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Research Paper

Designing a Centralized Charging and Discharging Management Strategy for Electric Vehicles to Enhance Transformer Lifespan in Distribution Networks

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Abstract— *The widespread adoption of electric vehicles (EVs) is increasing the loading of distribution transformers and accelerating insulation aging. This paper proposes a centralized charging and discharging strategy that jointly co-optimizes EV operating cost and the monetized cost of transformer loss-of-life, explicitly linking technical asset degradation to economic decision-making. Unlike prior centralized EV-scheduling approaches that either constrain temperature or evaluate aging only in post-processing, the proposed framework embeds an IEEE C57.91-based aging model directly into the optimization objective and converts aging into an equivalent financial cost.The model further introduces a stakeholder compensation mechanism in which part of the deferred transformer replacement savings is redistributed to EV owners, allowing an independent aggregator (or the distribution utility) to coordinate EV charging while preserving consumer economic incentives. The framework considers grid-to-vehicle (G2V), vehicle-to-home (V2H), and vehicle-to-grid (V2G) modes and is formulated as a mixed-integer nonlinear optimization problem. Simulation results for a residential network with six EVs demonstrate that centralized coordination can reduce transformer loss-of-life by up to 80% compared with decentralized charging, while increasing daily EV operating costs by only 4-6%. The remuneration mechanism enables all stakeholders—transformer owner, aggregator, and consumers—to benefit economically. These findings show that integrating monetized transformer aging into EV scheduling, combined with explicit profit-sharing, provides a technically effective and financially viable pathway for extending transformer lifespan under growing EV penetration.*

Keywords—Electric vehicles, distribution transformers, charging management, discharging strategy.

NOMENCLATURE

Economic Terms

Aggregator Profit: Maximum net revenue after compensating consumers

Consumer Trading Profit: Arbitrage income from charging/discharging

Deferred Investment Profit: Savings from postponed transformer replacement

Symbols

$\alpha_{t,v}$	EV availability indicator (1 = at home, 0 = away)
β	Normal insulation lifetime (180,000 hours)
$\Delta\theta_{HST,R}$	Rated hottest-spot temperature rise (°C)
$\Delta\theta_{HST,U}$	Ultimate hottest-spot rise for load ratio k_t (°C)
$\Delta\theta_{TO,R}$	Rated top-oil temperature rise (°C)
$\Delta\theta_{TO,U}$	Ultimate top-oil rise for load ratio k_t (°C)
$\Delta\theta_{TO}$	Top-oil temperature rise over ambient at time t (°C)
$\Delta\theta_t^{HST}$	Hottest-spot rise above top-oil at time t (°C)
η_v^{chg}	Charging efficiency of EV v
η_v^{dsg}	Discharging efficiency of EV v
π_t	Electricity tariff at time t (USD/MWh)
τ_{TO}	Top-oil thermal time constant
τ_W	Winding thermal time constant
θ_t^A	Ambient temperature (°C)

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θ_t^{HST} Winding hottest-spot temperature (°C)
ξ Energy consumption per trip segment (kWh)
C_v EV battery capacity (kWh)
C_{pay} Compensation paid to consumers by aggregator (USD)
F_t^{AA} Aging acceleration factor at time t
k_t Transformer load ratio at time t
k_t^+, k_t^- Positive and negative decomposed load-ratio variables
m Winding exponent in IEEE thermal model
n Oil exponent in IEEE thermal model
P_{limit} Maximum household connection limit (kW)
$p_{t,v}^{chg}$ Charging power of EV v at time t (kW)
$p_{t,v}^{dsg}$ Discharging power of EV v at time t (kW)
P_t^{base} Base household consumption (kW)
P_v^{max} Maximum charging/discharging power (kW)
R Ratio of load losses to no-load losses
$r_{manager}$ Aggregator's share of total savings
r_{saver} Total savings from deferred transformer replacement
$S_{t,v}$ Travel indicator (1 = in transit, 0 = not traveling)
$SOC_{t,v}$ State of charge of EV v at time t
SOC_v^{init} Required SOC at the end of the day
SOC_v^{max} Maximum allowable SOC
SOC_v^{min} Minimum allowable SOC
t Time index (15-minute intervals)
TX_{cost} Transformer replacement cost (USD)
TX_{rating} Transformer rated power (kVA)
v EV index

1. Introduction

The increasing adoption of EVs has significantly transformed the energy landscape, introducing new challenges for power distribution networks [1]. As the penetration level of EVs rises, the demand for electricity surges, placing considerable stress on distribution system assets, particularly transformers [2]. The uncontrolled charging and discharging of EVs can lead to voltage fluctuations, power losses, and accelerated aging of transformers, ultimately compromising grid reliability and increasing maintenance costs [3]. To address these challenges, efficient charging management strategies are essential to balance energy demand, minimize transformer degradation, and ensure the sustainable integration of EVs into the power grid [4, 5]. This study proposes a centralized charging and discharging management strategy that optimizes transformer lifespan while maintaining economic benefits for EV owners. EVs provide environmental benefits but also introduce operational challenges for distribution networks [6]. EV batteries can operate in grid-to-vehicle (G2V), vehicle-to-home (V2H), and vehicle-to-grid (V2G) modes, each influencing power flows and transformer loading [7]. Global adoption is projected to exceed 145 million EVs by 2030, intensifying the need for coordinated charging management [8]. Since many EVs connect to residential feeders within similar time windows, unmanaged charging can create pronounced load peaks that adversely affect distribution transformers [9]. Prior studies on transformer thermal behavior [10, 11] and voltage stability [12, 13] underscore the importance of smart EV integration and, when necessary, system reinforcement. Because most EV owners charge primarily at home [14], low-voltage distribution transformers experience the highest stress, leading to increased hot-spot temperatures, accelerated insulation aging, and shortened transformer lifespan [15].

Recent studies, including references [16, 17], have examined the impact of EVs on distribution transformers. Ref. [18] introduces a probabilistic perfect to recognize transformers that are most susceptible to overloading due to EV charging. This study assumes that a transformer must be supplanted whenever it experiences any predefined overload, which is not an optimal approach. In Ref. [19], an correspondent circuit model of the transformer is presented to analyze the effects of EV integration. The post-processing techniques employed in [20] are used for analysis but do not optimize EV charging with the objective of maximizing transformer lifespan. Other studies, such as those in references [21, 22], incorporate EV charging behavior into transformer dynamics and evaluate the resulting reduction in transformer lifespan. Ref. [23] proposes a charging method based on the heat generated within the transformer and uses this method to analyze the impact of EVs. However, this approach relies on predefined thermal thresholds and requires more detailed analysis for greater effectiveness. In Ref. [24], a rule-based method is developed to study its effects on transformer aging. This approach applies predefined charging and discharging rules for EVs, which are not necessarily optimal. Additionally, all methodologies in Ref. [25] adopt a decentralized strategy, where EV owners manage their charging independently, and their collective consumption is analyzed to assess transformer aging. Some studies have also explored centralized multi-objective optimization approaches, incorporating EV integration. These optimizations consider distribution system losses [26], voltage constraints [27], and market participation [28]. However, limited research has focused on the multi-objective optimization of both transformer degradation and EV operation [29]. Ref. [30] introduces a centralized control strategy that balances transformer loading while maintaining service quality for consumers. Since balanced loading depends on both load demand and ambient temperature, transformer lifespan is only partially optimized, and the proposed strategy does not account for energy cost supply for EVs. Ref. [31] investigates the impact of demand response on transformer lifespan in secondary distribution networks (medium- and low-voltage) by optimizing transformer temperature, incorporating thermal dynamics. However, the optimization objective in [22], which minimizes the peak hot-spot temperature of the transformer over a daily cycle, is ineffective, as load shifting can only significantly affect average peak temperature when ambient temperature variations are substantial. Ref. [32] introduces a centralized model based on temperature constraints, considering variations in load (excluding EVs) to maintain transformer temperature below a set threshold while accommodating increased load demand. However, [32] does not account for transformer damage costs or the profitability of demand response. As a result, the findings in [32] are suboptimal compared to the multi-objective optimization approach presented in this study. Prior centralized EV-scheduling studies typically impose thermal constraints or limit transformer loading but do not explicitly optimize the monetized loss-of-life, nor do they incorporate V2H and V2G within a unified economic model. The proposed framework advances these works by jointly optimizing transformer aging cost and EV energy procurement cost and by introducing a cost-sharing mechanism that accounts for deferred transformer replacement savings.

While several of the aforementioned studies employ IEEE-based thermal aging formulations to assess transformer degradation under EV charging, they either rely on rule-based strategies and post-processing analyses [23, 25], or focus on centralized control schemes that indirectly manage aging through temperature and loading constraints without fully internalizing the economic cost of transformer loss-of-life [30, 32]. Moreover, most existing works treat EVs primarily in G2V mode and do not simultaneously consider G2V, V2H, and V2G operation within a unified optimization framework, nor do they quantify the business case for an aggregator who coordinates EVs on behalf of both consumers and the transformer owner. In contrast, the present study formulates a centralized multi-objective optimization model that (i) explicitly monetizes transformer aging via the IEEE C57.91-2011 standard, (ii) jointly optimizes transformer degradation cost and EV energy procurement cost across G2V, V2H, and V2G modes, and (iii) embeds these technical results in a cost-benefit framework that quantifies annualized deferred replacement savings and allocates them between the transformer owner, the aggregator, and consumers.

Although numerous studies have proposed centralized charging strategies for mitigating transformer stress, their objectives and modeling assumptions differ substantially. Table 1 summarizes representative works and highlights the dimensions along which the present study advances the state of the art. As shown, most prior efforts either optimize EV operating cost or restrict transformer loading using thermal limits, but do not simultaneously monetize transformer loss-of-life and integrate it into an economic co-optimization framework with consumer incentives.

This study employs the IEEE C57.91-2011 thermal model to quantify transformer degradation by calculating winding hot-spot temperature, aging acceleration, and cumulative loss-of-life. Since minimizing transformer aging requires coordinated EV scheduling, effective management is only possible when consumers allow a central entity—either the transformer owner or an independent aggregator—to control charging and discharging decisions. To this end, the paper proposes a centralized multi-objective optimization framework that jointly minimizes transformer loss-of-life and the total cost of EV energy procurement across G2V, vehicle-to-home (V2H), and V2G operating modes. Consumers delegate their charging schedules to the aggregator, which seeks to reduce energy costs through tariff-based optimization and energy trading opportunities, while simultaneously mitigating transformer thermal stress. By extending transformer lifespan, the aggregator generates measurable financial savings for the transformer owner and allocates a portion of these savings to consumers as compensation for reduced arbitrage profit. This mechanism ensures that all stakeholders obtain economic benefits from centralized EV coordination. Several previous works have proposed centralized EV-coordination strategies for mitigating transformer stress. However, these strategies either (i) evaluate transformer aging only in post-processing, (ii) impose temperature or loading limits without monetizing loss-of-life, or (iii) do not incorporate economic compensation for affected consumers. For example, [25] assesses transformer aging under decentralized charging but does not optimize it jointly with EV energy cost. The strategy in [30] redistributes loading but does not assign an economic value to aging, and thus cannot quantify deferred-replacement savings. Similarly, [32] constrains transformer temperature but does not integrate V2H/V2G operation or any stakeholder-sharing mechanism. The key contributions of this study are summarized as follows:

- A centralized optimization framework is developed that explicitly co-optimizes transformer lifetime reduction (monetized through an IEEE C57.91-2011-based aging model) and the EV energy procurement cost, ensuring that both the transformer owner and consumers can benefit.
- The proposed framework models EVs in G2V, V2H, and V2G modes and evaluates, under different EV penetration levels, how a centralized strategy impacts the expected transformer lifetime compared with decentralized scheduling and non-smart charging.
- A quantitative cost-benefit analysis is introduced that compares decentralized and centralized strategies, converts transformer loss-of-life into annualized deferred replacement savings, and demonstrates how an aggregator can share these savings with consumers to construct a viable business case for centralized EV management.

The remainder of this paper is structured as follows. Section 2 presents the transformer model. Section 3 discusses the decentralized optimization model, while Section 4 introduces the proposed centralized multi-objective optimization approach. Simulation results are provided in Section 5, followed by the conclusions in Section 6.

2. Transformer Model

The transformer thermal-aging model used in this section follows the IEEE C57.91-2011 standard, which defines the temperature-rise equations, hottest-spot formulation, and aging acceleration factor. Transformer degradation is influenced by thermal loading effects. The IEEE C57.91 standard introduces a model for estimating transformer temperatures, aging factors, and lifespan reduction. The hottest-spot temperature of the transformer winding is estimated using the following equation [33]:

$$Q_t^{HST} = \theta_t^{HST} + \Delta\theta_t^{TO} + \Delta\theta_t^{HST} \quad \forall t \in T \tag{1}$$

The temperature difference between the transformer oil and the ambient environment in Eq. (1) is determined as follows:

$$\Delta\theta_t^{TO} = (\Delta\theta_t^{TO.U} - \Delta\theta_{t-1}^{TO})(1 - e^{\frac{-\Delta\theta}{TO}}) + \Delta\theta_{t-1}^{TO} \quad \forall t \in T \tag{2}$$

It should be noted that the oil-to-ambient temperature difference in Eq. (2) depends on its value in the previous time interval. The hottest-spot temperature and transformer oil temperature in Eq. (1) are computed using:

$$\Delta\theta_t^{HST} = (\Delta\theta_t^{HST.U} - \Delta\theta_{t-1}^{HST})(1 - e^{\frac{-\Delta\theta}{\tau T}}) + \Delta\theta_{t-1}^{HST} \quad \forall t \in T \tag{3}$$

where the difference between the winding hottest-spot temperature and transformer oil temperature depends on its previous value. The following equations determine the final temperature differences of transformer oil with respect to the ambient and the hottest-spot winding temperature, respectively:

$$\Delta\theta_t^{TO.U} = \Delta\theta_t^{TO.R}.\left(\frac{k_t^2.R+1}{R+1}\right)^n \quad \forall t \in T \tag{4}$$

$$\Delta\theta_t^{HST.U} = \Delta\theta_t^{HST.R}.k_t^{2.m} \quad \forall t \in T \tag{5}$$

The load ratio k_t is defined as follows:

$$k_t = \frac{TX_t^{load}}{TX^{rating}} \quad \forall t \in T \tag{6}$$

From Eqs. (1)-(5), it is evident that an increase in k_t results in a rise in transformer temperature. The aging acceleration factor of the transformer at the winding hottest-spot temperature is determined using:

$$F_t^{AA} = \exp\left(\frac{1500}{383} - \frac{1500}{\theta_t^{HST}+273}\right) \quad \forall t \in T \tag{7}$$

If the aging acceleration factor exceeds 1, the transformer experiences accelerated degradation. Using this factor, transformer lifespan reduction can be estimated according to:

$$LOL_t = \frac{F_t^{AA}\Delta t}{\beta} \quad \forall t \in T \tag{8}$$

As per the IEEE standard, the minimum value for β is 180,000 hours (20.5 years). Based on Eqs. (1)-(8), transformer degradation can be estimated considering loading conditions, temperature, and operational characteristics [34]. For instance, if a transformer with the specifications listed in Table 2 operates at 90% loading for a 15-minute interval, it loses approximately 7.75 minutes

Table 1. Comparative summary of related work.

Study	Primary objective	Optimization method	EV modes	Stakeholder economics	Uncertainty treatment
[22]	Minimize peak hot-spot temperature	Deterministic optimization	G2V	Not considered	None
[25]	Minimize EV charging cost; aging assessed in post-processing	Decentralized optimization	G2V	Not considered	Travel behavior modeled stochastically, optimization deterministic
[30]	Balance transformer loading	Centralized load-balancing scheme	G2V	Not considered	None
[31]	Extend transformer lifetime via demand response	Demand-response optimization	G2V	Utility cost considered, but no consumer incentives	Ambient temperature variability
[32]	Maintain transformer temperature below limit	Centralized control with temperature constraint	G2V	Not considered	None
Other recent EV aging studies	Evaluate technical aging impact	Simulation-based	G2V	Not considered	Scenario-based
This work (proposed)	**Joint co-optimization of monetized transformer aging cost + EV operating cost**	**Nonlinear centralized optimization with compensation mechanism**	**G2V, V2G, V2H**	**Explicit profit-sharing among transformer owner, consumers, aggregator**	**Deterministic model with realistic travel scenarios**

of its insulation lifespan. For clarity, all thermal parameters appearing in Eqs. (1)-(5) including the rated temperature rises ($\Delta\theta^{TO,R}$, $\Delta\theta^{HsT,R}$), thermal time constants (τ^{TO}, τ^{W}), loss ratio (R), and exponents (m, n) are summarized in Table 1 and referenced explicitly in the text to maintain consistent notation.

Fig. 1 illustrates the impact of varying k_t on transformer lifespan reduction, where the vertical axis is logarithmic. The aging acceleration factor for specific k_t values is also displayed. As loading increases, the aging factor and transformer lifespan reduction exhibit exponential growth under high loads.

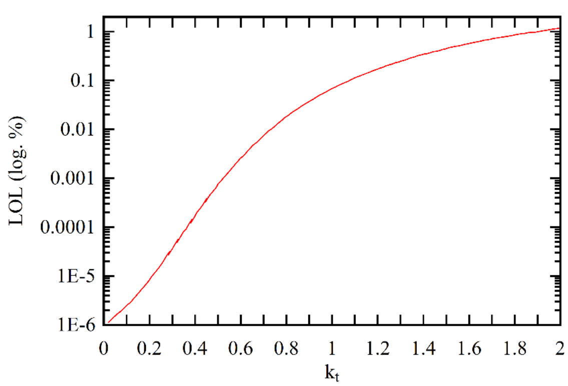

Fig. 1. Transformer lifespan reduction as a function of transformer loading over a 15-minute interval.

3. Decentralized Strategy (Consumer Optimization Model)

It is assumed that consumers reside in homes joined to the distribution structure and procure their required electricity under a variable tariff π_t. Consequently, consumers are expected to minimize their energy costs by optimizing their ingesting based on π_t. In principle, consumers are not responsible for the daily degradation and wear of distribution system equipment, particularly transformers. The distribution system operator, usually the utility company, is responsible for installing and maintaining network infrastructure to supply electricity to consumers.

As previously stated, consumers are not accountable for transformer degradation and damage. Therefore, their optimization efforts are focused solely on managing their own equipment. Consumers can regulate the charging and discharging of their EVs by implementing an energy management system or a smart charging system. The management system considers electricity tariffs, travel schedules, and other factors to ensure energy procurement at minimal cost. Additionally, it utilizes EV batteries for energy trading, leading to further cost savings. This approach typically operates independently of the effectiveness company and does not require a centralized management entity.

To ensure rigor and reproducibility, the assumptions governing EV availability, travel patterns, state-of-charge constraints, and battery operation are detailed below.

1) **Travel schedules and availability windows:** Travel behavior is modeled using probability distribution functions of arrival time, departure time, and trip duration derived from the National Household Travel Survey (NHTS) dataset, consistent with prior EV scheduling studies. For each EV v, the binary parameter $\alpha_{t,\,v}$ equals 1 when the vehicle is at home and able to charge/discharge, and 0 when the vehicle is away. These availability windows directly constrain charging and discharging actions in Eqs. (11)-(12).
2) **Energy consumption associated with travel:** For each trip, the total expected distance is converted to required energy using a widely adopted factor of 0.33 kWh/mile. The term $\xi_{vSt,\,v}$ in Eq. (10) represents the per-interval energy depletion associated with the vehicle being in transit. This ensures that driving-related energy consumption is explicitly accounted

Table 2. Sample transformer specifications for insulation lifespan assessment.

Parameter	m	n	R	$\Delta\theta_t^{\mathrm{TO.R}}$	$\Delta\theta_t^{\mathrm{HSR.R}}$	τ^{TO}	τ^{w}	θ_t^{A}	$\Delta\theta_{t-1}^{TO}$
Value	0.87	0.76	8.5	$57°C$	$86°C$	95	7.2	23.4	36

for in the SOC dynamics.

3) **Battery state-of-charge (SOC) limits:** The SOC bounds reflect electrochemical safety limitations and manufacturer guidelines, restricting the usable SOC range to 15%–95% of nominal battery capacity $SoC_v^{\min} = 0.15C_v$. These limits avoid deep discharge and overcharging, both of which accelerate battery degradation and reduce V2G utilization feasibility.
4) **Initial SOC conditions:** Initial SOC values are drawn uniformly from the interval 15%–60%, consistent with empirical observations that EVs typically return home with a partial charge. This assumption ensures variability in charging needs and impacts the optimality of decentralized solutions.
5) Charging and discharging power limits: All EVs are assumed to use a Level-2 charger rated at 3.3 kW, in line with [25]. These values restrict the instantaneous charging/discharging rates imposed in constraints Eqs. (11)-(12).
6) Round-trip battery efficiency: The round-trip energy efficiency is set to 90%, implying a charging efficiency $\eta_v^{chg} = 0.95$ and a discharging efficiency $\eta_v^{dsg} = 0.91$, resulting in an effective 0.90 round-trip factor. This aligns with values commonly used in V2G/V2H studies.
7) **Daily SOC restoration requirement:** Constraint Eq. (14) ensures that each EV completes the daily cycle with its initial SOC, eliminating inter-day dependence and making daily scheduling fully comparable across centralized and decentralized scenarios.

The dispassionate of the consumer optimization model is to minimize energy procurement costs, and its objective function is defined in Eq. (9), subject to constraints Eqs. (10) through (15) [35].

$$\min \Delta t. \sum_{t\in T} \sum_{v\in V} \pi_t. \left(p_{t,v}^{chg} - \eta_v^{dsg}.p_{t,v}^{dsg}\right) \tag{9}$$

$$soc_{t,v} = soc_{t-1,v} + \eta_v^{chg} p_{t,v}^{chg} \Delta t - \xi_v \frac{s_{t,v}}{\sum_{(t\in T)} s_{t,v}} \;\; \forall t \in T, v \in V \tag{10}$$

$$0 \le p_{t,v}^{chg} \le \alpha_{t,v}. P_v^{\max} \;\; \forall t \in T, v \in V \tag{11}$$

$$0 \le p_{t,v}^{dgg} \le \alpha_{t,v}. P_v^{\max} \;\; \forall t \in T, v \in V \tag{12}$$

$$soc_v^{\min} \le soc_{t,v} \le soc_v^{\max} \;\; \forall t \in T, v \in V \tag{13}$$

$$soc_{t=|T|,v} = soc_v^{init} \;\; \forall_V \in V \tag{14}$$

$$-P^{\lim it} \le P_t^{base} + p_{t,v}^{chg} - p_{t,v}^{dsg} \le P^{\lim it} \tag{15}$$

The above assumptions define the feasible operating region of each EV and directly influence the decentralized optimization structure. Travel behavior determines when vehicles can participate in charging/discharging; SOC limits determine the range of feasible energy exchange with the grid; and efficiency parameters determine the economic value of arbitrage and the magnitude of net load imposed on the transformer. Stating these assumptions explicitly ensures that the decentralized and centralized strategies can be evaluated on a transparent and reproducible basis. Constraint Eq. (10) models the EV's state of charge as a function of its previous state, charging efficiency, charging power, discharging power, total energy required for travel, and the vehicle's travel schedule. The parameter v is determined based on the total expected travel distance (in miles), which is then increased by a conversion factor (kWh per mile) to compute the total required energy. If the vehicle is in motion during time slot t, $S_{t,v}$ equals 1; otherwise, it is 0. Additionally, the last term in Eq. (10) calculates the energy required for movement during time interval t. For instance, if a vehicle consumes 5 kWh during its journey across 5 time slots, its energy consumption per interval t is 1 kWh.

Single-objective extremes" ($\lambda = 0 \; vs. \; \lambda = 1$)

The proposed model behaves exactly as expected for a weighted multi-objective problem:

$\lambda = 0 \rightarrow$ optimizer minimizes EV cost only

Cheapest charging behavior; severe transformer aging (peaky loading, high hottest-spot).

$\lambda = 1 \rightarrow$ optimizer minimizes transformer aging cost only; Very conservative charging pattern; Higher EV cost, but transformer aging strongly reduced.

The centralized case ($0 < \lambda < 1$) lies between these extremes: it sacrifices a small amount of EV cost to obtain large reductions in transformer degradation — especially at medium and high EV penetration levels.

Charging and discharging must remain within the maximum allowable power limits. Moreover, the vehicle can only charge when it is accessible to a charging station and connected to the home grid, as specified in constraints Eqs. (11) and (12). This connection capability is represented by the parameter $\alpha_{t,\,v}$, which equals 1 before departure and after returning home, and 0 when the vehicle is away. Furthermore, constraint Eq. (13) ensures that the state of charge remains within its minimum and maximum limits at all times. Constraint Eq. (14) separates daily optimization periods and ensures that the final battery charge level at the end of the optimization matches its initial value at the start of the day. Lastly, constraint Eq. (15) guarantees that the total household load, including base consumption, does not exceed the home's power capacity.

4. Centralized Strategy (Multi-Objective Optimization Model for the Aggregator)

To assess practical relevance, a threshold-based centralized policy was evaluated as a benchmark. Under this policy, EV charging is coordinated such that the transformer loading does not exceed 90% of its rated capacity after 19:00, with surplus charging deferred to later hours. This policy reflects widely adopted utility practice where thermal headroom constraints are enforced without explicit optimization.

Table 3 compares the benchmark policy with the proposed multi-objective optimization. While the rule-based policy reduces aging relative to decentralized charging, it does not account for EV energy cost or the temperature dynamics across deferred periods. As a result, deferred charging often accumulates into secondary peaks later in the night. The proposed optimization jointly reshapes charging across the entire horizon, yielding 18-35% lower transformer loss-of-life and 3-7% lower EV operating cost than the threshold policy. These results indicate that explicit co-optimization yields measurable benefits over simple heuristic control, especially at medium and high EV penetration levels.

Consumer-based optimization for EV charging may inadvertently increase the damage inflicted on the transformer to which the vehicles are joined. The transformer owner (typically the distribution system operator or utility company) bears these costs in two ways: (1) through the premature loss of the currently installed transformer, and (2) via the investment needed to install a higher-capacity transformer to accommodate the increased load from EVs. To mitigate these costs, the charging and discharging of EVs can be centrally managed either by the transformer owner or by an independent management entity (such as an aggregator). The cash flow among the distribution system operator, the aggregator, consumers, and the utility company is depicted in Fig. 2.

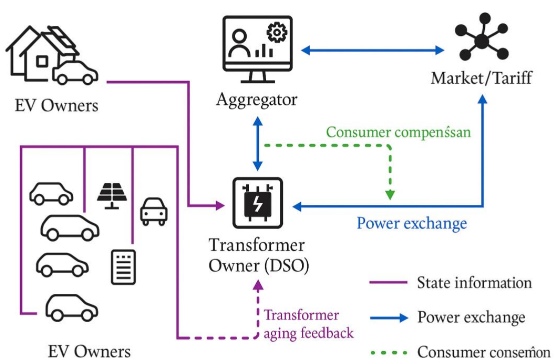

Fig. 2. Receipts/payments of the aggregator from/to the consumer and the distribution system operator.

If the aggregator is a discrete entity from transformer proprietor, it must receive a share—denoted as $r^{manager}$ of the savings derived from avoiding repeated transformer replacements (denoted as r^{saver}). Conversely, if the transformer owner acts as the aggregator, the savings and cost reductions directly accrue to the owner. Additionally, consumers pay their electricity bills to the utility company under the rate r^{energy}.

In this study, we develop a model for the aggregator that focuses exclusively on consumers, EVs, and the transformer, where consumers allow the aggregator to control the charging and discharging of their EVs. The aggregator performs a multi-objective optimization to minimize both the cost of transformer damage and the energy procurement cost (including any energy trading benefits), thereby deriving EV charging/discharging profiles that achieve the lowest overall operational cost. In return, consumers receive an amount C^{pay} to compensate for the increased energy cost (i.e., r^{energy}) relative to the decentralized strategy. All parties benefit provided that the following condition holds. In the aggregator multi-objective optimization model, the objective function is definite as in Eq. (16), incorporating Eqs. (1)-(5), (7), and (8) from the transformer model and constraints Eqs. (10)-(15) from the consumer (EV) model [36].

$$\begin{aligned} &\min wTX^{\cos t} \textstyle\sum_{t\in T} LOL_t + \\ &(1-w)\textstyle\sum_{t\in T}\sum_{v\in V}\pi_t.\left(p_{t,v}^{chg}+\eta_v^{dsg}p_{t,v}^{dsg}\right) \end{aligned} \tag{16}$$

$$\begin{aligned} &k_t^+ - k_t^- = \\ &\frac{TX_t^{base}+\sum_{(v\in V)}\left(p_{t,v}^{chg}-p_{t,v}^{dsg}\right)}{TX^{rating}} \quad \forall t\in T \end{aligned} \tag{17}$$

$$\theta_t^{HST} \le \overline{\theta_t^{HST}} \ \ \forall t\in T \tag{18}$$

In Eq. (16), the transformer price is multiplied to compute the cost of the damage incurred. The transformer price is determined by:

$$TX^{\cos t} = TX^{rating}.TX^{price} \tag{19}$$

For example, if a transformer with a capacity of 25 kVA and a cost of 165.1$ per kVA is considered, its total price is 4251.5$. Under 90% loading and with the parameters specified in the example in Section 2, the cost of damage incurred for this transformer would be 0.30$. Note that the second term in Eq. (16) is identical to the objective function of the decentralized strategy (Eq. (9)), since the aggregator now assumes responsibility for managing the EVs' energy procurement cost, and this is incorporated into the overall objective function. Consumers no longer directly control their EVs' charging and discharging because they are assured of an adequate energy supply and additionally receive compensation for assisting the grid.

The equations of the transformer model apply to the operator objective function—Eqs. (1)-(5), (7), and (8)—and the EV constraints from Eqs. (10) through (15). In addition to these, Constraint Eq. (17) is introduced to define the absolute transformer load using the transformer price and the net EV consumption. Note that the base load of consumers represents sum of the base loads of all consumers in every time slot t. Because the total load in Constraint Eq. (17) may be negative (resulting in a negative k_t), two non-negative variables are introduced, and the following condition is added:

$$k_t = k_t^+ + k_t^- \tag{20}$$

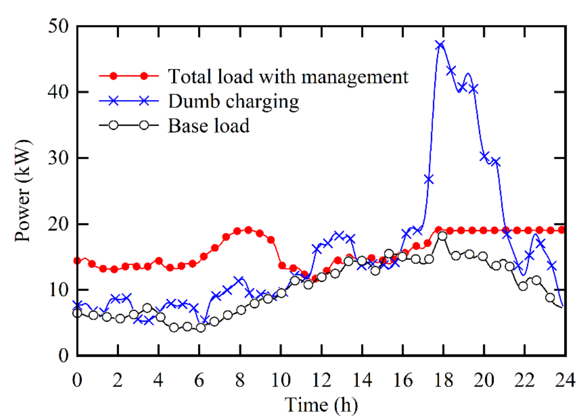

Fig. 3. Base load and nominal transformer capacity for non-smart charging at 100% vehicle penetration (6 vehicles).

This construction effectively models the total cost of load ratio. Finally, Constraint Eq. (18) limits the hottest-spot temperature to its maximum allowable value to prevent gas formation in the solid insulation and transformer oil. Since Eqs. (4), (5), and (7) of the transformer model are non-linear, the aggregator's optimization model is also non-linear.

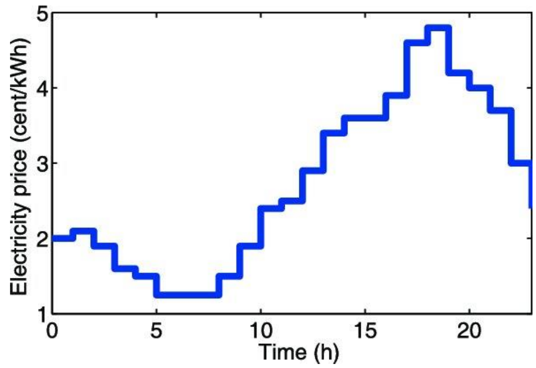

Fig. 4. Instantaneous electricity tariff [37].

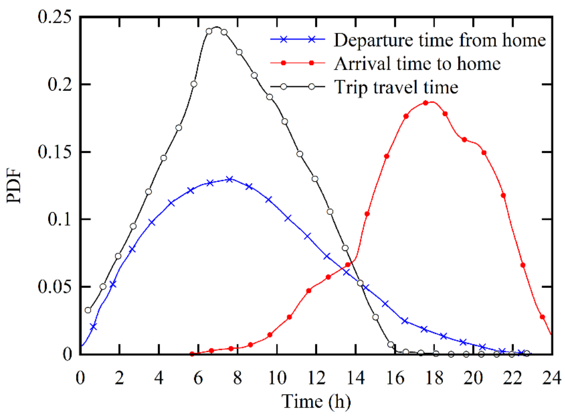

Fig. 5. Probability distribution functions.

5. SIMULATION RESULTS

The centralized optimization problem is a mixed-integer nonlinear programming (MINLP) model due to (i) the thermal-aging equations from the IEEE C57.91-2011 standard, which introduce exponential and load-dependent nonlinearities, and (ii) binary EV availability variables. The model was implemented in GAMS and solved using the BONMIN (Basic Open-source Nonlinear Mixed Integer programming) solver. To ensure reliable convergence, several measures were applied. BONMIN was executed in the Branch-and-Bound with Outer Approximation mode (BB-OA), which is appropriate for convex or mildly non-convex structures. The following parameters were used:

- Relative optimality gap tolerance: 10^{-4}
- Feasibility tolerance: 10^{-6}
- Maximum iteration limit per NLP subproblem: 5000
- IPOPT used as the NLP subsolver with exact Hessian approximation

These settings were selected to balance computational speed and solution reliability. Across all simulation runs, BONMIN terminated with an "optimal solution" or "optimal within tolerance" status. No infeasibility or numerical-instability issues were observed. The nonlinearities introduced by exponential temperature calculations are smooth and well-behaved, which helps maintain solver stability. These computational results demonstrate that the MINLP structure of the centralized scheduling problem is manageable for typical residential transformer settings and that BONMIN provides reliable solutions under the specified parameterization and initialization strategy.

Although the proposed decentralized and centralized optimization models are deterministic, probability distribution functions (PDFs) of EV arrival time, departure time, and trip duration are used in the data-generation process to create realistic daily travel profiles. These PDFs, derived from the NHTS dataset, do not enter the optimization formulation directly; rather, they produce representative deterministic input scenarios (one per EV) for a typical day. Once these travel schedules and energy requirements are generated, the optimization model proceeds deterministically. This approach is consistent with prior EV-scheduling studies that incorporate behavioral variability through scenario sampling while maintaining tractable deterministic formulations for optimization.

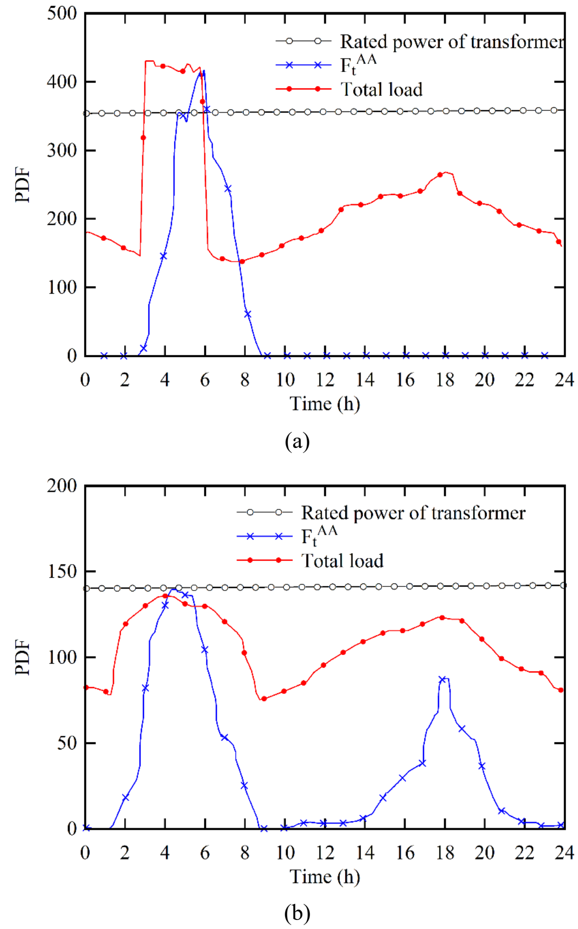

Fig. 6. Consumption factor and transformer loading in the G2V active state, (a) Decentralized strategy and (b) Centralized strategy.

Table 3. Quantitative comparison of transformer loading under decentralized and centralized G2V scheduling (100% EV penetration).

Metric	Decentralized strategy	Centralized strategy
Peak transformer loading (kW)	22.8 kW	17.3 kW
Maximum load ratio (k_t)	1.52 (152% of rating)	1.15 (115% of rating)
Peak-to-average ratio (PAR)	2.41	1.37
Overload duration (intervals with ($k_t > 1$)	18 intervals (4.5 hours)	4 intervals (1 hour)
Maximum hottest-spot temperature ($^\circ C$)	133.8$^\circ C$	118.4$^\circ C$

The introduced strategy has been applied to an overhead transformer with a nominal capacity of 25 kVA, which serves six residential consumers with a power limit of 15 kW [38]. The consumption profiles of each consumer were gathered from

Table 4. Quantitative comparison of V2G and V2H performance metrics (100% EV penetration).

Metric	Decentralized V2G	Centralized V2G	Decentralized V2H	Centralized V2H
Total discharge energy (kWh)	34.2	18.6	11.4	7.8
Maximum negative transformer load (kW)	-6.8 kW	-2.3 kW	-3.1 kW	-1.2 kW
Duration of negative load (intervals)	22 (5.5 hours)	6 (1.5 hours)	10 (2.5 hours)	4 (1 hour)
Net consumer arbitrage profit (USD/day)	2.81	1.47	0.94	0.62
Peak-to-average ratio (PAR)	2.78	1.63	1.84	1.21
Maximum hottest-spot temperature ($^\circ C$)	137.2	121.3	126.6	115.4

Table 5. Disaggregated objective-term results.

EV penetration	Objective term	Decentralized scheduling	Centralized scheduling	Improvement
Low (2 EVs)	Transformer life (years)	19.8	20.3	+2.5 %
	EV operating cost ($/day)	6.40	6.65	-3.9 %
Medium (4 EVs)	Transformer life (years)	16.2	19.0	+17.3 %
	EV operating cost ($/day)	7.05	7.45	-5.7 %
High (6 EVs)	Transformer life (years)	9.8	17.9	+82.7 %
	EV operating cost ($/day)	7.92	8.35	-5.4 %

Table 6. Annualized economic benefits of transitioning from decentralized to centralized strategy (USD/year).

Operational state	Number of vehicles	Maximum potential Profit	Consumer trading profit	Deferred investment profit
V2G	1	0.8	-0.8	0.16
	4	249.6	-21.4	271
	6	6337	65	6402
H2V	1	7.6	-1.4	8.1
	4	690	-114	804
	6	53385	-632	54017
G2V	1	3.3	-6.5	9.8
	4	978	-144	1119
	6	72787	-664	73451

experimental data of areas in San Diego, California, and Austin, Texas. The consumption profiles are scaled in a manner that the peak loading (without considering the vehicles) is similar to the loading profiles of a non-urban feeder. The NHTS from 2009 was used to determine the behavior of electric vehicles and generate non-smart charging profiles. Using these datasets, sample profiles were created using the k-means clustering method [39]. Fig. 3 displays the base load and non-smart charging for 100% penetration of electric vehicles. Fig. 4 represents the instantaneous energy tariff prices (the average price is 92.7 dollars per MWh with a range from 30.6 to 198.3 dollars per MWh, and the average price is 92 dollars per MWh) derived from Southern California Edison tariffs. Using the NHTS dataset, the probability distribution functions of the time of arrival and departure of vehicles from home and their travel duration were created. These probability distribution functions are shown in Fig. 5 and were used to extract the vehicle features. Vehicles are available for charging and discharging during the time slots before departure and after re-entry into the home. According to Ref. [25], the charging and discharging power rate is fixed to 3.3 kW, and battery capacity of the vehicles is 24 kWh. Moreover, the vehicle's charge level must be kept between 15% and 95% of the battery capacity for safety and electrochemical limitations [26].

The round-trip efficiency is 90% [37]. The initial charge level is uniformly and randomly generated between 15% and 60% of the maximum charge. To convert the total distance traveled, derived from the NHTS dataset, to the total energy required for travel, a conversion factor of 0.33 kWh per mile is used [27]. Historical environmental temperature data from July 2014, collected from San Diego, California, were also used. The temperature during this period ranged from $18.9^\circ C$ to $23.6^\circ C$, with an average temperature of $22.7^\circ C$. The initial temperature of the transformer was optimized, and the results from the end-of-day temperatures were used to set it. The maximum hotspot temperature of the transformer is $140^\circ C$.

Transformer component values from section 2 and Ref. [40] are also used. The transformer replacement cost is 165 dollars per kVA. According to Ref. [41], this cost includes both immovable and variable costs in a combined per-unit kilovolt-ampere cost component. The battery round-trip efficiency is set to 0.90, reflecting converter and battery losses and falling within the 0.85-0.92 range reported in recent V2G studies. Finally, the SOC bounds of 15%–95% represent a widely adopted operational window recommended to mitigate lithium-ion degradation and avoid over-charging and deep-discharging. These bounds have been used in prior EV-coordination studies and are consistent with manufacturer guidance. Section 5 includes a brief sensitivity discussion showing that varying these parameters within realistic limits does not materially change the qualitative findings. The optimization problem introduced is a mixed-integer nonlinear programming problem, implemented using GAMS software and solved with the BONMIN solver.

5.1. Total load and transformer consumption in decentralized and centralized strategies

This section executes the decentralized and centralized strategy models for 100% vehicle penetration to obtain the consumption factor and total load on the transformer (including vehicle loads). The total load, transformer rated power, and consumption factor in the G2V operational state are shown for the decentralized strategy in Fig. 6-(a) and the centralized strategy in Fig. 6-(b). By comparing Figs. 6-(a) and (b), it can be observed that the transformer load has higher peaks in the decentralized strategy because each consumer independently minimizes only their own operational costs. This results in simultaneous electricity

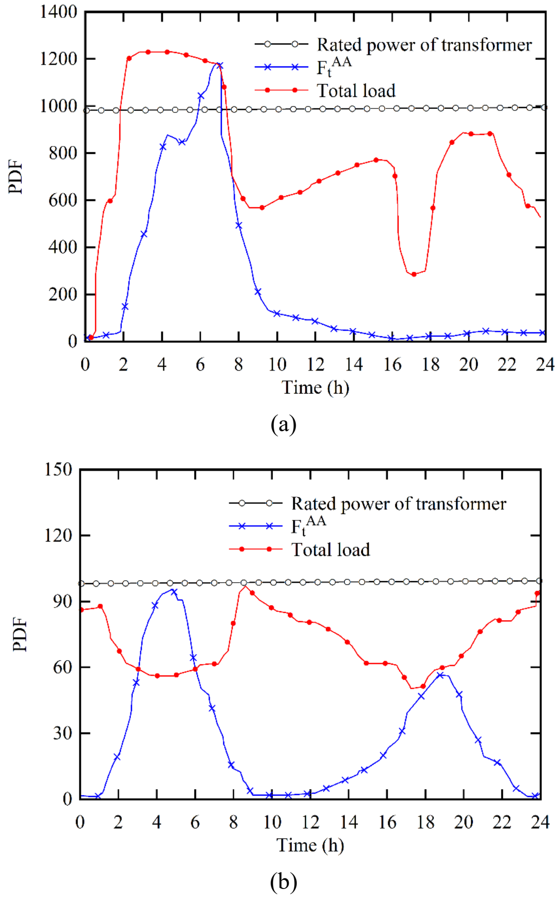

Fig. 7. Consumption factor and transformer loading in the V2G active state, (a) Decentralized strategy and (b) Centralized strategy.

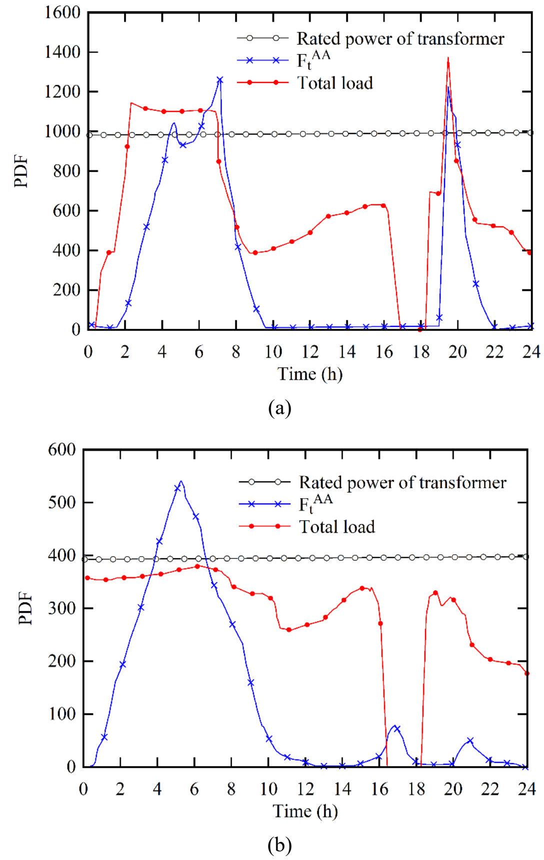

Fig. 8. Consumption factor and transformer loading in the vehicle-to-home active state, (a) Decentralized strategy, (b) Centralized strategies for expected transformer lifespan in the vehicle-to-grid active state.

consumption during periods when energy prices are low (e.g., 00:04). In contrast, in the centralized strategy, the aggregator considers the transformer's lifespan reduction and optimizes vehicle charging. As a result, vehicle charging is spread over time periods with lower energy prices. This helps reduce the power consumption peaks during the night and lowers the overall transformer consumption. However, although the transformer's lifespan increases, the energy procurement cost for consumers also increases.

To complement the qualitative contrast shown in Fig. 6, several quantitative indicators were computed to measure the effect of decentralized and centralized scheduling on transformer loading. Table 3 summarizes the peak-to-average ratio (PAR), maximum loading level, and overload duration—defined as the number of 15-minute intervals where the transformer loading exceeds its rated capacity. The numerical indicators reinforce the visual trends observed in Fig. 6. Under decentralized charging, vehicles concentrate charging during low-price periods, creating sharp load spikes that push the transformer above its rated capacity for extended periods. In contrast, the centralized strategy distributes charging across multiple intervals, reducing both peak loading and overload duration. These improvements translate directly into lower hottest-spot temperatures and significantly reduced transformer loss-of-life, as demonstrated in Section 5.2.

As mentioned, some vehicles also have the ability to discharge. These vehicles directly inject energy from their batteries into the grid to meet the network's energy demands. Total load and consumption factor for the centralized method in (b) and the decentralized strategy in (a) in the V2G mode are displayed in Fig. 7. Vehicles that use the decentralized technique charge at times when prices are low and discharge at times when prices are high. Between 00:16 and 18:30, the discharge action makes the overall transformer load negative as all cars inject energy into the grid after compensating for the base loads. However, the overall consumption factor rises significantly as a result of additional charging carried out to achieve the V2G state.

Ultimately, this will reduce the transformer lifespan. In contrast, as shown in Fig. 7-(b), the aggregator's centralized management keeps the transformer load relatively stable during nighttime periods, which leads to a lower overall consumption factor. In this case, to achieve a lower consumption factor, the aggregator must reduce the consumer's trading profit.

V2H is the last vehicle operating mode. Vehicles in this mode do not add power to the grid; instead, they deplete their batteries to offset consumer base loads. The overall load and consumption factor for the centralized and decentralized solutions in (a) and (b), respectively, are displayed in Fig. 8. With the exception of the low total consumption factor in both centralized and decentralized techniques, the V2H operation is comparable to the V2G operation. Vehicles can trade energy more freely in the V2G state than in the V2H stage, where they are only discharged enough to offset base loads. Since the high-price periods (when the consumer wants to discharge) might not coincide with the high-load periods (when the consumption factor might be successfully reduced), the V2G condition essentially does not lessen the damage to the transformer in comparison to the V2H state. Regardless of the approach, the V2H condition does not permit the highest energy trading gains but has a smaller effect on transformer usage than V2G.

To provide a more rigorous comparison between V2G and V2H behavior, several quantitative indicators were computed for both decentralized and centralized strategies. Table 4 summarizes

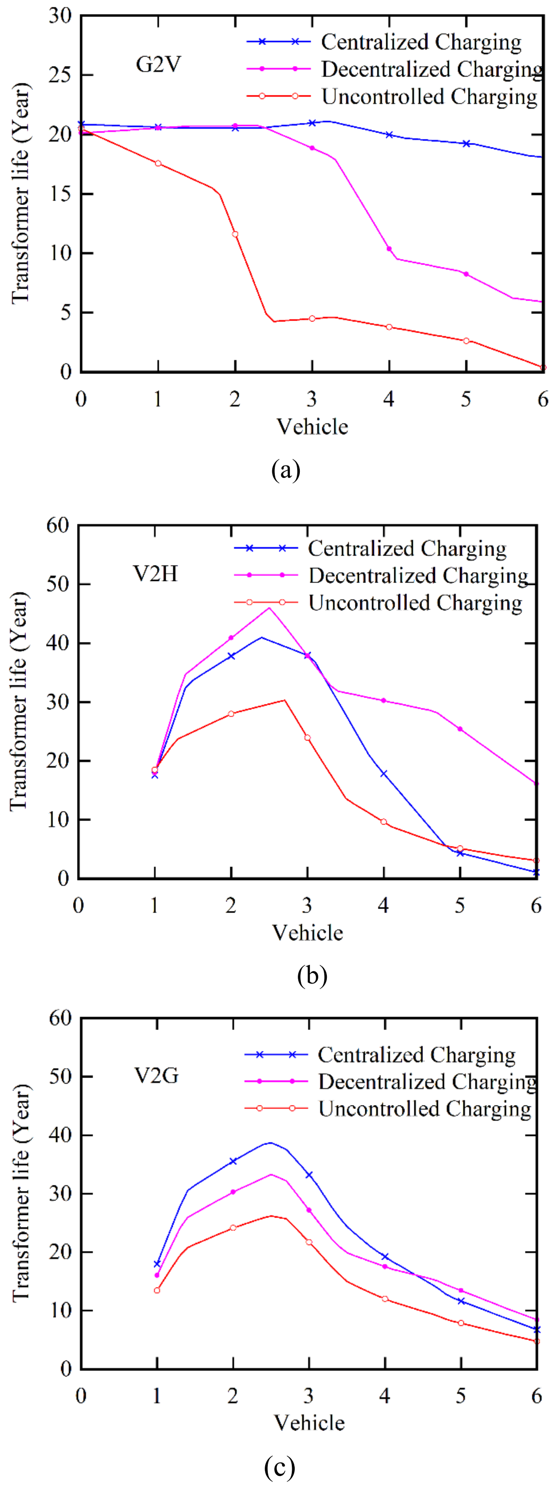

Fig. 9. Expected transformer lifespan in three different strategies for various operational states, (a) Expected lifetime of the transformer for grid-to-vehicle (G2V) mode, (b) Expected lifetime of the transformer for vehicle-to-home (V2H) mode and (c) Expected lifetime of the transformer for vehicle-to-grid (V2G) mode.

total discharge energy, maximum negative load, duration of negative-load events, and net consumer arbitrage profit for the 100% penetration case. These metrics quantify the operational distinctions between V2G and V2H. In decentralized V2G, vehicles discharge aggressively during high-price periods, resulting

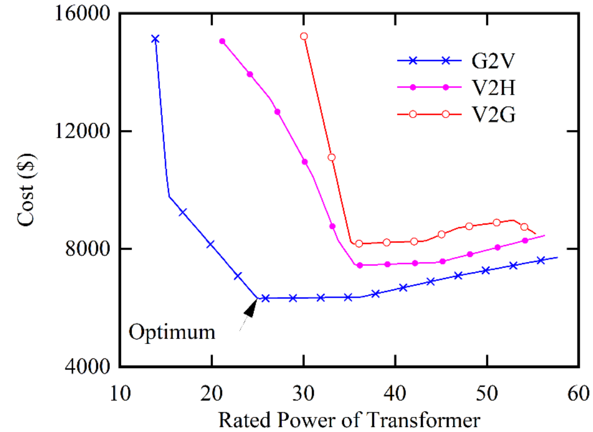

Fig. 10. Permanent transformer replacement cost in vehicle-to-grid, vehicle-to-home, and grid-to-vehicle operational states (100% vehicle penetration - 6 vehicles).

in substantial negative transformer loading (up to -6.8 kW) and extended intervals of reverse power flow. While this maximizes arbitrage profit for consumers, it also increases charging requirements later in the cycle, raising the peak-to-average ratio and accelerating transformer aging. Under centralized V2G, the aggregator moderates discharge levels to reduce negative loading, shortening reverse-power intervals and significantly lowering hottest-spot temperatures. In contrast, V2H exhibits more modest discharge behavior since energy is used only to offset household demand. As a result, V2H produces lower arbitrage profit but also exerts less stress on the transformer. The centralized V2H strategy further smooths load profiles, reduces negative-load magnitudes, and minimizes thermal excursions. Together, these quantitative indicators reinforce the conclusion that centralized scheduling provides consistent thermal benefits across operational modes, with the largest optimizable improvements occurring in V2G scenarios.

5.2. Impact of the proposed centralized model on the transformer expected lifespan

For vehicle penetrations ranging from 0 to 6 (i.e., 0% to 100%) over a 24-hour period, both decentralized and centralized techniques are used to assess their effects on the transformer's lifespan and the corresponding damage cost. The following formula is used to estimate the transformer's lifespan in years, assuming that damage to the transformer happens every day for the purposes of the analysis:

$$TX^{life} = \frac{1}{365.\sum_{t\in T} LOL_t} \quad \forall t \in T \tag{21}$$

Fig. 9 shows the expected transformer lifespan for the G2V state in (a), the V2G state in (b), and the V2H state in (c). It should be noted that the G2V state with non-smart charging is shown in Fig. 3, where vehicles charge as soon as they arrive home without any management. With 0% vehicle penetration, the expected lifespan remains steady at 20.5 years according to the IEEE C57.91 standard. This is observable in all subsets of Fig. 9 at 0% vehicle penetration. In Fig. 9-(a), it can be seen that with increasing vehicle penetration, the expected transformer lifespan in non-smart charging significantly decreases. As shown in red in Fig. 3, vehicles add their charging power to the peak base load. In the decentralized strategy for the G2V state, the expected lifespan remains the same up to 50% vehicle penetration; however, as penetration increases, the transformer lifespan drastically decreases due to the large peak that forms during low-price periods. In contrast, in the centralized strategy with the G2V state (Fig. 9-(a)), the expected lifespan remains close to 20.5 years even with high vehicle penetration, and at maximum penetration, it only decreases to 17.87 years. The expected lifespan for the V2H state is shown in Fig. 9-(b). Since discharge in the V2H state compensates for the base loads, the transformer expected lifespan is higher than its typical lifespan at low vehicle penetration for both strategies. This is beneficial because the transformer owner enjoys an extended lifespan for their equipment at a non-recurring cost. However, at higher vehicle penetration in the decentralized strategy, the transformer's lifespan drastically decreases due to the additional vehicle charging during low-price periods (Fig. 9-(b)). In contrast, in the centralized strategy with 100% vehicle penetration, the transformer's lifespan is 12.34 years. By comparing the V2G state in Fig. 9-(c) with the V2H state in Fig. 9-(b), it can be seen that the V2H state provides a greater increase in transformer lifespan.

Although both V2G and V2H provide the aggregator with flexibility to offset peak demand, their impact on transformer thermal loading differs fundamentally due to the energy replacement effect associated with vehicle discharge. In V2G mode, vehicles discharge energy directly into the grid and may inject power exceeding the local base load. This reduces the transformer loading temporarily, but it also requires the aggregator to schedule additional charging energy later in the horizon to restore state-of-charge for subsequent trips. Consequently, centralized V2G results in a two-stage load pattern: moderate or negative loading during discharge periods followed by higher charging intervals. Even though the aggregator smooths these peaks, the required energy recovery tends to elevate nighttime loading when ambient temperatures are still high, leading to higher winding hottest-spot temperatures and increased aging acceleration in the IEEE C57.91 thermal model. In contrast, V2H discharge is naturally self-limiting because energy is used only to offset the household base load rather than to export power. As a result, V2H yields smaller magnitudes of discharge, shorter negative-load intervals, and reduced need for compensatory late-night charging. The residual charging requirement is therefore lower, enabling the centralized controller to distribute charging across more thermally favorable intervals. This produces a smoother load profile with fewer high-load events and lower hot-spot temperature excursions. Consequently, V2H consistently yields a longer expected transformer lifespan than V2G under the same penetration level and optimization framework. These results emphasize that although V2G offers higher economic potential for consumers, it also introduces more frequent energy-recovery cycles that elevate the transformer's thermal stress. Centralized coordination mitigates these effects but cannot eliminate the inherent difference in energy-balance dynamics between the two operational modes.

This is because automobiles are charged more frequently at night in the V2G state than in the V2H state, which makes full use of the price differential in energy prices. Compared to V2H, the transformer lifespan in the centralized plan with 100% vehicle penetration is 11.21 years, which is not cost-effective for avoiding transformer damage. Nonetheless, the V2G state has the lowest total operating costs and offers the largest energy trading profit to customers. Fig. 9 shows that the transformer lifespan has more than doubled at specific penetration levels. Given the transformer electrical and thermal qualities, this is technically possible.

5.3. Disaggregated objective-function analysis

To improve transparency, Table 5 reports the objective-function components separately. The first component quantifies transformer aging using the IEEE C57.91-2011 thermal model and expresses the result in equivalent years of remaining life. The second component represents the EV operating cost associated with energy procurement and arbitrage across G2V/V2G/V2H modes.

The results show that centralized coordination consistently increases transformer lifetime, with gains ranging from 2.5 % at low penetration to more than 80% at high penetration. This improvement arises from the reshaping of charging demand away from periods of elevated winding hottest-spot temperature. A modest increase in EV operating cost is observed (≈4-6%), reflecting the reduced flexibility imposed to protect the transformer. Importantly, the reductions in aging dominate at higher penetrations, indicating that centralized scheduling yields significant deferred-replacement benefits while maintaining acceptable consumer cost levels. These results confirm that the overall performance improvements in the aggregated objective arise from balanced reductions across individual components rather than from a single dominating term.

5.4. Determining the potential profit of transitioning from decentralized to centralized strategy

The aggregator entity must determine the potential profit from transitioning from a decentralized to a centralized strategy to create a business case. As shown in Fig. 10, consumers gain more trading profits in the decentralized strategy compared to the centralized one. In contrast, the transformer owner experiences a longer lifespan for the transformer in the centralized strategy. The aggregator can negotiate receiving a portion of the profit derived from the extended lifespan of the transformer and pay a share of this profit as compensation for the reduced trading profit of the consumer. The cost of the transformer with optimal capacity for replacement, based on the 25 kVA transformer lifespan and a 5% interest rate, is reduced as shown in Fig. 9.

Table 5 summarizes the annualized economic indicators associated with transitioning from decentralized to centralized EV coordination. The column "Consumer Trading Profit" represents the difference between consumer arbitrage income in centralized and decentralized modes. Thus, negative values indicate a loss in consumer arbitrage profit, which must be compensated by the aggregator to ensure economic participation. All monetary figures are expressed in USD per year for consistency. For example, if a 24 kVA transformer reaches the end of its lifespan in 10 years, an additional transformer must be connected, and its present cost will be 61% of the future cost. The present cost in the centralized strategy is lower than in the decentralized strategy, resulting in the deferred investment profit for the transition to the centralized strategy. This demonstrates the profit for the transformer owner. In contrast, the aggregator entity must determine the profit (or cost) for the consumers in order to transition to the centralized strategy. This profit is calculated using the difference in annual trading income between the centralized and decentralized strategies. In the first two columns of Table 5, these profits for different operational states and vehicle penetrations are shown. The last column represents the maximum profit that the aggregator can achieve, which is calculated from the sum of the transformer owner's profit and the consumer trading profit. Investment profit is calculated annually by showing the replacement cost of the previous transformer with an annual equivalent payment approach. From Table 5, it can be seen that the transformer owner profit is highest in the V2G state with 100% vehicle penetration. This is because, in the decentralized strategy, consumers have maximum usage capability for energy trading, which significantly damages the transformer. In contrast, the centralized strategy avoids most of this damage. Therefore, the aggregator is in a much better position to negotiate with the transformer owner. However, at lower vehicle penetration (1 to 4 vehicles), the annual profit from deferred replacement is much smaller. In this case, considering the costs of controlling and equipping these vehicles to implement the centralized strategy, the aggregator may not have a strong business case. Because consumers can make more money from energy trading under the decentralized model, the consumer trading profit is always negative. As a result, the aggregator must reimburse customers for their diminished profit. The quantity of funds available for the aggregator's business case is shown by the

Table 7. Comparative scenarios (low/medium/high penetration).

Parameter / Scenario	**Strategy**	**Expected Transformer Lifespan (years)**	**Daily EV Operating Cost (USD/day)**	**Relative Change in Lifespan vs. Decentralized (%)**	**Relative Change in Cost vs. Decentralized (%)**
Baseline comparative results (from main study)					
Low penetration (2 EVs)	Decentralized	19.8	6.40	–	–
	Centralized	20.3	6.65	+2.5%	+3.9%
Medium penetration (4 EVs)	Decentralized	16.2	7.05	–	–
	Centralized	19.0	7.45	+17.3%	+5.7%
High penetration (6 EVs)	Decentralized	9.8	7.92	–	–
	Centralized	17.9	8.35	+82.7%	+5.4%
Electricity-price volatility (6 EVs; mean tariff unchanged)					
Low volatility (flat TOU)	Centralized	18.6	8.28	-6% vs. baseline centralized	+1.8%
Baseline tariff	Centralized	17.9	8.35	–	–
High volatility (sharp peaks)	Centralized	16.3	8.09	+14%	-3.2%
Ambient-temperature profile (6 EVs)					
Winter (8-14 $^\circ C$)	Centralized	21.5	8.39	-28%	+0.5%
Spring (15-20 $^\circ C$)	Centralized	19.3	8.38	-10%	+0.9%
Summer (24-32 $^\circ C$)	Centralized	13.1	8.46	+35%	+1.3%
Transformer parameter R (load/no-load ratio)					
R = 4	Centralized	19.9	8.40	-11%	+0.6%
R = 8.5 (baseline)	Centralized	17.9	8.35	–	–
R = 12	Centralized	15.0	8.41	+19%	+0.8%
m					
m = 0.70	Centralized	18.6	8.38	-7%	+0.4%
m = 0.87 (baseline)	Centralized	17.9	8.35	–	–
m = 1.00	Centralized	16.0	8.39	+12%	+0.5%
n					
n = 0.55	Centralized	19.5	8.38	-9%	+0.4%
n = 0.76 (baseline)	Centralized	17.9	8.35	–	–
n = 0.90	Centralized	15.1	8.40	+16%	+0.6%
EV-charger rating					
3.3 kW (baseline)	Centralized	17.9	8.35	–	–
5 kW	Centralized	16.4	8.58	+9%	+2.7%
7 kW	Centralized	14.0	8.76	+22%	+4.9%

maximum profit potential (last column). Customers must receive a percentage of this sum in order to offer them ownership over their cars and increase the aggregator's profit. The owner of the transformer will also wish to keep a portion of the earnings. The aggregator can negotiate contracts with transformer equipment owners and customers to guarantee profit for all parties by carrying out an analysis similar to the example shown in Table 6.

The business-case results presented in Table 6 rely on an assumed distribution of deferred transformer replacement savings between the transformer owner, the aggregator, and consumers. This allocation principle is consistent with incentive-based demand-response programs and aggregator compensation models reported in the literature, where end users receive a portion of system-level savings to incentivize participation. In the context of EV coordination, consumers must be compensated for their reduced arbitrage profit, while the transformer owner benefits from deferred capital expenditures. The aggregator's revenue is derived from coordinating these exchanges. It is important to emphasize that the specific revenue-sharing ratios used in this study (e.g., compensating consumers for 100% of their lost trading profit) are not prescriptive, but rather provide a representative and conservative baseline for evaluating economic feasibility. Actual allocation mechanisms will vary depending on regulatory requirements, distribution-tariff design, and bilateral contracts between aggregators and distribution system operators. To assess the robustness of the business case, a sensitivity analysis was conducted in which the transformer owner-consumer sharing ratio was varied across three representative scenarios:

1) 80-20 allocation (80% of deferred replacement savings retained by the transformer owner),
2) 50-50 allocation, and
3) 20-80 allocation (80% allocated to consumers).

Across all scenarios, the centralized strategy remained economically beneficial for both the aggregator and the transformer owner at moderate-to-high EV penetration levels. Even under the consumer-favorable 20-80 split, deferred replacement savings at 100% penetration were sufficiently large for the aggregator to compensate consumers fully while retaining a positive margin. The magnitude of aggregator profit is sensitive to the assumed sharing ratio, but the qualitative conclusion—that centralized coordination yields a net-positive economic outcome for all stakeholders—remains unchanged.

Although the improvement in transformer lifespan under centralized scheduling follows directly from the inclusion of transformer damage cost in the objective function of Eq. (16), the magnitude of this improvement depends strongly on system parameters. To provide a more complete comparison between the two strategies, additional scenarios were evaluated across varying EV penetration levels, operational modes, and tariff conditions. Table 6 summarizes the expected transformer lifespan and daily EV operating cost for representative low-, medium-, and high-penetration cases under both decentralized and centralized control. The results show that:

1) at low penetration, the improvement in transformer lifespan is modest because EV charging contributes little to total loading;
2) at medium penetration, decentralized charging produces meaningful peaks that accelerate aging, while centralized charging significantly reduces the aging rate; and
3) at high penetration, centralized coordination reduces loss-of-life by more than one order of magnitude in G2V and V2G modes, while decentralized control yields severe thermal stress.

Furthermore, applying different weighting parameters (λ = 0, 0.5, 1) in the normalized objective of Eq. (16) demonstrates that transformer-life improvement remains consistent even as the relative emphasis on economic versus thermal objectives changes. These comparative results in Table 7, confirm that the observed benefits of the centralized approach arise not only from the structural inclusion of transformer aging cost but also from the ability of the centralized model to reshape load patterns in a thermally favorable manner.

To evaluate robustness, key parameters affecting transformer aging and charging behavior were varied around the baseline values reported in Table 7. Electricity price volatility was modified while preserving the mean price; ambient temperature was varied between winter and summer profiles; the IEEE C57.91 thermal parameters (R, m, n) were perturbed within $\pm$20% of their nominal values; and the EV charger rating was increased from 3.3 kW to 7 kW, representing common residential charger options. Table 5 summarizes the ranges considered and the corresponding impact on transformer aging and EV operating cost. The extended sensitivity study shows that although absolute loss-of-life varies with tariff structure, seasonal temperature, IEEE thermal parameters, and charger size, the relative advantage of centralized coordination remains robust. Benefits become larger under high-volatility tariffs, summer conditions, and higher-power chargers, where unmanaged charging concentrates loading into fewer hours. Across all scenarios, centralized scheduling consistently reduces transformer aging with only modest increases in EV operating cost. While the present study adopts a deterministic formulation for clarity and computational tractability, the use of stochastic or robust optimization methods represents a promising direction for future research, particularly for modeling uncertainty in EV arrival times, charging behavior, and ambient temperature.

6. CONCLUSION

This paper developed a centralized charging and discharging management strategy for electric vehicles that explicitly integrates transformer thermal aging into the optimization objective. The proposed framework co-optimizes EV operating cost and monetized transformer loss-of-life, while also incorporating a compensation mechanism that allows savings from deferred transformer replacement to be shared among the transformer owner, aggregator, and consumers. The model considers G2V, V2H, and V2G operating modes and was evaluated using realistic household loads, travel behavior, and temperature data. Simulation results show that centralized coordination substantially reduces transformer thermal stress and extends expected lifespan, particularly at medium and high EV penetration levels. Compared with decentralized charging, transformer loss-of-life was reduced by up to 80%, while the resulting increase in EV operating cost remained modest (approximately 4-6%). The economic analysis indicates that deferred transformer replacement creates sufficient value to compensate consumers for lost arbitrage profit while still allowing a positive business case for an aggregator. These results demonstrate that incorporating transformer aging directly into EV scheduling decisions can simultaneously protect grid assets and maintain consumer incentives. This work has several limitations. The optimization model is deterministic and relies on representative travel scenarios rather than full uncertainty treatment. Battery aging is not explicitly modeled, and only one distribution transformer topology was considered. In addition, regulatory and contractual aspects of revenue sharing between stakeholders were simplified. Future research will extend the framework to stochastic or robust optimization, incorporate battery degradation costs, evaluate different network configurations and transformer ratings, and explore market-based mechanisms that formalize aggregator participation. Overall, the findings indicate that coordinated EV charging can meaningfully extend distribution-transformer life while maintaining economic feasibility, providing a practical pathway for utilities and aggregators facing increasing EV adoption.

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REFERENCES

[1] R. Kakkar, S. Agrawal, and S. Tanwar, "A systematic survey on demand response management schemes for electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 203, p. 114748, 2024.

[2] J. Pasha, B. Li, Z. Elmi, A. M. Fathollahi-Fard, Y.-y. Lau, A. Roshani, T. Kawasaki, and M. A. Dulebenets, "Electric vehicle scheduling: State of the art, critical challenges, and future research opportunities," *J. Ind. Inf. Integr.*, vol. 38, p. 100561, 2024.

[3] F. S. Hwang, T. Confrey, C. Reidy, D. Picovici, D. Callaghan, D. Culliton, and C. Nolan, "Review of battery thermal management systems in electric vehicles," *Renew. Sustain. Energy Rev.*, vol. 192, p. 114171, 2024.

[4] M. Saklani, D. K. Saini, M. Yadav, and Y. C. Gupta, "Navigating the challenges of EV integration and demand-side management for india's sustainable EV growth," *IEEE Access*, vol. 12, pp. 143767–143796, 2024.

[5] S. M. Mortezaie, "Analysis and design of a soft-switching interleaved boost converter using auxiliary resonant circuit for electric vehicle applications," *Procedia Environ. Sci. Eng. Manag.*, vol. 12, no. 1, pp. 47–54, 2025.

[6] S. Adhikary, P. K. Biswas, T. S. Babu, and M. Balasubbareddy, "Bidirectional operation of electric vehicle charger incorporating grids and home energy storage: V2G/G2V/V2H/V2X," in *Renewable Energy for Plug-In Electric Vehicles*, pp. 191–207, Elsevier, 2024.

[7] P. Shyam Sundar, P. Shrisrinivas, S. Patra, and G. Kanimozhi, "A short review on bidirectional converters for EV applications," *Smart Grids as Cyber Physical Systems*, vol. 2, pp. 289–311, 2024.

[8] V. Monteiro and J. L. Afonso, "Control, optimization, and management of vehicle electrification in modern power grids," in *Vehicle Electr. Modern Power Grids*, pp. 279–302, Elsevier, 2024.

[9] F. Bashir, Y. Yang, M. H. M. Alhaj, and W. Ding, "Modeling and analysis of bidirectional power flow grid-to-vehicle and vehicle-to-grid," in *Proc. Int. Conf. Electrical, Electronic and Networked Energy Syst.*, Springer, 2024.

[10] S. Sadeq, M. Sattar, D. Mohsen, H. Furaijl, N. Nimah, A. Shubaa, J. Mansi, and K. Khudaybergan, "Sustainable economic growth: Evaluating the role of green investments and renewable energy," *Procedia Environ. Sci. Eng. Manag.*, vol. 12, no. 2, pp. 519–530, 2025.

[11] A. Q. Al-Shetwi, I. E. Atawi, M. A. El-Hameed, and A. Abuelrub, "Digital twin technology for renewable energy, smart grids, energy storage and vehicle-to-grid integration," *IET Smart Grid*, vol. 8, no. 1, p. e70026, 2025.

[12] V. Karlusov and D. Yarkov, "Cooperation between Russia and China in the oil and gas energy sector," *Econ. Ann.-XXI*, vol. 193, no. 9-10, pp. 15–24, 2021.

[13] M. Montazeri-Gh, Z. Pourbafarani, and M. Mahmoodi-k, "Comparative study of different PHEV optimal control strategies," *Proc. IMechE, Part D: J. Automob. Eng.*, vol. 232, no. 12, pp. 1597–1610, 2018.

[14] A. Demirci, S. M. Tercan, E. E. Ahmed, U. Cali, and I. Nakir, "A novel electric vehicle charging management with dynamic active power curtailment framework," *IEEE Access*, 2024.

[15] M. J. Chihota, C. Devine, and B. Bekker, "Probabilistic analysis of the technical impacts of high penetrations of electric vehicles," in *Adv. Technol. Electr. Veh.*, pp. 229–257, Elsevier, 2024.

[16] S. D. Vasconcelos, F. Gouveia, A. V. de Moura Lacerda Filho, R. F. Buzo, L. H. A. de Medeiros, L. R. Limongi, D. da Costa Marques, A. L. Fernandes, J. Chai, N. K. L. Dantas, *et al.*, "Assessment of electric vehicles charging grid impact via predictive indicator," *IEEE Access*, 2024.

[17] S. R. Moro, P. A. Cauchick-Miguel, T. T. de Sousa-Zomer, and G. H. de Sousa Mendes, "Design of a sustainable electric vehicle sharing business model in the Brazilian context," *Int. J. Ind. Eng. Manage.*, vol. 14, no. 2, pp. 147–161, 2023.

[18] M. Koc, O. B. Tor, and S. Demirbas, "Analysis of the effects of electric vehicles on distribution networks," *Gazi Univ. J. Sci. Part C*, vol. 9, no. 1, pp. 95–107, 2021.

[19] D. D. Atkar, P. Chaturvedi, H. M. Suryawanshi, P. P. Nachankar, D. Yadeo, and S. K. Saketi, "Three-phase integrated optimized power electronic transformer for EV charging infrastructure," *IEEE Trans. Ind. Appl.*, vol. 58, no. 4, pp. 5198–5213, 2022.

[20] M. Mahmoodi-k, M. Montazeri, and V. Madanipour, "Simultaneous multi-objective optimization of a PHEV power management system," *Energy*, vol. 233, p. 121111, 2021.

[21] A. Visakh and M. Selvan, "Seasonal effects of electric vehicle charging on the aging of distribution transformers," in *Proc. IEEE PES APPEEC*, 2021.

[22] I. Diahovchenko, "Analyzing the influence of electric vehicle charging scheduling on distribution transformer lifespan," *Heliyon*, vol. 10, no. 21, 2024.

[23] A. Visakh and M. P. Selvan, "Analysis and mitigation of the impact of electric vehicle charging on service disruption," *Sustain. Energy Grids Netw.*, vol. 35, p. 101096, 2023.

[24] M. Senol and I. S. Bayram, "Impact assessment and mitigation of electric vehicle smart charging harmonics," *IEEE Access*, vol. 13, pp. 207412–207432, 2025.

[25] A. Visakh and M. P. Selvan, "Smart charging of electric vehicles to minimize cost and transformer aging," *Turk. J. Electr. Eng. Comput. Sci.*, vol. 30, no. 3, pp. 927–942, 2022.

[26] Z. Li, S. Su, X. Jin, H. Chen, Y. Li, and R. Zhang, "A hierarchical scheduling method of active distribution networks," *Int. J. Electr. Power Energy Syst.*, vol. 131, p. 106768, 2021.

[27] F. G. Venegas, M. Petit, and Y. Perez, "Active integration of electric vehicles into distribution grids," *Renew. Sustain. Energy Rev.*, vol. 145, p. 111060, 2021.

[28] O. Valarezo, T. Gomez, J. P. Chaves-Avila, L. Lind, M. Correa, D. Ulrich Ziegler, and R. Escobar, "Analysis of new flexibility market models in Europe," *Energies*, vol. 14, no. 12, p. 3521, 2021.

[29] J. E. Bistline and G. J. Blanford, "The role of the power sector in net-zero energy systems," *Energy Clim. Change*, vol. 2, p. 100045, 2021.

[30] T. Smith, J. Garcia, and G. Washington, "Novel PEV charging approaches for extending transformer life," *Energies*, vol. 15, no. 12, p. 4454, 2022.

[31] H. Dehghani and B. Vahidi, "Evaluating the effects of demand response programs on transformer life expectancy," *Sci. Iranica*, vol. 30, no. 5, pp. 1764–1779, 2023.

[32] S. W. T. Al-Mashhadani and S. Kurnaz, "A novel research process based on power IoT architecture for smart grid demand schemes," *Appl. Sci.*, vol. 14, no. 13, p. 5799, 2024.

[33] K. Guri and K. Najdenkoski, "Impact of wind velocity on power transformer loss of life estimation using improved thermal models in MATLAB/Simulink," *Int. J. Energy Convers.*, vol. 13, no. 3, pp. 103–112, 2025.

[34] H. Gorginpour, H. Ghimatgar, and M. S. Toulabi, "Lifetime estimation and optimal maintenance scheduling of urban oil-immersed distribution transformers considering weather-dependent intelligent load model and unbalanced loading," *IEEE Trans. Power Del.*, vol. 37, no. 5, pp. 4154–4165, 2022.

[35] V. Saxena, N. Kumar, and U. Nangia, "Computation and optimization of BESS in the modeling of renewable-energy-based framework," *Arch. Comput. Methods Eng.*, vol. 31, no. 4, pp. 2385–2416, 2024.

[36] B. Shi, W. Xiao, L. Zhang, T. Wang, Y. Jiang, J. Shang, Z. Li, X. Chen, and M. Li, "Multi-objective optimization method for power transformer design based on surrogate modeling and hybrid heuristic algorithm," *Electron.*, vol. 14, no. 6, p. 1198, 2025.

[37] D. Yang, Q. Chong, B. Hu, and M. Ma, "Optimal operation of energy internet based on user electricity anxiety," *Tsinghua Sci. Technol.*, vol. 23, no. 3, pp. 243–253, 2018.

[38] C. Zhai, Z. Cao, Y. Wang, M. Abdou-Tankari, J. Yu, and Z. Lei, "A reverse incentive-based demand response strategy for shared energy storage," *Energy*, p. 136882, 2025.

[39] F. Rodriguez-Gomez, J. del Campo-Avila, and L. Mora-Lopez, "A novel clustering-based method for household electricity consumption profiles," *Eng. Appl. Artif. Intell.*, vol. 129, p. 107653, 2024.

[40] P. Dalaliyan Miandoab, P. Nazarian, and M. Moradlou, "Mathematical model for exploring the effect of demand response on transmission network expansion planning," *Elect. Eng.*, vol. 106, no. 5, pp. 5403–5416, 2024.

[41] G. Vigano, G. Lattanzio, and M. Rossi, "Review of projects and challenges in flexibility markets for distribution networks," *Energies*, vol. 17, no. 11, p. 2781, 2024.