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# *Quantitative Analysis of Heterogeneous Electric Bicycle Load Based on Monte Carlo Simulation*

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***Abstract.*** To solve the grid pressure due to the chaotic charging of more than 40 million electric two-wheelers in Guangdong Province, this research develops a simulation system focused on regulating the demand side resources. The users are divided into three categories: commuting, delivery and sharing. By using Monte Carlo simulation, we create load curves under both chaotic and intelligent charging conditions, and the benefits of load shifting are calculated through the load shift curve. Intelligent charging can shift 3.1 GW of evening peak load to the night time valley. As a result, the daily charging peak-valley difference of the province decreases from 2060 MW to 1544 MW, and the load factor increases from 0.514 to 0.571. The valley-filling capacity is greater than the peak-shaving capacity, indicating an improved utilization efficiency of the grid assets. The large-scale charging of e-bikes can be changed from a 'rigid disturbance source' to a 'flexible regulation resource', which provides important decision-making assistance for the provincial grid planning and enhancement of operational resilience.

***Keywords:*** electric two-wheelers, smart charging, Monte Carlo simulation, grid peak shaving, demand-side response

## 1. Introduction

### 1.1. Research background

With the worldwide shift to electric vehicles, it is now an important issue to reduce the burden on the power system [1]. By the end of 2024, the registered number of electric two-wheelers in Guangdong Province has reached over 40 million, which forms a large-scale distributed charging load. However, the common "chaotic charging" phenomenon, i.e., charging immediately after returning at the peak electricity consumption time in the evening, occurs at the same period as the residential electricity demand. This coincidence intensifies the peak-valley difference of the grid, endangers the normal operation of the distribution network and raises the investment cost of the facilities. Therefore, it is of great engineering importance to study the spatial-temporal characteristics of such a huge load and to assess the advantages of intelligent charging.

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## 1.2. Literature review

Existing research agrees that disordered charging increases grid peak stress, whereas smart ordered charging can effectively reduce and fill the peak and valley loads [2]. At present, the Monte Carlo method is still the main approach used for simulating stochastic charging loads [3]. However, there still exist two main gaps:

• Most researches concentrate on small-scale cases, and there is little investigation on a provincial level involving tens of millions of vehicles.

• Research mainly focuses on Electric Vehicles, ignoring the regulatory possibilities of Electric Two-Wheelers.

## 1.3. Research content and contributions

To bridge these gaps, this study establishes the charging load model for 40 million e-bikes in Guangdong Province, taking into account the user differences among commuting, delivery and sharing groups. By using Monte Carlo simulations, the system load curves under uncontrolled and intelligent charging modes are then compared. The main achievements are:

• Provincial Scale Quantification: Overcoming the micro-level constraints, this is the first research to evaluate the gigawatt-scale effect of e-bike charging on provincial power grid peak regulation.

• Precise Benefit Assessment: According to the load shifting curve $\Delta P_{shift}(t)$ , we precisely evaluate the contributions of peak shaving and valley filling, offering important assistance in regional power grid planning and improving operational stability.

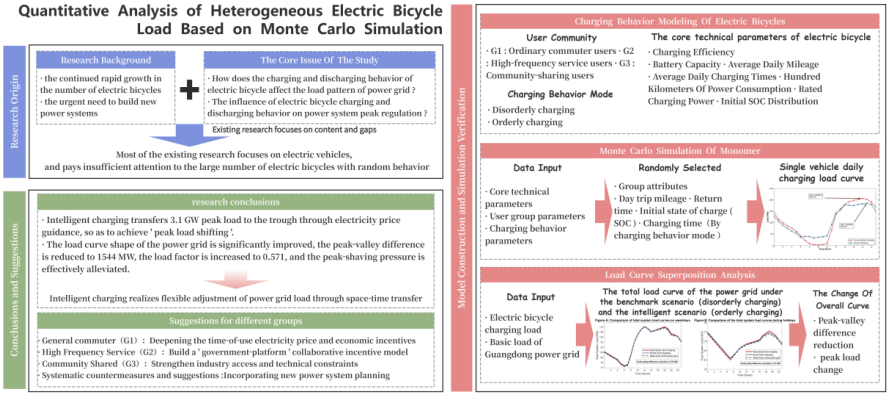


Figure 1. Technical roadmap of E - bike charging load optimization

## 2. Model construction

### 2.1. User classification and parameter setting

This research concentrates on the charging load of electric two-wheelers in Guangdong Province, which contains more than 40 million registered vehicles. To examine the behavioural differences, the users are classified into three groups: G1 (commuting), G2 (delivery) and G3 (sharing). As presented in Table 1.

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Table 1. Key technical parameters of user groups

| Group | Ratio | Response Rate | Battery (kWh) | Power (kW) | Daily Mileage (km) | Charge Freq. |
|---|---|---|---|---|---|---|
| G1 :Commuting | 75% | 30% | 0.96 | 0.178 | 15 | 1 |
| G2 :Delivery | 17% | 20% | 1.54 | 0.308 | 80 | 2.5 |
| G3: Sharing | 8% | 100% | 1.54 | 0.308 | 120 | 1 |

Data sources include GB standards, traffic administration statistics, and market surveys [4].

## 2.2. Charging behavior modeling and Monte Carlo simulation

Given the stochastic nature of individual charging decisions, a Monte Carlo framework is established. Each e-bike is treated as an independent agent, and its daily charging event is generated based on probability distributions specific to its user group $G_m$.

The core variable is the charging energy demand $E_{need}(i,j)$, which is constrained by both travel consumption and battery capacity limits:

$$E_{need}(i,j) = min(C(i) \cdot (SOCtarget - SOCstart(i,j)), \frac{100 \cdot D(i,j) \cdot e_{100}(i)}{100}) \quad (1)$$

Here, $C(i)$ is the battery capacity, $SOCstart(i,j)$ follows the distribution in Table 1, and D(i,j) is the driving distance. The charging start time $T_{start}$ is determined by the response strategy: immediate charging in unscheduled mode; in smart mode, according to the response rate Rm, the load is shifted to off-peak periods (such as 23:00-07:00) [5].

By iterating the above process for N=40million vehicles, the provincial total load is obtained by aggregating individual power curves:

$$P_{total}^{unordered}(t) = \sum_{i=1}^{N} P_{daily,unordered}(i)(t), \; P_{total}^{smart}(t) = \sum_{i=1}^{N} P_{daily,smart}(i)(t) \quad (2)$$

The net effect of smart charging is quantified by the Load Shift Curve:

$$\Delta P_{shift}(t) = P_{total}^{smart}(t) - P_{total}^{unordered}(t) \quad (3)$$

To evaluate the impact on grid operation, the load shift is superimposed onto the Guangdong provincial baseline load $P_{base}(t)$:

$$P_{sys}^{opt}(t) = P_{base}(t) + \Delta P_{shift}(t) \quad (4)$$

The optimization effects are quantified by three metrics: Peak-Valley Difference Reduction and Peak Load Reduction, which measure the alleviation of grid stress and operational stability, and the Load Factor Improvement, which indicates the enhancement of asset utilization efficiency.Additionally, the contributions of peak shaving and valley filling are calculated by integrating $\Delta P_{shift}(t)$ over specific time windows.

## 3. Results

According to the Monte Carlo simulation of 40 million electric two-wheelers in Guangdong Province, the daily charging load curves for both disordered and smart charging modes were

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obtained as depicted in Fig. 2.

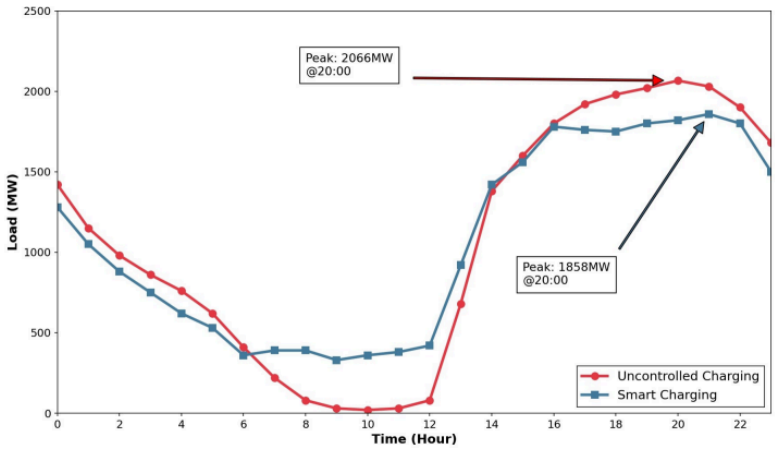


Figure 2. Comparison of electric two-wheeler charging load curves

The unorganized charging load shows a sharp single peak (2066 MW at 20:00), which is consistent with the residential evening peak and results in a large peak-valley difference (2060 MW) with a low load factor. On the other hand, smart charging utilizes price signals to transfer the load from peak to valley periods; although the average load remains the same (1062 MW), the peak decreases by 10.1% (to 1858 MW), the valley increases by 4963% (to 315 MW) and the load factor becomes 0.571. Moreover, the G3 sharing group plays a main role as the baseload during the deep valley period (00:00-06:00), converting the charging load from a "rigid influence" into a "flexible regulation" resource for the power system.

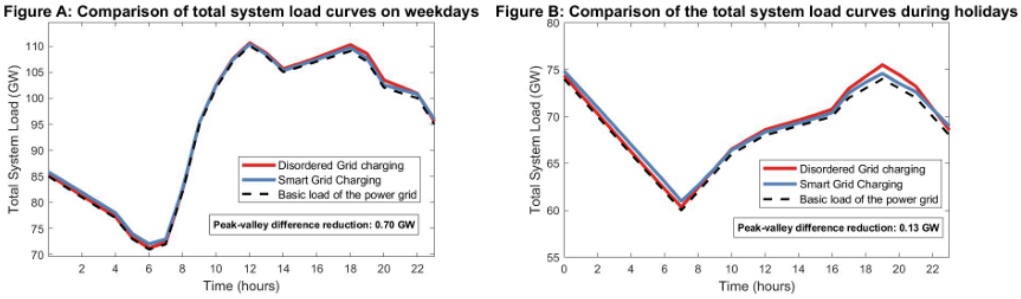


Figure 3. Comparison of system total load curves on weekdays and holidays

From Fig. 3, the effects of the smart charging method are different in different time periods. During weekdays with regular commuting schedules, the grid base line exhibits obvious changes. By shifting the load from 18:00 to 22:00 to the off-peak hours from 23:00 to 07:00, the variation of the curve is significantly decreased. However, on holidays, the base line load is relatively stable due to the high mobility and various G1 charging habits. Although the total load is still heavy, the smart charging can maintain a stable "filling of the valley" effect. The satisfactory results in both large and small fluctuations confirm the efficiency and flexibility of the proposed method.

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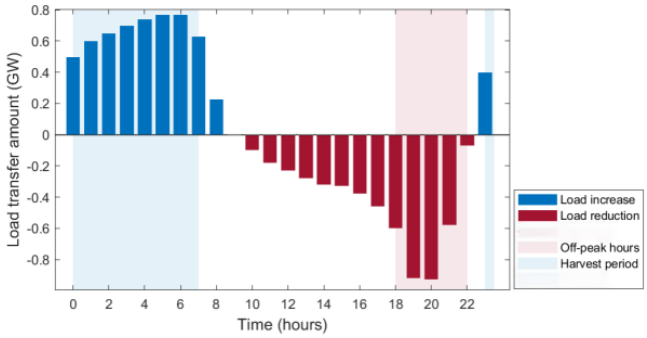


Figure 4. Load shift curve

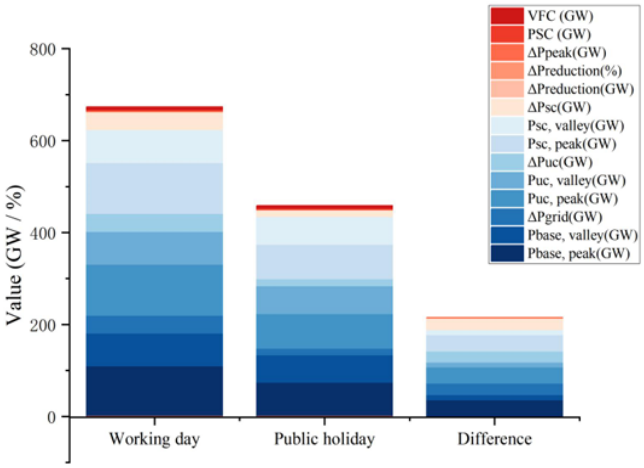


Figure 5. Comparison of peak shaving benefits

Fig. 4 shows the load shift curve $\Delta P_{shift}(t)$, which represents the time distribution of energy. At the evening peak (18:00-22:00), $\Delta P_{shift}(t)$ has negative values, indicating a peak shaving effect up to 3.1 GW, which can effectively reduce the overload risk of the distribution network. On the other hand, during the nighttime valley (23:00-07:00), the curve becomes positive, indicating a valley filling contribution of 5.76 GW. The large transfer of charging load to the off-peak hours not only improves the operation of conventional generators but also offers important flexibility for handling the intermittent renewable energy, such as wind power.

By adding the shifted load to the Guangdong grid base line (Fig. 5), the total advantages of intelligent charging are calculated. The method decreases the peak-valley difference by 0.7 GW (1.8%) and increases the load factor by 0.0033 (0.4%), thus smoothing out the load pattern and reducing the system's spinning reserve costs. As for the peak control, the 0.35 GW increase in load during the valley hours is compensated by the 3.1 GW decrease in evening peak load, resulting in an efficient balance. In addition, the contribution analysis shows that the valley filling (5.76 GW) is greater than the peak shaving (3.10 GW). This suggests that the present penetration rates mainly utilize the surplus generating capacity at night rather than only limiting electricity usage.

## 4. Conclusion

At the behavioral level, the smart charging effectively shifts the 3.1 GW peak load which is concentrated between 19:00 and 22:00 to the off-peak hours by using time-of-use electricity pricing, thus accomplishing peak reduction and valley filling. At the grid level, the weekday peak-valley

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difference of the system decreased by 0.700 GW (a reduction of 1.79%) and the load factor increased by 0.0033. Province-wide, the daily charging load peak-valley gap reduced from 2060 MW to 1544 MW, and the load factor rose from 0.514 to 0.571. This demonstrates the important influence of electric two-wheeled vehicles as cost-free flexible resources in grid peak regulation, and confirms the effectiveness of the optimization under different conditions.

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