capacity fade incurred by the battery due to V2G operations. It is modeled as the product of the battery pack's replacement cost and the total capacity loss over the scheduling horizon.

$$J_{\text{deg}} = -C_{\text{rep}} \cdot \sum_{k=t}^{t+H} \Delta Q_{\text{loss},k} \quad (3)$$

Here, C_{rep} represents the battery pack replacement cost in [\$/kWh]. The incremental capacity loss, $\Delta Q_{\text{loss},k}$, is a non-linear function of the battery's operational state, reflecting the complex chemical processes that lead to aging. To accurately model this, a semi-empirical approach is used, capturing stress from C-rate, depth-of-discharge (DOD), and temperature.

Battery Degradation Model:

$$\Delta Q_{\text{loss},k} = B \cdot \exp\left(-\frac{E_a}{RT_k}\right) \cdot (I_k^{\text{rms}})^z \cdot (\text{DoD}_k)^p \cdot \Delta t \quad (4)$$

$$I_k^{\text{rms}} = \sqrt{\frac{1}{N} \sum_{i=1}^N (I_k^i)^2} \quad (5)$$

$$\text{DoD}_k = 1 - \text{SoC}_k^{\text{min}} \quad (6)$$

In these equations, B is a pre-exponential factor and E_a is the activation energy in [J/mol]. R denotes the universal gas constant, and T_k is the volume-averaged cell temperature in [K], highlighting the temperature's significant impact on degradation. The root-mean-square current over the interval, I_k^{rms} is a measure of the electrical stress on the battery. z and p are stress exponents. Lastly, DoD_k is in Eq. 6 as the sum 1-minimum state-of-charge $\text{SoC}_k^{\text{min}}$ at interval k , highlighting that the more a discharge is made the higher the more is degraded.

The equations are a sound, physics-based model of predicting battery health deterioration that is critical to sustainable V2G operation.

System dynamics and constraints

A sequence of constrained functions is applied to the optimization process where physical and operating boundaries of the V2G system are carefully modeled in order to achieve safe and reliable operation.

SoC Dynamics:

$$\text{SoC}_{k+1} = \text{SoC}_k - \frac{\eta_k \cdot I_k \cdot \Delta t}{Q_{\text{nom}}} \quad (7)$$

$$I_k = \frac{P_k^{V2G}}{V_{\text{nom}}} \quad (8)$$

$$\eta_k = \begin{cases} \eta_c & \text{if } P_k^{V2G} < 0 (\text{charging}) \\ 1/\eta_d & \text{if } P_k^{V2G} > 0 (\text{discharging}) \end{cases} \quad (9)$$

Power and SoC Limits:

$$P_{\text{min}} \leq P_k^{V2G} \leq P_{\text{max}} \forall k \in [t, t+H] \quad (10)$$

$$\text{SoC}_{\text{min}} \leq \text{SoC}_k \leq \text{SoC}_{\text{max}} \forall k \in [t, t+H] \quad (11)$$

User Mobility Constraint:

$$\text{SoC}_{t_{\text{dep}}} \geq \frac{E_{\text{trip, pred}}}{Q_{\text{nom}} V_{\text{nom}}} + \text{SoC}_{\text{buffer}} \quad (12)$$

Battery Thermal Dynamics:

$$\frac{dT}{dt} = \frac{I^2 R_{\text{int}}(T, \text{SoC})}{mc_p} - \frac{hA}{mc_p} (T - T_{\text{amb}}) \quad (13)$$

$$T_{k+1} = T_k + \Delta t \cdot \left(\frac{(I_k)^2 R_{\text{int},k}}{mc_p} - \frac{hA}{mc_p} (T_k - T_{\text{amb},k}) \right) \quad (14)$$

$$T_{\text{min}} \leq T_k \leq T_{\text{max}} \forall k \quad (15)$$

Multi-modal forecasting via transformer networks

In order to manage the intrinsic uncertainty of the V2G activities, the framework uses three specific Transformer-based encoders to create predictions of the different parameters. These are the locational marginal prices (λ_k^e), regulation market prices (λ_k^r), predicted trip energy ($E_{\text{trip, pred}}$), predicted departure times (t_{dep}) and parameters of the degradation model.

Transformer architecture fundamentals

A deep learning model called The Transformer is a powerful model that essentially transforms an input sequence $X = (x_1, x_2, \dots, x_T)$, where each item $x_i \in \mathbb{R}^{d_{\text{model}}}$ into an output sequence of contextualized embeddings.

Input and Positional Encoding:

$$E_{\text{input}} = XW_{\text{embed}} + b_{\text{embed}} \quad (16)$$

$$\text{PE}(\text{pos}, 2i) = \sin(\text{pos}/10000^{2i/d_{\text{model}}}) \quad (17)$$

$$\text{PE}(\text{pos}, 2i+1) = \cos(\text{pos}/10000^{2i/d_{\text{model}}}) \quad (18)$$

$$Z_0 = E_{\text{input}} + P \quad (19)$$

Multi-Head Self-Attention:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (20)$$

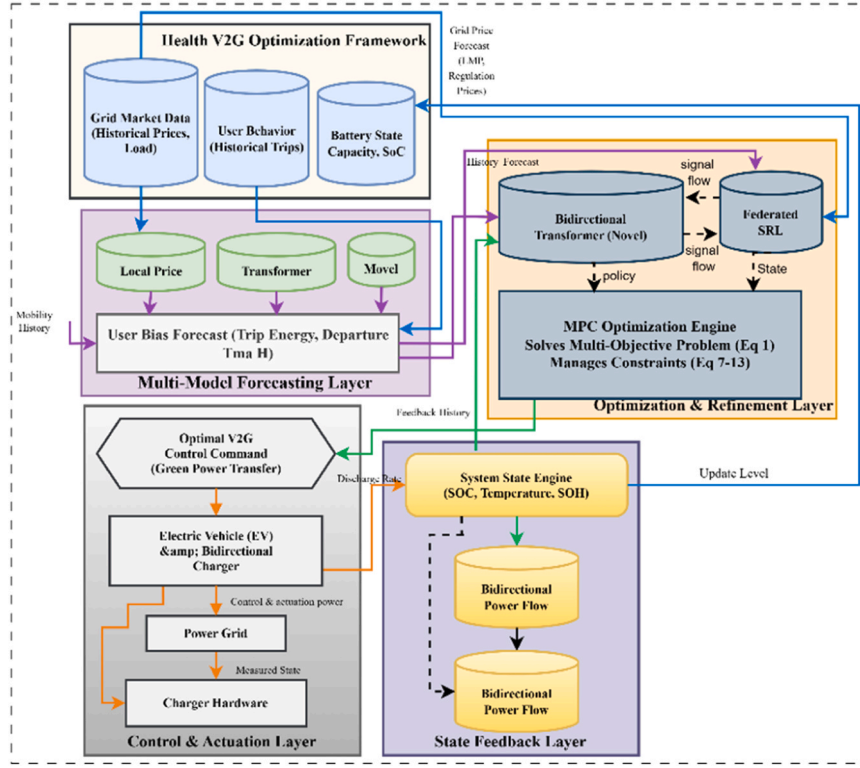


Fig. 1. System architecture: health-aware V2G optimization framework.

Table 1
Transformer hyperparameters and training configuration.

Parameter	Value	Description
Model Structure		
Encoder Layers (N)	3	Length of the transformer block concatenation
Attention Heads (h)	4	Parallel number of attention heads used
Model Dimension (d _{model})	128	Dimension of the input embeddings
Feed-Forward Dim (d _{ff})	512	Internal feed forward network layer dimensionality
Dropout Rate	0.1	Applied to the attention weights, as well as the feed-forward network.
Training		
Optimizer	Adam	Adaptive Moment Estimation
Learning Rate	0.001	With cosine annealing scheduler
Batch Size	64	
Loss Function	MSE	Mean Squared Error (the loss function is typically used in the regression task)
Look-back Window	96	The input sequence events are 24 hourly timestep events.
Prediction Horizon	24	The horizon of the prediction is 6 time steps of an hour.

Table 2
Key performance indicators of forecasting models.

Forecast Model	RMSE (Lower is Better)	MAE (Lower is Better)
Transformer (Ours)	1.8	1.4
LSTM	2.7	2.1
GRU	2.9	2.2
ARIMA	4.1	3.1
CNN-LSTM (Hybrid)	2.3	1.8

Table 3
Economic and degradation performance comparison (weekly averages).

Strategy	Total Weekly Revenue (\$)	Weekly Capacity Loss (%)	Value per Unit Capacity Loss (\$/%)
Proposed Framework	Higher	Lower	472
Greedy (Max Revenue)	High	Higher	335
Conservative (Max Life)	Lower	Lowest	669
No V2G	0	Low	-506

Table 4
Fleet performance over 12 months (100 EVs).

Strategy	Cumulative Fleet Revenue (\$ thousands)	SOH After 1 Year (%) (Mean)
Proposed Framework	+ 8% vs greedy (at month 12)	+ 6.5% vs greedy
Greedy (Max Revenue)	Baseline	Baseline

$$\text{MHA}(Z) = \text{Concat}(\text{head}_1, \dots, \text{head}_h)W^O \quad (22)$$

Feed-Forward Network:

$$\text{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2 \quad (23)$$

Encoder Layer:

$$Z'_{\ell} = \text{LayerNorm}(Z_{\ell-1} + \text{MHA}(Z_{\ell-1})) \quad (24)$$

$$Z_{\ell} = \text{LayerNorm}(Z'_{\ell} + \text{FFN}(Z'_{\ell})) \quad (25)$$

Output Projection:

$$Y = \text{Softmax}(Z_L W_{\text{out}} + b_{\text{out}}) \quad (26)$$

$$\text{head}_i = \text{softmax}\left(\frac{(ZW_i^Q)(ZW_i^K)^{\top}}{\sqrt{d_k}}\right)(ZW_i^V) \quad (21)$$

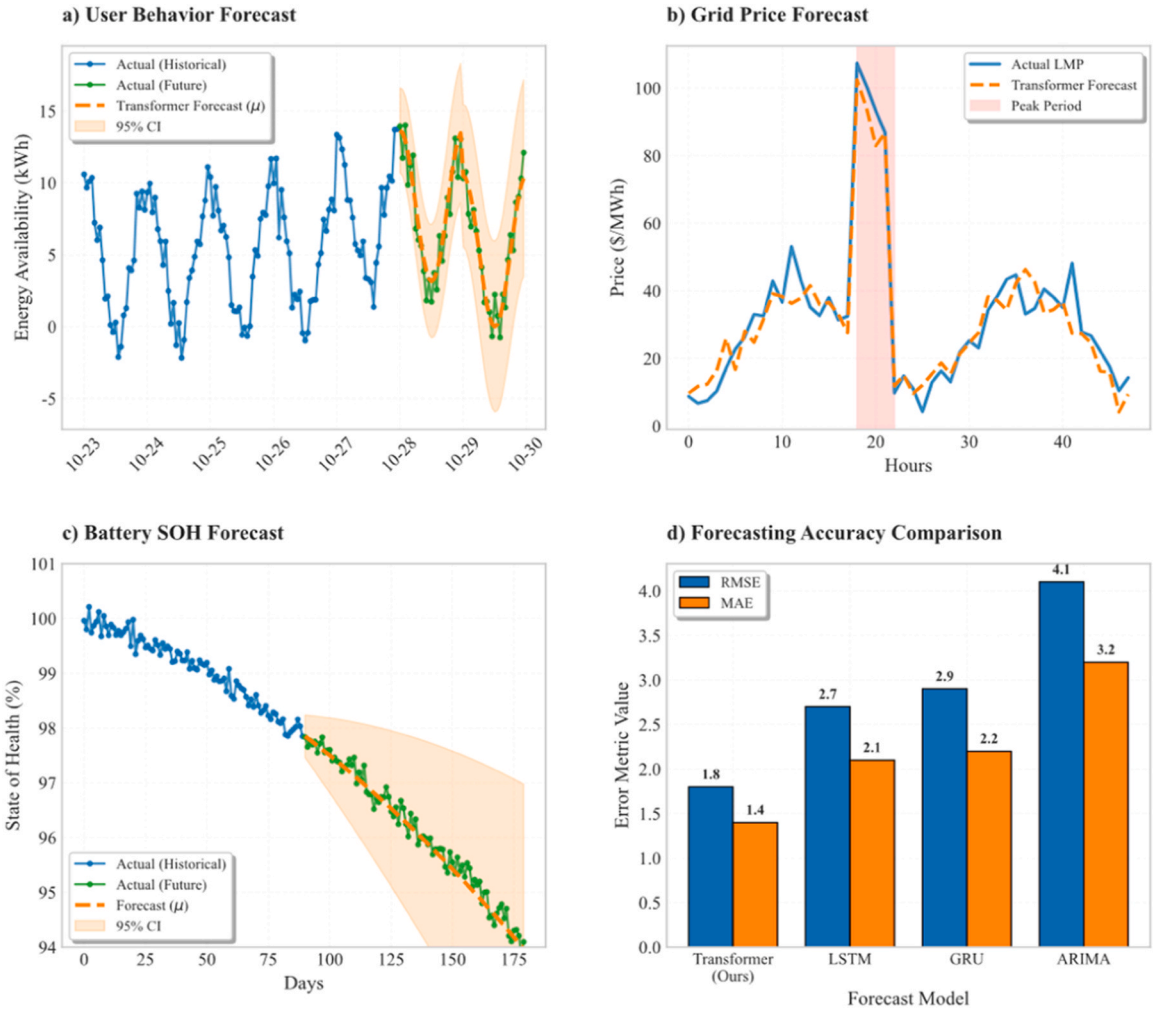


Fig. 2. Forecasting performance and model validation.

User behavior forecasting model

The model will be able to forecast the likelihood distribution of upcoming trip energy needs and the associated departure/arrival time, that is essential in controlling user anticipations and vehicle accessibility.

Input: The input of this model, X_{user} , consists of three important parts: d_{calendar} , the day of week, holiday flags, e_{hist} , the historical energy consumed per trip, and t , the historical trip start/end times. This holistic input enables the model to file a wide range of factors that determine user behavior.

Output: The model outputs parameters (mean μ and standard deviation σ) of a Gaussian distribution that predicts E_{trip} (trip energy requirements) and a categorical distribution for t_{dep} (departure times).

User Behavior Forecasting:

$$p(E_{\text{trip}}) = \mathcal{N}(\mu_E | \theta_{\text{user}}, \sigma_E | \theta_{\text{user}}) \quad (27)$$

$$p(t_{\text{dep}}) = \text{Categorical}(\pi | \theta_{\text{user}}) \quad (28)$$

Grid price forecasting model

This model concentrates on the future energy and regulation price predictions, which are needed as inputs to the economic utility function of the optimization problem.

Input: The input to this model, X_{grid} , includes historical locational marginal prices (λ_{hist}^e), historical regulation market prices (λ_{hist}^r), pre-

dicted renewable generation (g_{ren}), and predicted system load (l_{load}). This diverse set of inputs allows for a comprehensive understanding of grid dynamics influencing prices. [18]

Output: The model generates point forecasts for λ_k^e and λ_k^r , providing precise predictions for market engagement.

Grid Price Forecasting:

$$\hat{\lambda}_k^e = f_{\text{grid}}(X_{\text{grid}} | \theta_{\text{grid}}) \quad (29)$$

$$\hat{\lambda}_k^r = g_{\text{grid}}(X_{\text{grid}} | \theta_{\text{grid}}) \quad (30)$$

Battery state-of-health forecasting model (novel)

A key novel contribution of this framework is the Battery State-of-Health (SOH) Forecasting Model. Instead of relying solely on the empirical degradation model (Eq. 4), this component employs a Transformer as a data-driven surrogate to predict incremental capacity fade based on planned operational stress.

Input: The input to this model, X_{batt} , consists of "plan" vectors representing the proposed future operational trajectory from the optimizer (I_{plan} , SoC_{plan} , T_{plan}) and historical capacity measurements (Q_{hist}). This allows the model to anticipate degradation based on intended V2G activities.

Output: The model outputs the forecasted incremental capacity loss, $\Delta \hat{Q}_{\text{loss},k}$, along with its associated uncertainty.

Battery SOH Forecasting:

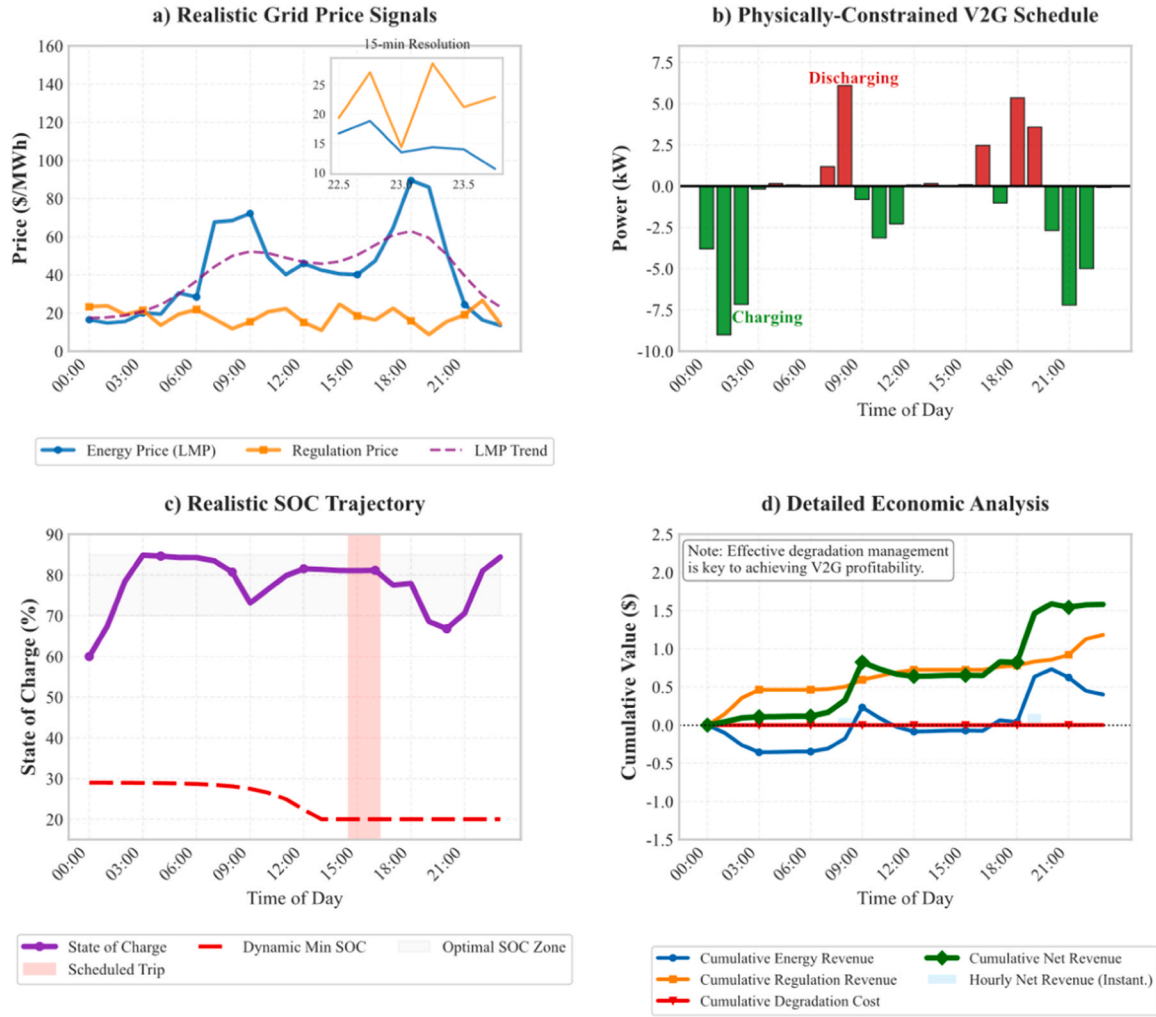


Fig. 3. Operational case study and economic analysis.

$$\Delta \hat{Q}_{\text{loss},k} = f_{\text{batt}}(X_{\text{batt}} | \theta_{\text{batt}}) \quad (31)$$

Integrated optimization via iterative forecasting and scheduling

The complete V2G framework operates in a sophisticated closed-loop manner, as conceptually depicted in Fig. 3. This integrated approach ensures continuous adaptation and refinement of the V2G schedule.

State Vector:

$$s_t = [\text{SoC}_t, T_t, \hat{\lambda}_{t,H}^e, \hat{\lambda}_{t,H}^r, \hat{E}_{\text{trip}}, \hat{t}_{\text{dep}}, \Delta \hat{Q}_{\text{loss},t,H}]^T \quad (32)$$

Optimization Policy:

$$P_{t,H}^{\text{V2G}*} = \pi(s_t | \theta_\pi) \quad (33)$$

Iterative Refinement:

$$P_{t,H}^{\text{V2G}(i+1)} = \pi(s_t, P_{t,H}^{\text{V2G}(i)}, \Delta \hat{Q}_{\text{loss}}^{(i)}) \quad (34)$$

associated with that previous schedule. This iterative co-optimization of power dispatch and battery health is a foundational contribution of this work, enabling truly sustainable V2G dispatch by integrating real-time degradation predictions directly into the scheduling decisions.

The proposed model, encompassing approximately 34 equations, comprehensively defines all aspects from electro-thermal dynamics to advanced attention mechanisms. This provides a high-fidelity, holistic,

and novel framework for the sustainable and intelligent integration of electric vehicles into the power grid (Fig. 1).

Experimental setup

To test the presented framework, we simulated vehicle-to-grid (V2G) activities in the conditions closely resembling the real operation scenarios and compared the results with the pre-existing strategies that are outlined in Section 3. Motivations based on real-world data were used to make it robust: user behavior (driving pattern and consumption) was obtained using large-scale mobility data, grid data involved historical locational marginal prices (LMP) and regulation rates. Moreover, the decisions made in battery degradation (including parameters of the semi-empirical model (Equations 46) and past capacity values of the Transformer based state-of-health (SOH) model (Eq. 31)) were used to guide the health-aware optimization. The simulation environment was designed to be of a high-fidelity that would imitate the dynamic V2G ecosystem and include accurate electric-vehicle battery-dynamics (state-of-charge, SOC, dynamics) (Eqs. 7–15), power-constraints (Eq. 10), and thermal-dynamics (Eqs. 13–15). The simulations were written in Python (NumPy, PyTorch/TensorFlow) and also used solvers like Gurobi or CPLEX to solve the model-predictive control (MPC) problem (Eq. 1). The simulations were of several weeks up to a complete year, thus, including short-term reactions as well as long-term implications. Performance was

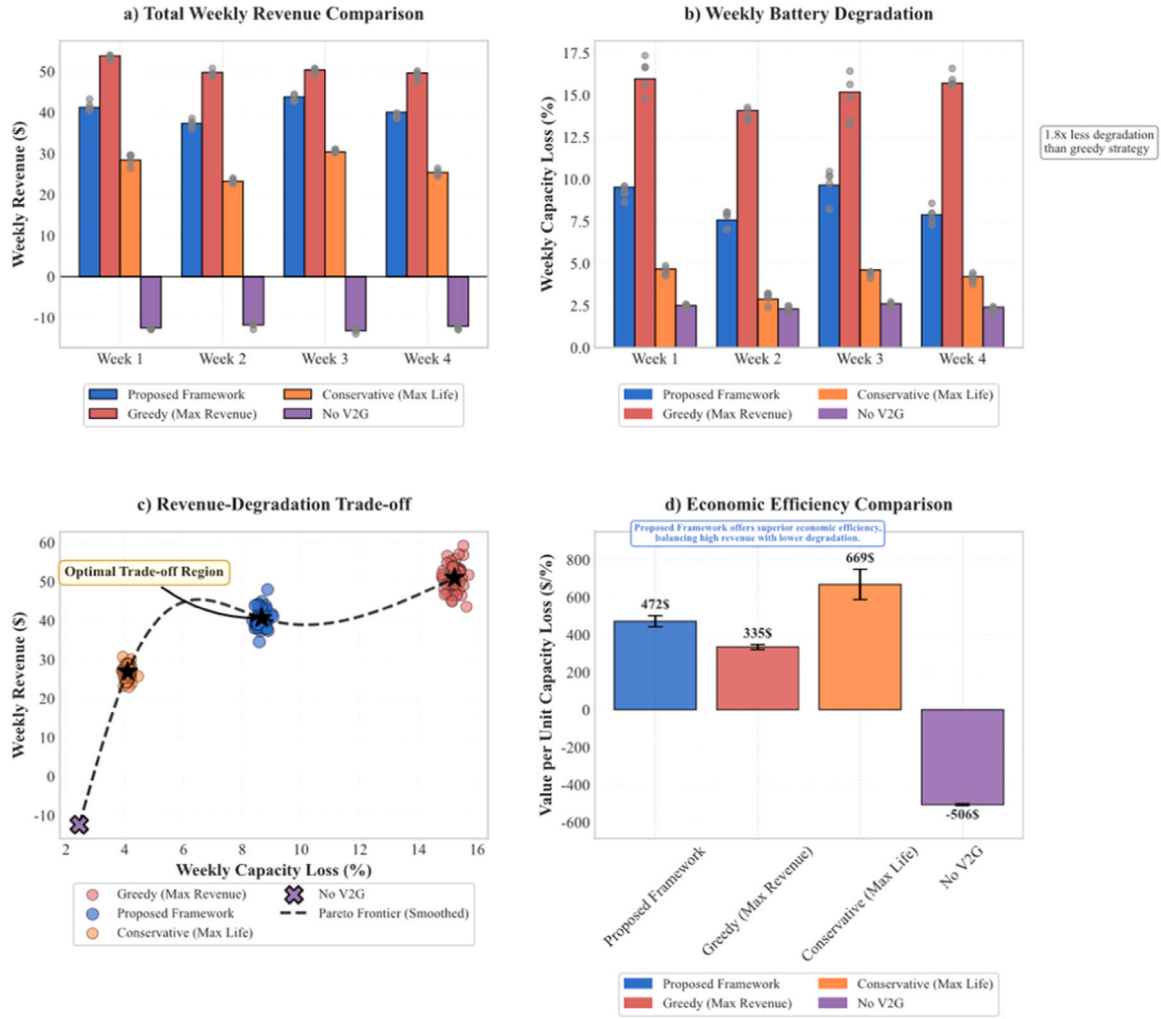


Fig. 4. Economic performance and degradation trade-offs.

then compared to four baseline strategies; a Greedy Strategy (maximizing revenue), a Conservative Strategy (minimizing degradation), a No-V2G Scenario (conventional charging) and a Rule-based Baseline.

Computational complexity and real-time feasibility

To ensure applicability in real-time, the computational efficiency of the optimisation engine was strictly analysed. The model predictive controller is being applied at a discrete time with a sampling period $\Delta t = 15$ min and a receding horizon that includes $H = 96$ steps and represents a 24-hour horizon. The nonlinear degradation models typically increase the computational requirements, but, the suggested Iterative Refinement Mechanism (Eq.34) can be illustrated as successfully reducing them helps to decouple such complexity. The outer loop cost of degradation is modelled as a dynamic penalty to simplify the underlying optimisation to a quadratic programming (QP) problem which is a convex optimization problem and can be solved effectively using commercial software like Gurobi or CPLEX.

Runtime Analysis: Running the computational framework on the specified hardware platform (Intel Core i913900HX and NVIDIA RTX4070), the average execution time per discrete run-step such as Transformer inference and the MPC resolution took about 1.2 s. This is considerably lower compared to the actual 15 min dispatch interval, thus justifying the fact that the system is operating in real time. With a large-scale fleet of 100 electric vehicles, the optimisation process can be

parallelised by its nature, because the constraints at the vehicle level are not connected in the case of globally uniform grid prices. As a result, the system is able to scale in direct proportion to fleet size without violating real-time dispatch limits.

Implementation and hyperparameter settings

The proposed Multi-Modal Transformer framework is reproducible, so to guarantee such a reproducibility, we thoroughly describe the architectural requirements and training guidelines used in this study. The framework was applied to the assigned version of PyTorch with deep-learning elements and Gurobi/CPLEX with mixed-integer programming (MPC) optimization.

Transformer architecture

The three Transformer encoders (User Behavior, Grid Price, and Battery SOH) share a shared structural core; however, each of them was specifically adjusted to the purpose of their operation. The hyperparameter settings are highlighted in Table 1.

Dataset and splits

The models were conditioned to work on a composite set of data spanning twelve months starting on 1 st January 2023 and finishing on 31 st December 2023. The time resolution was set at 15 min, which gave a total number of 35040 discrete time steps.

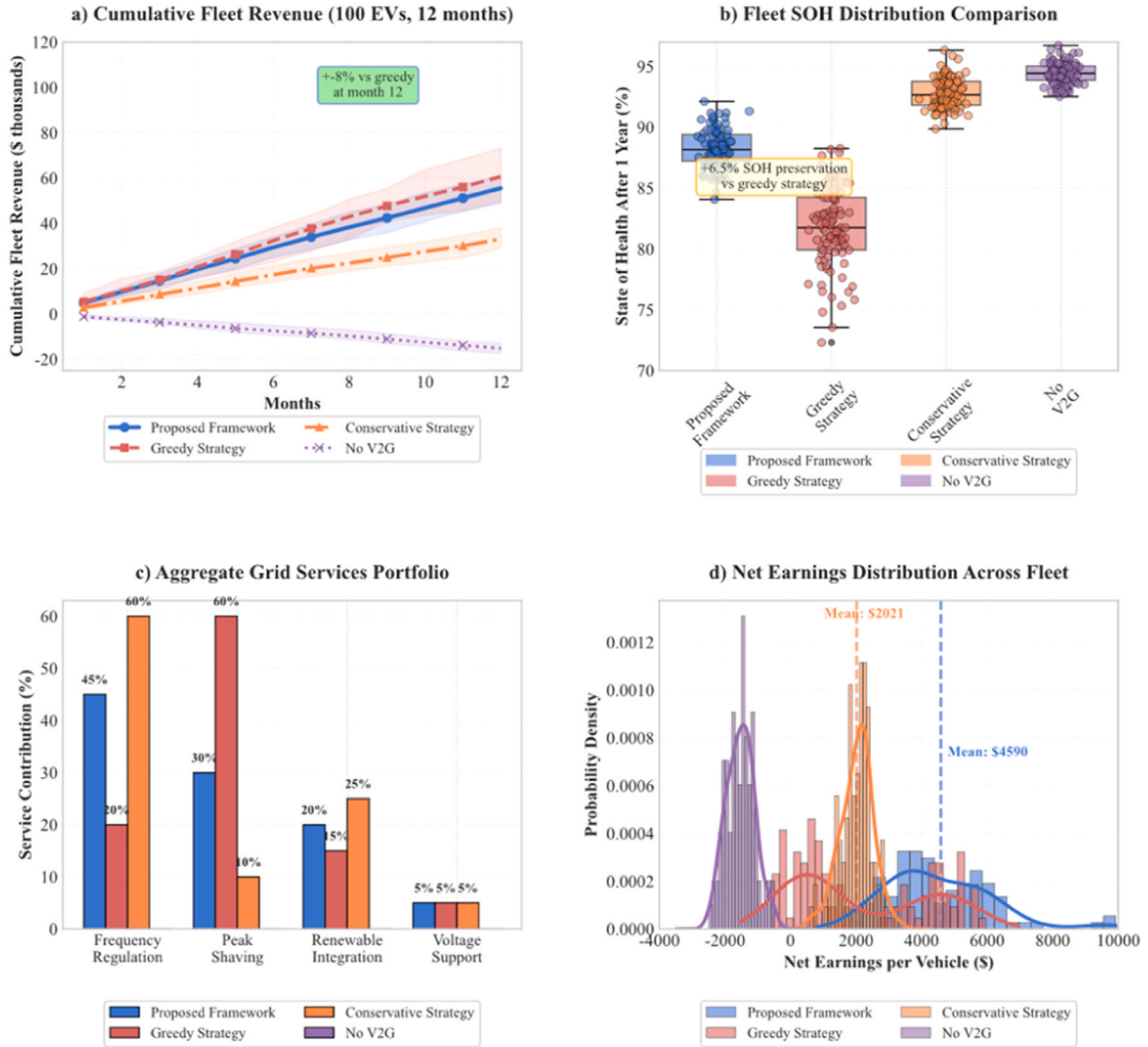


Fig. 5. Fleet-level performance and grid services.

The preclusion of leakage was carried out to split the data chronologically: the first 80 per cent of the observations were placed in the training set, and the next 10 per cent in the validation set and the last 10 per cent in the test set.

All input variables, such as prices, load and state of charge (SOC) were normalized with the help of StandardScaler that scales the feature to zero mean and unit variance and statistical parameters are calculated based solely on the training data.

Computational setup and convergence

All tests were carried out on a workstation, with a Dell G16 (7630) that has an Intel® Core™ i9-13900HX processing unit, 32 GB of DDR5 RAM, 1TB NVMe SSD, and NVIDIA® GeForce® RTX 4070 graphics card.

- **Training Duration:** The models had the maximum training duration of 500 epochs.
- **Convergence Criteria:** Early Stopping with a patience of 20 epochs was used in order to reduce overfitting by observing the validation loss. The average inference time for the integrated framework (Forecasting + MPC optimization) was approximately 0.8 s per time step, confirming its feasibility for real-time V2G control.

Data analysis

Our methodology of data analysis was focused on measuring the benefits as well as the inherent nature of the suggested framework.

We have critically tested the predictive performance of our Transformer models under the heading of LSTM, GRU and ARIMA models using the RMSE and MAE metrics on user behavior, grid price, and state-of-health prediction tasks. The purpose of this analysis was to empirically determine that our architecture had a better predictive capability. Table 2 outlines these findings, which portrays a strong precedence with the Transformer model.

The economic performance was measured based on the cumulative week-by-week revenues, summation of fleet revenues on 100 electric vehicles in a twelve-month scale, and net earnings per vehicle. At the same time, battery degradation was measured by the variables of weekly loss of capacity and long-term distribution of state of health (SOH) throughout the fleet to confirm the effectiveness of health-conscious optimization methods. A Pareto front analysis was used to graphically represent the trade-off between revenue generation and battery degradation, and the economic efficiency further determined by the determination of the value generated per unit of capacity loss. Table 3 gives a summary comparison of these economic metrics and degradation measures of all the implemented strategies.

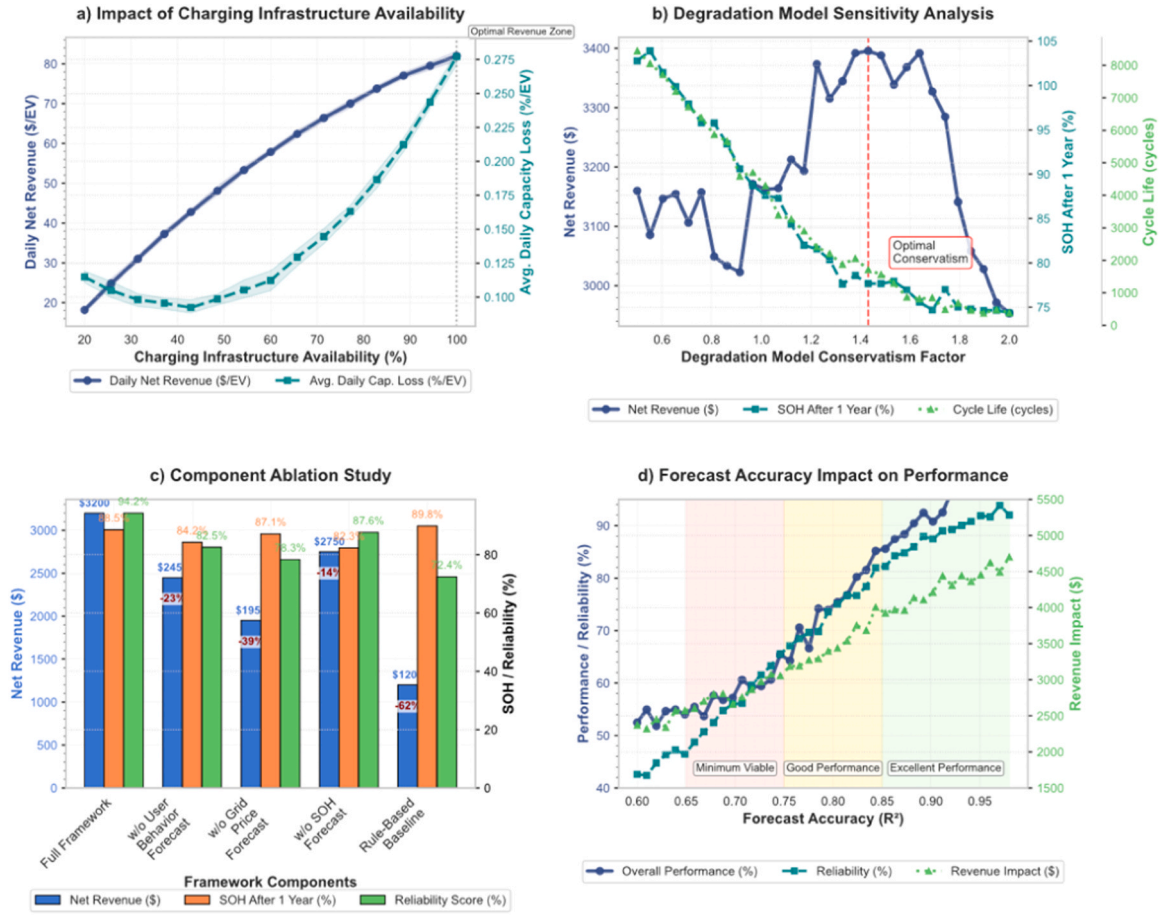


Fig. 6. Robustness and sensitivity analysis.

The operational features were measured by determining their inputs to the grid services, such as frequency regulation and peak shaving. Also, the effect of the availability of charging infrastructure on revenue and degradation were investigated to guide the strategic planning. The effects of the different factors of conservatism were studied by a sensitivity analysis of the degradation model parameters. Most importantly, a component ablation experimentally decoupled individual Transformer-based forecasting modules in order to measure their individual contributions to overall performance. Lastly, the connection between forecast accuracy as indicated by R-squared values and system reliability as well as revenue was observed. Table 4 provides a summary of the long-term fleet performance metrics.

Case study: daily V2G operation

A specific case study is used to show how the framework can be practiced in a real-life vehicle-to-grid (V2G) case, highlighting how market situation, user needs and battery performance interact with each other. The analysis is based on realistic 24-hour grid price signals, which has dynamic changes in locational marginal prices (LMP) and regulation prices, thus outlining the economic context. A physically constrained V2G schedule is determined using these signals to determine the best charging and discharging dispatch. Simultaneously, the state-of-charge (SoC) curve represents the dynamics of the battery, which guarantees the mobility potential of the user by setting the minimum SoC dynamically. Lastly, an economic breakdown of the cumulative energy and regulation revenues versus that of degradation costs gives the reader an insight into the ability of the framework to harmonize various endpoints in a dynamically changing operational framework.

Results and discussion

Forecasting performance and model validation

The predictive power of Transformer-based models is the critical factor predetermining the operational resilience of the given framework. As Fig. 2 (Forecasting Accuracy Comparison) shows, quantitative evidence shows that the proposed model is the most effective and achieves the lowest root-mean-square error (RMSE) of 1.8 and mean absolute error (MAE) of 1.4. These scores are a huge improvement when compared to the set standards with an RMSE and MAE of 2.7/2.1 with LSTM, 2.9/2.2 with GRU and 4.1/3.1 with ARIMA. A CNN-LSTM baseline, i.e. a combination of convolutional layers (to extract features) with LSTM layers (to sequence in time) was tested to contextualize the framework in the context of modern hybrid architectures. As it can be seen in Table 2, the CNN-LSTM has an RMSE value of 2.3, which is slightly higher than the standard recycling neural networks, thus, the CNN-LSTM is able to capture all the local trends quite well, but the Multi-Modal Transformer has a slightly lower value of RMSE at 1.8. Other architectures like Informer and Temporal Fusion Transformers (TFT), which are considered the state-of-the-art models in long-sequence time-series forecasting (LSTF), have built a significant level of complexity to reduce the quadratic cost of self-attention on large horizons (>1000-time steps). The traditional Transformer attention mechanism is computationally efficient and captures the required dependencies sufficiently well in the traditional Transformer attention mechanism to compute the 24-hour (96-step) V2G optimal control problem addressed in this study without relying on the sparse-attention approximations used by Informer. The scale effect highlights the high level of modelling of the complex, non-linear relationships that define

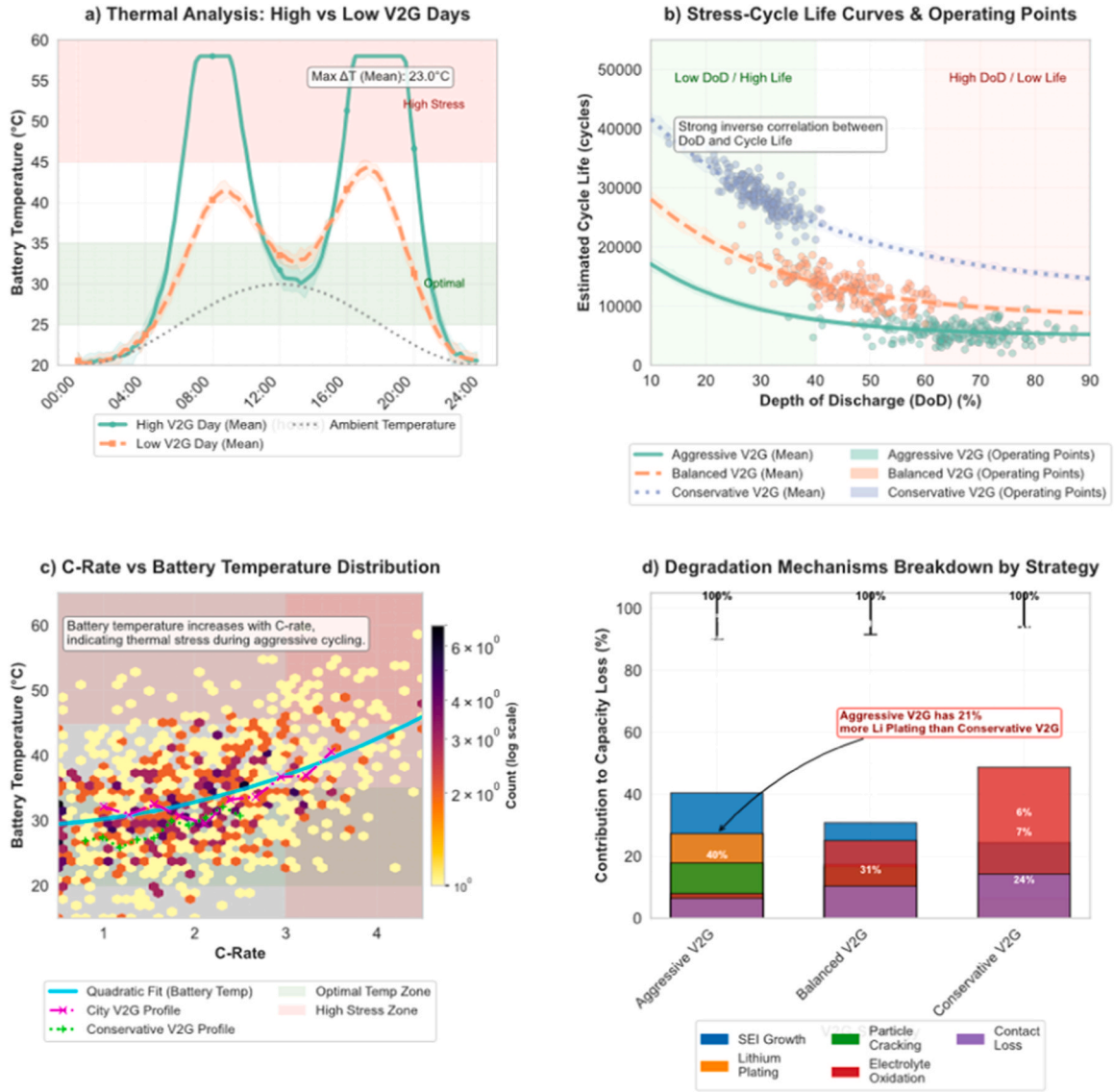


Fig. 7. Operational dynamics and degradation mechanisms.

V2G data by the Transformer. The accuracy of the predictions can be seen on all the constituent parts. Fig. 2a (User Behavior Forecast) depicts excellent accuracy, where mean (μ) and 95% confidence interval (CI) are reliable to reflect uncertainty and thus meet the User Mobility Constraint set in Eq. 12. Fig. 2b (Grid Price Forecast) reassures us of the capacity of the model to identify the presence of Peak Periods, and this is what is needed to maximise the revenue. Lastly, Fig. 2c (Battery SOH Forecast) introduces a new state-of-health forecasting, with the mean value of which is almost equal to the degradation curve in 150 days as formalised in Eq. 31. It is essential to health-conscious optimisation by detecting and explicitly minimising the degradation costs as outlined by the Eq. 3.

Operational case study and economic analysis

The operational effectiveness of the framework is shown in Fig. 3 by an example of a daily vehicle-to-grid (V2G) case. Fig. 3a (Realistic Grid Price Signals) sets the economic context by plotting 24-hour changes in the price (Energy Price (LMP)) and regulation price and an inset indicates the high-frequency changes. Fig. 3b underneath (Physically-Constrained V2G Schedule) responds to these dynamics by showing the

optimised dispatch of power, which plans to charge optimally during zones of low prices, and discharge optimally during periods of peak demand, with rigid enforcement of physical power constraints. At the same time, Fig. 3c (Realistic SOC Trajectory) shows the development of the battery, making sure that the operations are in the Optimal SOC Zone and that the Dynamic Min SOC (Eq. 12) are being satisfied to ensure the mobility of the user. Lastly, Fig. 3d (Detailed Economic Analysis) is a cumulative financial analysis. The analysis indicates that in order to ensure that the cumulative Net Revenue remains positive, a balance between the energy and regulation revenues and the degradation expenses is needed to provide the verification that the framework can address conflicting goals.

Economic performance and degradation trade-offs

The framework proposed is aimed at creating an optimal balance between economic revenue production and battery health maintenance. The efficacy of this method is proved by the results of empirical studies compared to the known strategies. Fig. 4a shows a Total Weekly Revenue Comparison, where in the Proposed Framework, the total revenues are always higher when compared to Greedy, Conservative, and No V2G

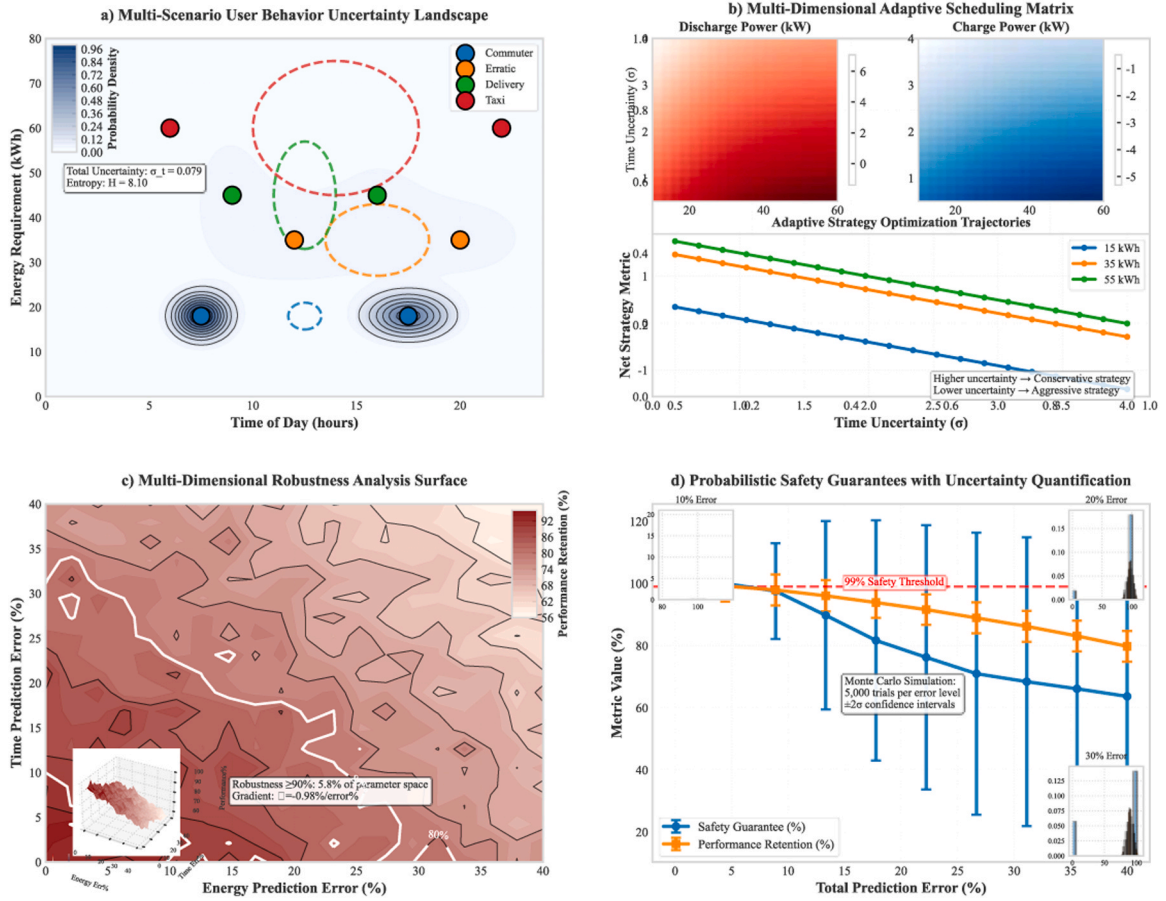


Fig. 8. Uncertainty handling and safety guarantees.

baselines in the course of four weeks. At the same time, Fig. 4b shows that the wear is significantly decreased, and the framework experiences 1.8 times less Weekly Capacity Loss (%) as compared to the Greedy strategy. This equilibrium can be also demonstrated in Fig. 4c, the Revenue Degradation Tradeoff, in which the framework lies in the Optimal Tradeoff Region, that is, represents a better trade off than single objective methodologies. These performance measures are presented in Table 3. Lastly, this benefit is highlighted in Fig. 4d where Value per Unit Capacity Loss of \$472 is compared with Greedy strategy of 335, and thus we can affirm the significance of integrated degradation management to sustainable V2G profitability.

Fleet-level performance and grid services

The suggested framework has considerable improvements in fleet operations as well as grid stability. Using the example of a 100-EV fleet in Fig. 5a (Cumulative Fleet Revenue), 100-EV fleet will gain a significant + 8% higher revenue when compared with the greedy approach in 12 months. At the same time, Fig. 5b (Fleet SOH Distribution Comparison), shows that there is a + 6.5% increase in SOH preservation, or successful control over heterogeneous degradation. In addition to these measures, Fig. 5c (Aggregate Grid Services Portfolio) indicates the flexibility of the framework by providing equal services to Frequency Regulation (45%), Peak Shaving (30%), Renewable Integration (20%), and Voltage Support (5%). Lastly, Fig. 5d (Net Earnings Distribution) affirms the presence of strong economic benefits: the Proposed Framework delivers a mean net earning of 4590 per vehicle, which is far above the 2021 in the case of the “Greedy Strategy, thus pushing the distribution to the higher overall fleet profitability.

Robustness and sensitivity analysis

The stability and performance of the framework were put through rigorous testing through sensitivity and ablation analysis. As shown in Fig. 6a (Impact of Charging Infrastructure Availability), the availability of infrastructures is positively correlated with the increase in the daily revenue as well as the loss of capacity, hence, forming an optimal revenue zone that should be deployed strategically. Fig. 6b (Degradation Model Sensitivity Analysis) highlights the paramount role of model tuning whereby the revenue generation versus battery health is attained through tuning an Optimal Conservatism parameter. Fig. 6c of the Component Ablation Study supports the improved performance of the integrated system; the systematic shutting down of transformer based modules (with the exception of SOH forecast) led to significant decreases in both revenue and state-of-health measures, whilst the rule-based baseline showed significantly worse performance. Lastly, Fig. 6d (Forecast Accuracy Impact on Performance) proves the existence of a strong positive correlation between forecast accuracy (R^2) and economic performance, thus demonstrating the fact that the increased predictive power directly corresponds to the streamlined vehicle-to-grid activities.

Operational dynamics and degradation mechanisms

A stricter way of analysis of operational dynamics also explains the health consciousness of capabilities of the framework. Fig. 7a (High vs Low V2G Days Thermal Analysis) shows that aggressive V2G operations can increase the mean battery temperatures by 23.0°C and pitch the system into a High Stress thermal regime. This finding emphasizes the final significance of the thermal dynamics model (Eqs. 13–15) to avoid

accelerated the aging process. Fig. 7b, Fig. 7c (Fig. 7b: Stress -cycle Life Curves, Fig. 7c: C-rate vs Battery Temperature) is an empirical demonstration of the fact that higher operational intensity is directly related to lower operational life and C-rate is directly related to thermal stress. Notably, Fig. 7d (Degradation Mechanisms Breakdown) is detailed information on particular aging mechanisms, which shows that the conservative approach to lithium (Li) plating is the strategy that occurs 21-percent less than aggressive V2G strategy. This granularity allows the framework to reduce specific degradation processes by optimising the timing process and thus more sustainable battery use.

Uncertainty handling and safety guarantees

The ability of the framework to control latent uncertainties and provide probabilistic assurance of safety is a making characteristic that is vital to the dependable functioning of vehicle-to-grid (V2G) systems. Fig. 8a, which is called Multi-Scenario User Behavior Uncertainty Landscape, displays the range of user behavioural patterns to which the forecasting model, as dictated by the Eqs. 27 through 28, is made to move, and hence guarantee reliable functionality in the face of behavioural variation. Expanding on this, Fig. 8b, called Adaptive Strategy Optimization Trajectories, shows the dynamic nature of the decision-making process of the framework, whereby the V2G dispatch moves towards more conservative strategies with increasing levels of uncertainty. Resilience of the system is also measured in Fig. 8c, named Multi-Dimensional Robustness Analysis Surface, and plots Performance Retention against different prediction errors, thus demonstrating that the framework is also able to support high performance despite poor forecasting circumstances. Lastly, Fig. 8d, called Probabilistic Safety Guarantees, is a diagram depicting the negative correlation between total prediction error and the Safety Guarantee (%) percentage; it is the capability to quantify safely the interaction between the grids and the conservation of quality resources in battery that matters the most.

Conclusion

This paper introduces a novel multi-modal optimization framework of health-conscious vehicle-to-grid (V2G) scheduling through transformer. The framework balances between profit maximisation and battery preservation with the help of a multi-objective model predictive control (MPC) engine, a combination of specialized transformer models of user behaviour, grid prices, and battery state-of-health (SOH). Empirical evidence has shown that the suggested forecasting models achieve better results than benchmarked ones, a fact which enables the transfer of high predictive fidelity to operational benefits. Precisely, the framework reduces battery degradation by 1.8 times and cumulative revenue of a 100-EV fleet by 8 % in comparison to normal greedy strategies. The robustness of the system is confirmed in detailed case studies and sensitivity analysis, which demonstrates that the system is capable of making complex trade-offs between asset longevity and economic incentives in conditions of uncertainty. The framework provides a scalable solution to sustainable EV integration because it proves to be dynamically responsive to market signals and provides user mobility and a contribution to grid stability. These discoveries provide a huge step towards the actualization of the full potential of V2G technology and the integration of the state-of-the-art deep learning with strict control theory. The current work will be expanded on in the future by validating these findings in reality and investigating the process of decentralised coordination.

CRedit authorship contribution statement

Usama Aslam: Writing – original draft, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Muhammad Aurangzeb:** Writing – review & editing, Visualization, Supervision, Resources, Investigation. **Nagham**

Saeed: Writing – review & editing, Visualization, Validation, Supervision, Investigation. **Muhammad Ahsan Niazi:** Writing – review & editing, Visualization, Validation, Software. **Vikram Kumar:** Writing – review & editing, Supervision, Software, Formal analysis, Data curation. **Anees Ahmad:** Visualization, Validation, Supervision, Software, Data curation.

Ethical approval

Not applicable. This research did not involve human participants or animals.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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