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Addressing EV Users' Bi-Directional Charging Anxiety in Workplaces: A Survey-Based Approach

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Executive Summary

The rise of bi-directional Electric Vehicles (EVs) offers new opportunities for optimizing energy usage in workplace environments. However, existing studies often overlook the psychological impact of bi-directional charging anxiety (BDCA) on user satisfaction, which can hinder employee participation in bi-directional charging programs. To address this gap, we conducted a comprehensive survey among industry, government, and research institute partners in Germany to model BDCA and classify users into four distinct anxiety patterns: Low, Linear, Exponential, and High anxiety. We formulated the problem as a Mixed-Integer Quadratically Constrained Programming (MIQCP) optimization model aimed at minimizing costs while addressing user concerns. Our model shows a significant increase in user satisfaction without compromising costs. By integrating user preferences through surveys into optimization models, we facilitate the adoption of bi-directional charging and ensure a smoother transition to this technology.

Keywords Electric Vehicle, Smart Charging, Charging Anxiety, Bi-Directional, MIQCP.

1 Introduction

Electric vehicles (EVs) have emerged as a pivotal solution in the fight against climate change, significantly contributing to the reduction of greenhouse gas emissions and the promotion of sustainable energy use [1, 2]. As global EV adoption accelerates, understanding the psychological barriers that affect user behavior, such as range anxiety and time anxiety, becomes increasingly important [3]. Range anxiety refers to the fear of depleting battery power before reaching a charging station [4], while time anxiety encompasses concerns about not having sufficient charge to meet immediate needs, especially during unexpected circumstances [5]. These anxieties can significantly influence charging behaviors, often leading users to adopt overly conservative charging strategies that may not align with optimal energy management practices.

The introduction of bi-directional charging—such as Vehicle-to-Home (V2H) and Vehicle-to-Grid (V2G) [6]—adds further complexity for users, introducing uncertainties that heighten user anxieties around optimal charging times and discharging decisions [7].

This research introduces bi-directional charging anxiety (BDCA), the uncertainty and stress users face when managing EV charging and discharging. Addressing BDCA is essential for EV adoption, especially in workplaces where employees may hesitate to join bi-directional charging programs due to this anxiety. While current studies focus on technical and economic aspects of charging optimization, psychological factors remain largely overlooked.

To better understand the challenges of bi-directional charging, particularly its technical and psychological dimensions, we review key literature exploring these themes.

Bi-directional charging technology offers significant potential for cost reduction, peak shaving, and renewable energy integration. While several studies have explored bi-directional charging in various contexts focusing on optimization that covers its technical feasibility and potential economic benefits [8, 3], less attention has been given to its integration in workplace environments with centralized control systems. This represents a key limitation, as EV fleets can generate substantial energy flows during specific periods. With proper optimization and management, these flows present significant opportunities for improving energy use and enhancing grid stability. For instance, [9] highlights the importance of real-time optimization, integrating V2G and bi-directional capabilities to manage charging demands and uncertainties while maximizing renewable energy utilization. Moreover, [10] presents a flexible methodology for sizing photovoltaic-powered Electric Vehicle Charging Stations (PVCS), optimizing PV plant size and charging strategies. This approach is ideal for workplace EV fleets.
In addition to the technical challenges, psychological factors influencing EV users' behavior have also been investigated. As a case in point, [11] introduces an energy scheduling method that integrates range anxiety as a cost factor in smart grids, promoting wider participation in V2G systems while optimizing energy usage and reducing expenses. In contrast, [12] focuses on developing a charging station model that balances psychological and practical factors, aiming to reduce both investment and user costs. To further address range anxiety, [13] applies deep reinforcement learning to manage charging behaviors, factoring in user preferences around State Of Charge (SoC) gaps to enhance user experience. Furthermore, time anxiety has emerged as a critical factor. [5] categorizes EV users into four behavioral types and introduces an advance EV charging station management framework, formulating the charging problem as a non-cooperative game that minimizes costs while accounting for different levels of time anxiety.

Research Objective and contributions: This research aims to develop a cost-effective, user-centered bi-directional charging strategy that addresses BCDA while handling power peaks and optimizing renewable energy use. The contributions of this research are as follows:

1. Models and classifies EV users into four distinct BDCA patterns based on their charging behavior and preferences.
2. Develops a bi-directional charging strategy that reduces BDCA, optimizes energy flow, supports peak shaving, and enhances PV utilization.
3. Evaluates the system's scalability and adaptability to different EV numbers, energy loads, and renewable energy capacities in workplace settings.
4. Supports sustainable energy transitions by aligning energy management with user behavior and preferences.

Research approach: This research follows these key steps:

- Survey: A survey was conducted to gather real-world data on EV users' charging behaviors and preferences. This data was analyzed and modeled to classify users into distinct BDCA patterns using multinomial logistic regression.
- Optimization: Mixed Integer Quadratically Constrained Programming (MIQCP) optimization is applied to balance costs and user preferences, reducing BDCA and improving satisfaction through efficient energy flow management.

2 Scenario

Our study focuses on a corporate workplace. Key elements include:

- **Charging Stations**: The workplace is equipped with bi-directional charging stations ranging from 4 to 22 kW, enabling EVs to both charge and discharge power back to the building.
- **EVs**: EV arrival and departure times follow a normal distribution, with a mean of 08:00 for arrivals and 17:00 for departures, allowing for up to one hour of variation. All EVs have bi-directional charging capabilities.
- **PV System**: The on-site PV system generates renewable energy, reducing grid reliance. Generation data is based on weather conditions in Dresden, Germany, during a typical summer day and scaled to match the corporate workplace's load.
- **Load**: Load data is drawn from real consumption patterns at a corporate workplace in Dresden, Germany, aligned with the PV generation data to create a realistic demand scenario.
- **Energy Costs**: Electricity prices are based on historical intraday market data, with a constant price applied in each 15-minute timeslot. Energy costs are calculated based on total energy consumption or export.

- **Power Network Hierarchy**: The corporate workplace's power network is modeled as a hierarchical fuse tree, with each node representing a fuse that connects to other nodes, charging stations, or the PV system.
- **Planning and Optimization**: EV user behavior data, including initial SoC, estimated departure time, and user preferences (categorized into anxiety patterns from the survey data), is used to optimize charging schedules, minimize costs, enable peak shaving, and ensure user satisfaction.

This scenario enables the modeling of realistic energy consumption profiles and charging behaviors, offering a solid framework for analyzing and optimizing energy distribution in corporate workplace settings.

3 Method

3.1 Survey Design and Data Collection

The study aimed to explore concerns around managing EV charging and discharging schedules during office hours at corporate locations. The survey was developed after a detailed review of relevant literature [5], [7], [14] and the authors' field observations to ensure the questions aligned with the study's objectives.
The survey was distributed to employees across industry, government, and research institute partners in Germany, known for their interest in EVs and smart charging. It garnered 149 valid responses, with around 34% of respondents having more than a year of experience with EVs, and approximately 75% familiar with V2G programs. This familiarity likely influenced their responses, particularly in terms of charging preferences and comfort with advanced charging strategies, which played a key role in analyzing BDCA patterns.
Structured into five key sections, the survey's first section collected demographic information, including gender, age, and education levels, while the second section focused on participants' EV experience and usage, specifically covering daily commute distances, EV experience duration, and the frequency of workplace charging. The third section explored charging preferences and awareness by evaluating respondents' charging goals and preferred charging times. The fourth section assessed participants' familiarity with V2G technology and their comfort with participating in bi-directional charging programs. Lastly, the fifth section captured timing concerns related to EV charging and discharging about the battery status throughout the workday.
Based on the responses in the fifth key section, participants were classified into four BDCA patterns, as shown in Fig. 1. These patterns were defined as described below:

- **Linear Anxiety 38.9%**: Anxiety increases steadily throughout the workday, with a preference for a gradual rise in charging capacity as the day progresses.
- **Exponential Anxiety 28.2%**: Anxiety rises slowly at first but spikes sharply closer to departure time, prompting a preference for faster charging in the late afternoon to alleviate concerns.
- **High Anxiety 23.5%**: Persistent concern about SoC requires consistent access to charging to ensure they won't run out of power.
- **Low Anxiety 9.40%**: Low, consistent anxiety throughout the day, with confidence that the SoC will meet their needs by the end of the day.

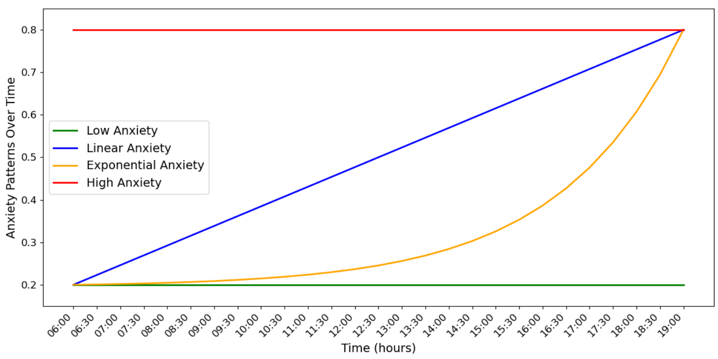

Figure 1: BDCA Patterns Progression Based on Survey.

The data were analyzed using a multinomial logistic regression model (MNL) [15], with maximum likelihood estimation (MLE) employed to estimate the model parameters. This approach allowed us to treat each anxiety pattern as distinct categories. The model coefficients quantify the influence of demographic factors, EV experience and usage, as well as charging preferences and familiarity with V2G technology on the likelihood of being classified into one of the anxiety patterns. For each category, the model calculates the log-odds of belonging to that category relative to the reference category, as shown in (1):

$$\begin{aligned}\text{Logit}(P(Y = C_i)) &= \log\left(\frac{P(Y = C_i)}{P(Y = C_{\text{ref}})}\right) \\ &= \alpha_i + \beta_1 x_1 + \cdots + \beta_m x_m \end{aligned} \tag{1}$$

Where $P(Y = C_i)$ indicates the probability of being in category C_i (Low Anxiety, Linear Anxiety, or Exponential Anxiety), $P(Y = C_{\text{ref}})$ is the probability of being in the reference category (High Anxiety), α_i presents the intercept for category C_i, and $\beta_1, \beta_2, \ldots \beta_m$ are the coefficients for the independent variables $x_1, x_2, \ldots x_m$.
The log-odds for each category, such as Low Anxiety (A_{Low}), Linear Anxiety (A_{Lin}), and Exponential Anxiety (A_{Exp}), are computed using similar equations.
To enhance model interpretability, we initially fitted the model using all available features. Variables with a Variance Inflation Factor (VIF) above 10 and non-significant p-values, such as gender, age groups, and education levels, were excluded to mitigate multicollinearity. The model was then refitted using only significant predictors. To ensure the validity of the model, we performed the Independence of Irrelevant Alternatives (IIA) test, confirming that irrelevant options did not affect the choice probabilities.
Table 1 shows the coefficients for each independent variable across the four BDCA patterns from the MNL. These coefficients indicate the log-odds of belonging to a specific pattern relative to High Anxiety, as noted here:

- **Positive Coefficients:** A positive coefficient indicates that an increase in the variable raises the likelihood of being classified into that BDCA pattern relative to High Anxiety. For example, a coefficient of 1.92 for Low Anxiety suggests that more EV experience increases the likelihood of belonging to the Low Anxiety pattern.
- **Negative Coefficients:** A negative coefficient suggests that as the variable increases, the likelihood of being classified into that BDCA pattern decreases relative to High Anxiety. For instance, a coefficient of -2.54 for Low Anxiety with respect to Charging Importance in the Late Afternoon indicates that as late afternoon charging becomes more important, individuals are less likely to belong to the Low Anxiety pattern.

The intercepts (α_1, α_2, α_3) are -1.75, 1.35, and 0.28 for Low Anxiety, Linear Anxiety, and Exponential Anxiety, respectively. These values represent the baseline log-odds for each category compared to the reference category when all other variables are held constant.
According to Table 1, the log-odds of belonging to each category are calculated as in (2) - (4):
For Low Anxiety:

$$\text{Logit}(P(A_{Low})) = -1.75 - 0.3x_1 + 1.92x_2 + \cdots - 1.18x_9 \tag{2}$$

For Linear Anxiety:

$$\text{Logit}(P(A_{Lin})) = 1.35 - 0.28x_1 - 1.75x_2 + \cdots - 0.82x_9 \tag{3}$$

For Exponential Anxiety:

$$\text{Logit}(P(A_{Exp})) = 0.28 - 0.53x_1 - 0.66x_2 + \cdots + 0.72x_9 \tag{4}$$

The softmax function is applied to convert the log-odds of each category into probabilities [16]. This ensures that the probabilities for all categories sum to 1, making them interpretable as likelihoods or percentages. The softmax formula for the probability of belonging to a particular category C_i is shown in (5):

$$P(Y = C_i) = \frac{e^{\text{Logit}(P(Y=C_i))}}{e^{\text{Logit}(P(A_{Low}))} + e^{\text{Logit}(P(A_{Lin}))} + e^{\text{Logit}(P(A_{Exp}))} + 1} \tag{5}$$

Table 1: Coefficients and Numerical Labels of Independent Variables for BDCA patterns in the MNL Model

Independent Variable	**Numerical Label Description**	**Low Anxiety**	**Linear Anxiety**	**Exponential Anxiety**	**High Anxiety**
Daily commute (x_1)	1 = $\leq$ 5 km, 2 = 5-11 km, 3 = 11-24 km, 4 = 24-40 km, 5 = $\geq$ 40 km	-0.30	-0.28	-0.53	1.18
EV experience (x_2)	1 = No experience, 2 = $\leq$ 1 Year, 3 = 1-3 years, 4 = 3-5 years, 5 = $>$ 5 years	1.92	-1.75	-0.66	-0.4
Frequently charging at workplace (x_3)	1 = Never, 2 = Rarely , 3 = Occasionally, 4 = Often, 5 = Daily	-1.44	0.28	1.4	-0.25
Charging importance to full capacity (x_4)	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Very important, 5 = Extremely important	-0.256	-0.45	0.67	3.35
Charging importance in morning (x_5)	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Very important, 5 = Extremely important	-1.45	0.24	-1.33	1.23
Charging importance in midday (x_6)	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Very important, 5 = Extremely important	-1.45	0.96	0.23	1.12
Charging importance in late afternoon (x_7)	1 = Not important, 2 = Slightly important, 3 = Moderately important, 4 = Very important, 5 = Extremely important	-2.54	-0.47	1.68	2.65
Awareness of V2G programs (x_8)	1 = Not aware, 2 = Slightly aware, 3 = Moderately aware, 4 = Very aware, 5 = Extremely aware	1.21	0.27	0.15	-0.78
Comfort with system scheduling charging sessions (x_9)	1 = Very comfortable, 2 = Somewhat comfortable, 3 = Neutral, 4 = Somewhat uncomfortable, 5 = Very uncomfortable	-1.18	-0.82	0.72	1.37

Here, $e^{\text{Logit}(P(Y=C_i))}$ represents the exponentiated log-odds for category C_i, and the denominator sums the exponentiated log-odds for all categories, normalizing the result into a valid probability distribution. The softmax function enables us to predict the probability of a participant falling into each category based on their independent variables, providing a clear and interpretable model for classifying BDCA patterns. The anxiety experienced by EV users tends to increase as they approach their departure time. To model this time-based progression, we use a normalized time variable $T_n(t)$ as defined in (6), which tracks the relative position of the current time t within the workday.

$$T_n(t) = \min\left(\max\left(\frac{t - t_a}{t_d - t_a}, 0\right), 1\right) \tag{6}$$

Where t_a represents the EV's arrival time and t_d its departure time. The BDCA at any given time t, denoted as $A_{n,t}$ in (7), is modeled for different anxiety patterns.

$$A_{n,t} = \begin{cases} A_{\min} & \text{for Low Anxiety} \\ A_{\max} \times T_n(t) & \text{for Linear Anxiety} \\ A_{\max} \times \left(\frac{e^{T_n(t)}-1}{e-1}\right) & \text{for Exponential Anxiety} \\ A_{\max} & \text{for High Anxiety} \end{cases} \tag{7}$$

Here, $A_{\min}$ and $A_{\max}$ represent the minimum and maximum BDCA thresholds, respectively. The normalized BDCA for each EV at time t is given in (8):

$$A_{n,t}^{norm} = A_{\min} + (A_{\max} - A_{\min}) \times \frac{A_{n,t} - A_{\min}}{A_{\max} - A_{\min}} \tag{8}$$

To reflect realistic psychological states, these BDCA thresholds are normalized to a range of 0.2 to 0.8.

3.2 MIQCP Optimization Model

In this work, we formulate a MIQCP problem aimed at minimizing both the cost and BDCA related to time constraints, while ensuring that peak power remains within a specified range and meeting the charging needs of EVs. Table 2 outlines the parameters and decision variables used in the MIQCP formulation, with a total of N EVs and a time slot duration, τ, set to 15 minutes.
The model optimizes two main objectives, as outlined in the objective function (9). The first objective, C_1, with weight factor w_1 [1/€] represents the total cost of energy from the grid calculated as shown in (10), where C_t^g is the unit cost of grid energy at time t, and D_t illustrates the demand from the grid at time t, as defined in (11). The term $\sum_{n=1}^{N} P_{n,t}$ denotes the total charging or discharging power for all EVs at time t.

$$\text{Minimize: } w_1 \cdot C_1 + w_2 \cdot C_2 \tag{9}$$

$$C_1 = \sum_{t=0}^{T} C_t^g \cdot \tau \cdot D_t \tag{10}$$

$$\text{where: } D_t = \max\left(\sum_{n=1}^{N} P_{n,t} - P_t^{PV} + P_t^{load}, 0\right) \tag{11}$$

The second objective, C_2, is unitless, with weight factor w_2 representing the total BDCA across all EV patterns, as defined in (12). The term $\delta_{n,t}$ is calculated using (13), which captures the difference between the normalized BDCA (8) and the SoC of each EV n at any given time t.

$$C_2 = \sum_{n=1}^{N} \sum_{t=t_n^{arr}}^{t_n^{dep}} \delta_{n,t} \tag{12}$$

$$\text{where: } \delta_{n,t} = \max(A_{n,t}^{norm} - SoC_{n,t}, 0) \tag{13}$$

The SoC of each EV at time t is updated based on (14). Here, E_n^{max} is the maximum battery capacity of each EV, while η_C and η_D denote the charging and discharging efficiencies, respectively. The updated

Table 2: Parameters and variables used in the MIQCP formulations

Variable	**Description**
t_n^{arr}	Arrival time of EV n
t_n^{dep}	Departure time of EV n
P^{peak}	Peak shaving fuse limit
P^{EV}	Maximum allowable total charging or discharging power for all EVs
P_{ub}^{ch}	Upper bound charging power
P_{lb}^{ch}	Lower bound charging power
P_{ub}^{dch}	Upper bound discharging power
P_{lb}^{dch}	Lower bound discharging power
E_n^{max}	Maximum battery capacity of EV n
SoC^{targ}	Target state of charge for all EVs
SoC^{min}	Minimum allowable state of charge
SoC^{max}	Maximum allowable state of charge
SoC_n^{arr}	Initial state of charge of EV n upon arrival
SoC_n^{dep}	Final state of charge of EV n upon departure
C_1	Total cost of energy from the grid
C_2	Total BDCA cost for all EVs across all patterns
C_t^g	Unit cost of grid energy at time t
D_t	Demand from the grid at time t
P_t^{PV}	Available PV power at time t
P_t^{load}	Load demand at time t
$A_{n,t}$	BDCA for EV n at time t
$SoC_{n,t}$	State of charge of EV n at time t
$P_{n,t}$	Charging or discharging power for EV n at time t
$\delta_{n,t}$	Difference between BDCA and SoC for EV n at time t
S_t^{demand}	Binary variable controlling bounds on demand from the grid at time t
$S_{n,t}^{ch/dch}$	Binary variable indicating whether EV n is charging or discharging at time t
$S_{n,t}^{zero}$	Binary variable indicating whether power $P_{n,t}$ is zero at time t
$S_{n,t}^{BDCA}$	Binary variable used to handle constraints related to BDCA and $I_{t,n}$ for EV n at time t

SoC remains a quadratic constraint to avoid the increased computational complexity that would result from linearization.

$$SoC_{n,t} = SoC_{n,t-1} + \frac{\tau \cdot P_{n,t-1} \cdot (1 - S_{n,t-1}^{ch/dsc}) \cdot \eta_C}{E_n^{max}} + \frac{\tau \cdot P_{n,t-1} \cdot S_{n,t-1}^{ch/dsc}}{E_n^{max} \cdot \eta^D} \tag{14}$$

The constraints related to the switches $S_{n,t}^{ch/dch}$ and $S_{n,t}^{zero}$ define an EV's charging and discharging behavior. The equations (15) and (16) ensure that when $S_{n,t}^{ch/dch} = 0$, the power $P_{n,t}$ is constrained to EV charging, while if $S_{n,t}^{ch/dch} = 1$, the EV is discharging. Additionally, (17) and (18) manage the idle condition, such that when $S_{n,t}^{zero} = 1$, no charging or discharging event occurs, resulting in $P_{n,t} = 0$. Logical consistency is maintained by (19) and (20), enforcing that $S_{n,t}^{ch/dch}$ is zero when $S_{n,t}^{zero} = 1$; preventing charging and discharging simultaneously. The big-M approach is used to handle these binary switches by applying large constraints on $P_{n,t}$, ensuring proper behavior based on the switch states.

$$P_{n,t} \leq M \cdot (1 - S_{n,t}^{ch/dch}) \tag{15}$$
$$P_{n,t} \geq -M \cdot S_{n,t}^{ch/dch} \tag{16}$$

$$P_{n,t} \leq M \cdot (1 - S_{n,t}^{zero}) \tag{17}$$
$$P_{n,t} \geq -M \cdot (1 - S_{n,t}^{zero}) \tag{18}$$

$$S_{n,t}^{ch/dch} \leq 1 - S_{n,t}^{zero} \tag{19}$$
$$S_{n,t}^{ch/dch} \geq -1 \cdot (1 - S_{n,t}^{zero}) \tag{20}$$

To define power limits based on the EV's charging or discharging state, the charging power limits are set between $P_{\text{lb}}^{\text{pos}} = 4$ kW and $P_{\text{ub}}^{\text{pos}} = 22$ kW, while discharging limits range from $P_{\text{ub}}^{\text{neg}} = -4$ kW to $P_{\text{lb}}^{\text{neg}} = -22$ kW, as shown in equations (21) and (22).

$$P_{n,t} \leq \mathrm{P}_{ub}^{\text{pos}} + (\mathrm{P}_{ub}^{\text{neg}} - P_{\text{ub}}^{\text{pos}}) \cdot S_{n,t}^{ch/dch} + M \cdot S_{n,t}^{zero} \tag{21}$$
$$P_{n,t} \geq \mathrm{P}_{lb}^{\text{pos}} + (\mathrm{P}_{lb}^{\text{neg}} - P_{\text{lb}}^{\text{pos}}) \cdot S_{n,t}^{ch/dch} - M \cdot S_{n,t}^{zero} \tag{22}$$

The total power drawn from the grid is constrained by the peak power P^{peak} as defined in (23). Additionally, the total charging or discharging power of all the EVs must not exceed the maximum allowable power for EVs i.e. P^{EV} constraint in (24)

$$\sum_{n=1}^{N} P_{n,t} + P_t^{Load} - P_t^{PV} \leq P^{peak} \tag{23}$$

$$\sum_{n=1}^{N} P_{n,t} \leq P^{EV} \tag{24}$$

In (25) the model ensures that the EV departs with the target SoC, while (26) maintains the SoC of EV n at time t within the defined minimum and maximum SoC limits.

$$SoC_n^{dep} \geq SoC^{targ} \tag{25}$$

$$SoC^{\min} \leq SoC_{n,t} \leq SoC^{\max} \tag{26}$$

The MIQCP constraints ensure operational feasibility across BDCA patterns, providing a robust framework for managing EV charging infrastructure under time-sensitive conditions.

4 Results

The optimization results presented here applied the MIQCP model to determine the optimal charging and discharging schedules for EVs throughout a typical workday. The model's objectives are threefold: minimizing charging costs, and reducing BCDA for the employees while achieving peak shaving. Table 3 outlines the key configurations that form the basis of this analysis.
The MIQCP model was solved using the Gurobi Optimizer (version 11.0.3) on a system with 16 logical processors. The model, consisting of 36,510 constraints, 29,044 variables, and 3,796 quadratic constraints, achieved an optimal solution in 7.83 seconds. Scalability was assessed by increasing the energy

Table 3: Key Configurations for the MIQCP Model

Assumption	**Description**
EV Fleet Size	50 EVs
Initial SOC	All vehicles arrive with an initial SOC of 30%
Anxiety Patterns	EVs are categorized into anxiety patterns (Low, Linear, Exponential, High)
Arrival and Departure Times	EVs arrive around 08:00 and depart around 17:00, with a variance of one hour
Optimization Objective	Minimize cost and minimize BDCA

load and expanding the EV fleet to 200 vehicles, achieving an optimal solution in 16.65 seconds. The system continued to perform efficiently, demonstrating its adaptability to larger workplace environments and higher energy demands.

Based on survey data, EVs were categorized into four BDCA patterns: Low, Linear, Exponential, and High Anxiety. The MIQCP model was used to optimize the charging schedules for these categories. Fig. 2 illustrates the SoC over time for one randomly selected EV from each pattern. All EVs arrive with 30% SoC, but their charging behaviors vary significantly. Low anxiety EV show high discharge flexibility, with a gradual increase in SoC, reaching around 50% by late afternoon and rising to nearly 80% by the end of the day. Linear anxiety EV steadily charge from 30% to 80% throughout the day, initially allowing more room for discharge. Exponential anxiety EV exhibit slow charging early in the day with a sharp increase toward departure, reflecting heightened anxiety, while also allowing significant discharge flexibility in the morning. High anxiety EV rapidly charge to around 80% shortly after arrival, maintaining a high SoC with small fluctuations throughout the day for peace of mind.

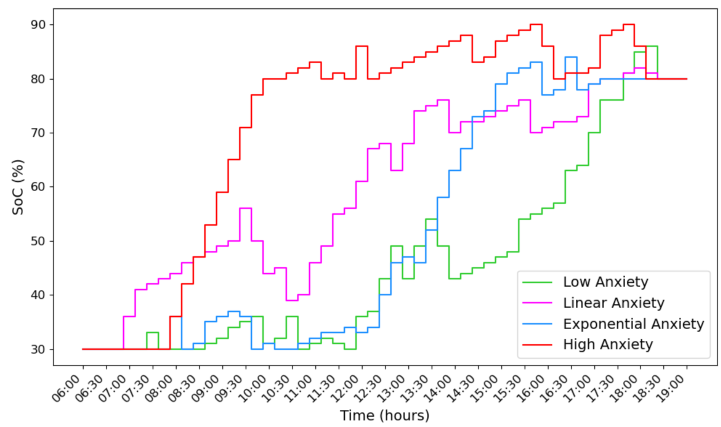

Figure 2: SoC Progression for EVs Based on BDCA Patterns.

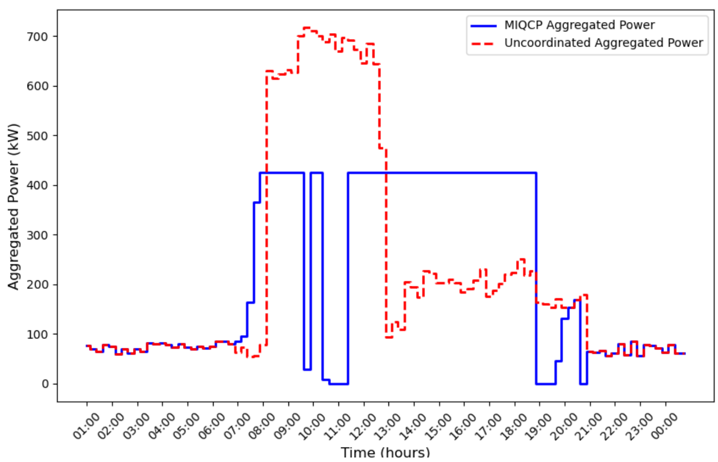

Figure 3: Comparison of Aggregated Power Demand.

Figure 3 represents a comparison of the aggregated power demand between the MIQCP method and uncoordinated charging. In uncoordinated charging, EVs begin charging immediately upon being plugged in, causing power spikes during peak hours as multiple vehicles charge simultaneously. This unscheduled approach leads to inefficient power distribution, significantly increasing grid demand and resulting in a peak power demand of nearly 700 kW.

In contrast, the MIQCP method optimizes charging schedules, distributing the load more evenly across off-peak hours, and reducing grid strain. It also lowers overall charging costs, by reducing daily costs from €287.84 in uncoordinated charging to €221.78 with the MIQCP method, representing a 23% cost savings.

Table 4 compares costs under three distinct BDCA scenarios: (1) All EVs Low Anxiety, where all EVs exhibit the Low Anxiety pattern; (2) Mixed Anxiety Patterns, reflecting the survey results with a mix of Low, High, Linear, and Exponential anxiety patterns; and (3) All EVs High Anxiety, where all EVs exhibit the High Anxiety pattern.

These comparisons are made under two different weighting setups:

i. Equal priority for grid and BDCA cost ($w_1 = 0.5$, $w_2 = 0.5$).

ii. Grid cost prioritized over BDCA cost ($w_1 = 0.9$, $w_2 = 0.1$).

As mintioned in Section 3.2, C_1 represents the grid cost, while C_2 corresponds to the BDCA cost. The weight factors w_1 and w_2 reflect the priorities given to minimizing grid cost and BDCA cost, respectively. The results indicate that higher anxiety patterns generally lead to increased user dissatisfaction. However, when we apply a mixed behavior scenario based on survey data as highlighted in the table, our algorithm significantly improves overall user satisfaction without substantial increases in cost, effectively balancing grid efficiency and user needs. This emphasizes the importance of addressing individual user concerns when handling BDCA, rather than assuming all users have high anxiety, to achieve a better balance between satisfaction and cost efficiency.

Table 4: Comparison of grid cost C_1 and BDCA cost C_2 under different anxiety patterns and different weight setups

Objectives weights	Behaviour	C1 (€)	C2
$w_1 = 0.5, w_2 = 0.5$	All EVs Low Anxiety	221.75	0
$w_1 = 0.5, w_2 = 0.5$	All EVs High Anxiety	225.64	341.3
$w_1 = 0.5, w_2 = 0.5$	Mixed Anxiety Patterns	221.78	24.03
$w_1 = 0.9, w_2 = 0.1$	All EVs Low Anxiety	221.75	0
$w_1 = 0.9, w_2 = 0.1$	All EVs High Anxiety	221.76	487.4
$w_1 = 0.9, w_2 = 0.1$	Mixed Anxiety Patterns	221.75	91.2

5 Discussion

Our method utilizes user survey data and the MIQCP model to generate optimized charging plans, balancing grid cost minimization with user satisfaction, improving cost efficiency, and reducing grid strain. While this study offers valuable insights, several limitations remain that future research should address to enhance the model's generalizability and accuracy:

- The survey primarily involved participants familiar with V2G technology, limiting the generalizability of the results. Additionally, the model considers only four anxiety patterns, whereas EV users likely exhibit more diverse behaviors. Future research should aim for a broader, more diverse sample of EV users to capture a wider range of behavioral patterns and preferences.
- The actual charging preferences may shift dynamically throughout the day due to factors such as travel needs or real-time grid pricing. Future models should incorporate these dynamic changes to better reflect practical scenarios.
- The model focuses on workplace environments that may not reflect the behavior in residential or public charging settings. Future research should explore stricter charging environments where users have less flexibility.
- Collaborating with experts in psychology and statistics could refine how anxiety and charging behavior are modeled for more accurate predictions.
- Future iterations of the model could benefit from incorporating additional objectives, such as environmental impact (e.g., CO_2 emissions) and EV health, which would make the model more reflective of authentic concerns beyond cost and anxiety.

6 Conclusion

This study underscores the importance of understanding user behavior in the adoption of bi-directional EV charging in workplace environments. Using real survey data, we classified EV users into four distinct BDCA patterns and applied a multinomial logistic regression model to predict these behaviors. These insights were integrated into our MIQCP optimization framework, which balances grid cost minimization with user satisfaction while reducing peak demand. The findings show that incorporating a mix of BDCA patterns enhances user satisfaction without sacrificing cost efficiency or peak shaving. The model's scalability and adaptability across different workplace settings further highlight its practical value.
By aligning real-world behavior with technical models, this work supports the broader adoption of bi-directional charging, addressing both technical and psychological barriers to unlock its full potential for a sustainable energy future. Future research should expand the model to encompass more diverse user behaviors and explore applications in residential or public charging contexts. Incorporating environmental impacts and grid stability will further enhance its real-world relevance.

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