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Understanding Human Mobility Patterns from Urban Energy Consumption Records: Through Electric Vehicle Charging Records

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ABSTRACT
This study pioneers a novel method to interpret urban energy consumption through human mobility patterns, utilizing electric vehicle (EV) charging data as a proxy. By applying algorithms like DBSCAN and a pre-trained human mobility model, the research effectively transforms EV charging logs into a detailed map of urban movement. Analyzing data from Shanghai, the study successfully correlates these synthesized mobility trajectories with actual human movement patterns, revealing a strong interplay between EV charging behavior and urban dynamics. This innovative approach not only offers fresh insights into urban energy dynamics but also respects individual privacy, marking a significant advancement in the field of urban planning and sustainable development.

Keywords: electric vehicle, urban energy system, human mobility patterns, data-driven methodology

1. INTRODUCTION

The narrative of urban energy consumption is deeply interwoven with human movement—each journey tells a part of the city's story. Trajectory data, the digital breadcrumbs of our daily travels, hold immense potential for the energy sector. From forecasting demand to optimizing grid performance, understanding these pathways is pivotal. However, the private nature of trajectory data raises significant barriers, rendering it a sensitive and often inaccessible resource. Consequently, the energy industry has traditionally been constrained, unable to delve deeply into research that leverages these insightful datasets.

The advent of electric vehicles (EVs) marks a transformative era in urban energy systems, significantly shaping the demand side of the equation. With the market penetration of EVs on a substantial rise, their charging behaviors have emerged as a major source of power consumption. EV charging activities account for a considerable proportion of electricity demand, a figure that is only expected to grow. Notably, the process of charging these vehicles generates detailed records that inadvertently map out human activity.

This paper introduces a novel framework capable of repurposing EV charging logs into a reconstructed tapestry of human movement patterns, effectively circumventing the traditional barriers faced by the energy sector in utilizing trajectory data for urban studies. Furthermore, the model we propose extends beyond EVs, offering potential applications for various facets of energy demand-side records.

The challenges of harnessing trajectory data for energy studies are manifold. Privacy regulations often preclude the direct use of such data, while the technical and logistical hurdles of anonymization can be formidable. The sensitivity of this data cannot be overstated, as it encapsulates the routines and habits of individuals across the urban landscape. This has led to a cautious approach within the energy sector, where the potential insights of trajectory analysis remain largely untapped.

Electric vehicles stand at the vanguard of this changing landscape. As cities move towards electrification, the data generated by EVs offer a granular lens into the comings and goings of urban life. The charging stations scattered across the city do not merely represent energy nodes but are proxy indicators of human presence and movement. By harnessing this data, researchers can glean insights into urban dynamics without infringing upon individual privacy.

The framework presented in this paper marks a methodological leap in the study of urban energy systems. Transforming EV charging data into a

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representation of human mobility, unlocks a new dimension of analysis that is both privacy-conscious and rich in detail. This approach allows for the dissection of energy demand patterns, revealing the underlying human behaviors that drive them.

The contribution of this work extends beyond technical innovation. It offers a new paradigm for urban energy studies—one that integrates the social patterns inherent in mobility with the physical infrastructure of energy consumption. By doing so, it provides a holistic view of urban energy dynamics that is crucial for the development of sustainable and resilient cities.

2. RELATED WORKS

The relationship between mobility, particularly human movement patterns, and energy consumption has been a subject of increasing interest in the field of urban planning and sustainable development. A notable study conducted in Trentino, Italy, demonstrated this connection by employing a highly parallelized feature extraction algorithm based on telecommunication data. This study highlighted that electric energy consumption exhibits cyclic characteristics, with predictable patterns that vary according to daily and weekly periods, and differ across residential, touristic, and city center or industrial areas [1]. This finding underscores the intricate relationship between human mobility patterns and energy demand.

Further exploring the intersection of mobility and energy, the impact of electric vehicles (EVs) on urban energy systems has garnered significant attention. Research in California, for instance, has delved into the grid impacts of increased EV adoption, exploring various scenarios for EV charging, including different levels of home charging access and workplace charging. This research has been instrumental in modeling potential grid load under these scenarios, thereby proposing solutions to mitigate the increased demand due to EV charging [2]. The unique electrical consumption patterns of EV chargers have necessitated thorough studies across various sectors [3]. Adding to this, Garwa and Niazi's comprehensive review paper sheds light on both the positive and negative impacts of EVs on power grids, such as the benefits of peak load reduction and ancillary services via V2G technology and the challenges like decreased power quality and increased transformer load due to EV charging [4].

The modeling of human mobility also plays a crucial role in understanding energy consumption patterns. Joubert et al. have employed Bayes Network to investigate the causality of human activity and generate mobility patterns using activity-based models [5]. These active-based methods have been increasingly adapted to generate human mobility trajectories, replacing traditional survey-based or census-based methods [6]. Luca et al. developed DITRAS, a framework for simulating human mobility patterns, which includes a data-driven algorithm to generate a mobility diary capturing individuals' routine-breaking tendencies [7]. Similarly, He et al. developed a framework for generating human mobility data in new cities by transferring knowledge from source cities [8]. Feng et al. proposed DeepMove, an attentional recurrent network, to address the challenges of complex sequential transition regularities, multi-level periodicity, and heterogeneity in human mobility prediction [9]. These models and frameworks are pivotal in enhancing our understanding of human mobility patterns and their consequent impact on energy consumption and urban planning.

3. METHODOLOGY

3.1 Extraction of key locations from EV charging records

Determining key locations is essential for unraveling the relationship between human mobility and urban energy demand. We utilized the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to cluster electric vehicle charging stations based on their activity levels. Stations surpassing a predefined activity threshold were classified as key locations, indicative of high charging density. The result of this process was a collection of geospatial coordinates pinpointing these key locations. To ensure privacy, these coordinates were then aggregated into a probability distribution, effectively anonymizing personal data while preserving the overall mobility trends.

3.2 Building Life pattern matrix

In this study, the term "life pattern" denotes the habitual mobility of individuals, characterized by regular activities and travel behaviors. These patterns are intricately linked to and can be inferred from location history data such as GPS, which reflects a person's routines and their interactions with various geographical locations. The analysis of life patterns involves high-dimensional data encapsulating both time and space dimensions, presenting a complex challenge in clustering and extracting meaningful patterns from large-scale, unlabeled datasets [10].

3.3 Utilizing a pre-trained human mobility generative model

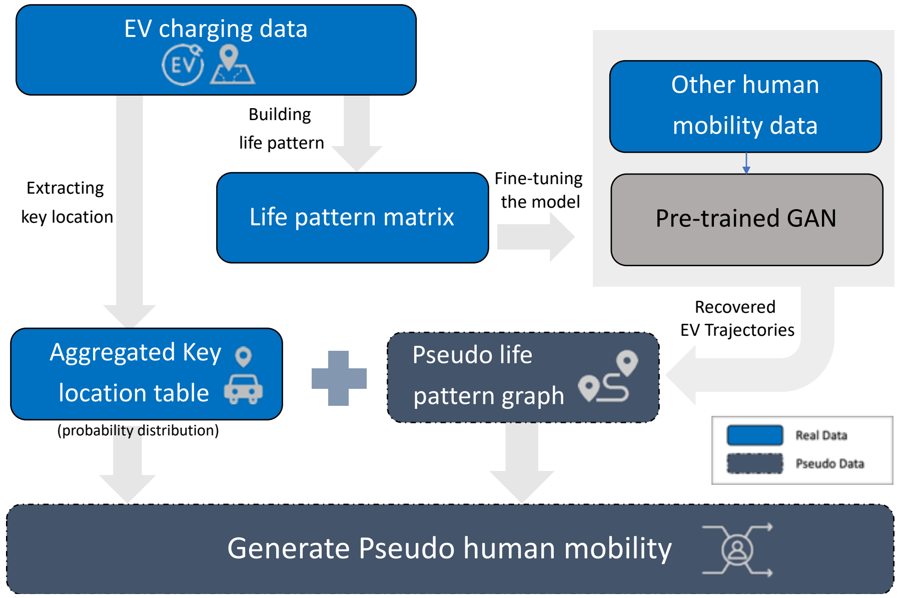


Figure 1. Framework of generating pseudo human mobility using EV charging data.

To enhance our analysis of key locations extracted from EV charging records, we incorporated a pre-trained model. This model was previously developed using extensive datasets capturing various aspects of urban human mobility [11]. The pre-trained model was integrated with the EV charging data to achieve a more nuanced understanding of the charging locations' significance in relation to typical life patterns in Shanghai. This integration enabled us to interpret the identified key locations not just as points of energy consumption, but as part of the broader tapestry of urban life. In our study, the model was employed to predict the daily life patterns of EV users based on the temporal and spatial characteristics of their charging activities. By doing so, we aimed to uncover the interdependencies between energy consumption and the rhythms of city life.

3.4 Synthesizing Trajectories from Life Patterns and Key Locations

Building upon the pre-trained life pattern model and the identified key locations, we proceeded to synthesize human mobility trajectories. This step is pivotal in translating discrete data points into continuous paths that represent the movement of individuals across the urban landscape.

We randomly sampled from the spatial coordinates probability table of key locations, which allowed us to anchor the life patterns within the physical space of the city. Then, we reconstructed the likely paths individuals might take between key locations by a map-matching algorithm OSMNX [12]. These paths were informed by the frequency and timing of EV charging events and were constrained by the road network and typical travel behaviors.

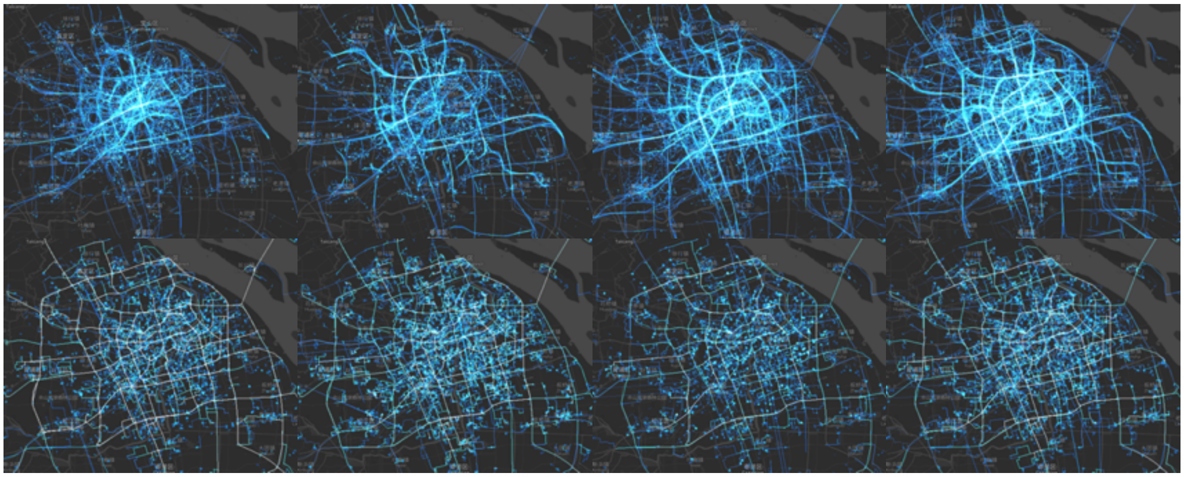
4. EXPERIMENTS

4.1 Data description

This study leverages a comprehensive dataset encompassing the charging records of 1,994 electric vehicles (EVs) in Shanghai, spanning from October to December 2022. The dataset, kindly provided by the Shanghai New Energy Vehicle Public Data Collection and Monitoring Research Center, underwent a meticulous data cleansing process. Erroneous entries, such as duplicates, incomplete records, and statistical outliers indicative of atypical charging behaviors, were removed. Additionally, inconsistencies in the dataset's formatting were standardized to ensure uniformity.

Figure 2. Visualization of the experimental area.

For the purpose of this analysis, we constrained the scope of our research to a defined experimental area, delineating an 11 by 14 kilometer rectangle within the urban matrix of Shanghai. Data points falling outside this



Ground truth

Pseudo trajectory

(a) 0:00 (b) 6:00 (c) 12:00 (d) 18:00

Figure 3. Visualization of the human mobility pattern of ground truth and pseudo trajectory every 6 hours.

specified region were excluded from the study. Figure 2 presents a visual representation of this experimental area, which also serves to approximate the mobility patterns of the EVs within the selected urban section.

besides, we have not only spatial and temporal records of EVs but also some detailed human movement records in this dataset. Therefore, we use the detailed movement as the ground truth trajectory while only using the charging information as the input of the experiments to show that we can generate pseudo-human mobility from only charging records.

To provide a comprehensive view of the EV charging data, we developed a visualization that maps the spatial distribution and frequency of charging events across the urban landscape. This geographic representation illustrates the density of charging activities at various locations, offering insights into urban mobility patterns. The visualization is color-coded to reflect the intensity of usage—darker hues correspond to higher frequencies of charging events. This allows for the immediate identification of hotspots where EV usage is most concentrated.

4.2 Experiment settings

The remainder of this paper is structured as follows: Section 2 reviews related work, highlighting the gap between energy demand studies and human mobility research. Section 3 details the methodology employed in developing the framework, while Section 4 presents the results of applying this framework to a dataset of EV charging records. Section 5 discusses the implications of these results for urban planning and smart city initiatives, and Section 6 concludes with a reflection on the findings and suggestions for future research.

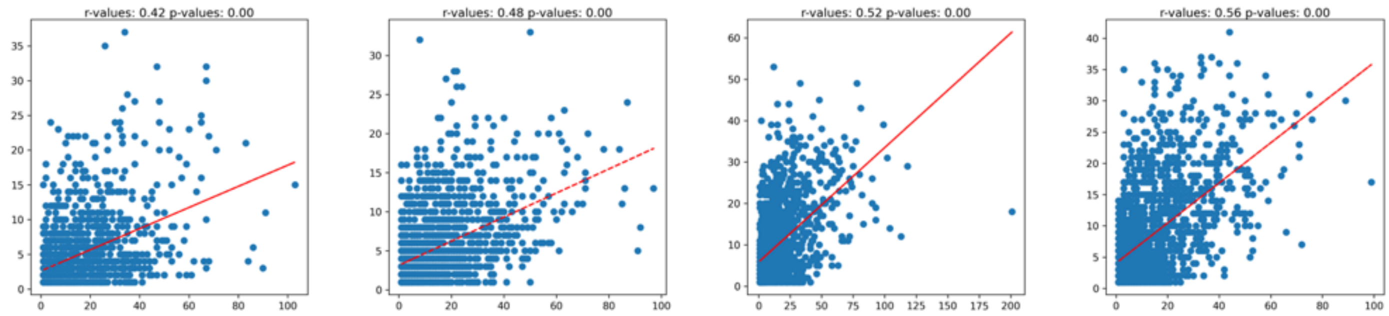
In the course of our investigation, we were able to successfully extract 5,111 key locations from the charging data of 1,975 electric vehicle users. These key locations, rich in detail, provided invaluable insights into the charging habits and mobility patterns within the urban landscape of Shanghai. However, given the sensitive nature of this data, which could potentially reveal personal information about the users, we took additional measures to ensure privacy.

To mitigate concerns regarding user privacy, we aggregated these key locations into a probability table. This process involved a thorough anonymization protocol that transformed the individual location data into a statistical representation, thereby preserving the privacy of the individual EV users. The resulting probability table does not disclose any individual's specific charging patterns but instead offers a generalized view of the spatial distribution of EV charging events across the city.

This approach allowed us to maintain the integrity of our research while adhering to stringent data protection standards. The probability table serves as a robust tool for analyzing urban energy dynamics without compromising personal privacy, thus striking a balance between the granularity of data and ethical research practices.

4.3 Experimental results

In Figure 3, we present a side-by-side visualization contrasting the generated pseudo-trajectories with the actual ground truth trajectories. This comparative analysis allows us to discern subtle variations between



(a) 0:00 (b) 6:00 (c) 12:00 (d) 18:00

Figure 4. Correlation of the hourly aggregated population distribution between ground truth and pseudo trajectories. Horizontal axis shows the population aggregated from pseudo trajectories while vertical axis is ground truth.

the modeled patterns and real-world behaviors. Notably, the visualization indicates that the ground truth data exhibits a propensity for users to travel along main thoroughfares. In contrast, the pseudo-trajectories depict a higher frequency of movement along smaller, less prominent roads.

The divergence in movement patterns suggests that while the pseudo-trajectories capture a broad aspect of mobility within the urban environment, they may overestimate the utilization of minor roads. This observation could be attributed to the model's tendency to distribute trajectories more evenly across the network, rather than replicating the concentrated flow typically observed on major roads due to factors such as convenience and accessibility.

4.4 Evaluation

Our correlation evaluation between the ground truth trajectories and the generated pseudo trajectories yields insightful results. As summarized in Table 1, we noted a correlation coefficient (r-value) of 0.74, indicative of a robust statistical relationship between the two datasets. This high degree of correlation reinforces the validity of our pseudo trajectories in mirroring real-world mobility patterns on an aggregate level. The p-value, approaching zero, further supports the statistical significance of the correlation, suggesting that the observed relationship is unlikely to have occurred by chance. This provides strong evidence that our generative model captures the essence of the mobility patterns inherent in the ground truth data.

Table 1. The correlation coefficient.

r-values	0.74
p-values	0.00

An hourly analysis of the population distribution, illustrated in Figure 4, presents a different perspective. Here, we observe a spread of r-values between 0.4 and 0.6, which, while lower than the overall correlation, still indicates a moderate positive relationship. These figures vary as they reflect the fluctuating nature of mobility patterns throughout the day. The task of aligning the pseudo trajectories with the hourly ground truth distribution poses a greater challenge due to the dynamic nature of human movements, influenced by daily schedules, traffic conditions, and social activities.

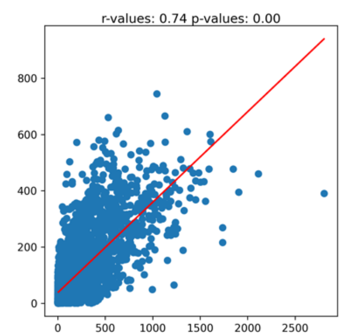


Figure 5. Correlation of the aggreged population distribution between ground truth and pseudo trajectories.

These lower hourly r-values, although expected, underline the complexities involved in temporal alignment. They suggest room for further refinement of the model, particularly in its capacity to adapt to the temporal granularity of mobility patterns. Enhancements to the model could involve integrating time-sensitive parameters that more accurately capture the ebb and flow of urban movement within each hour. Future iterations of this research may benefit from incorporating real-time traffic data and temporal behavioral models to achieve a closer match to the ground truth at finer temporal resolutions.

5. CONCLUSIONS

This study presented a novel framework for extrapolating human mobility patterns from urban energy consumption records, with a focus on electric vehicle (EV) charging data. By leveraging a pre-trained life pattern model and identifying key locations from EV charging records, we were able to synthesize trajectories that reflect the movement of individuals throughout Shanghai. The findings reveal a strong correlation between EV charging patterns and urban mobility, suggesting that EV charging data can serve as a reliable proxy for human movements in the context of urban studies.

While the study provides valuable insights, this study focused on EV charging data from Shanghai, which may not be generalizable to other cities with different urban layouts and transportation habits. Future research should aim to validate the model across different urban settings and explore the integration of additional datasets, such as public transport usage and ride-sharing data, to refine the synthesized trajectories. Further investigation into the temporal variations in mobility patterns could also yield deeper insights into urban energy consumption.

In conclusion, this study contributes to the growing body of literature on data-driven urban studies and opens new pathways for research in the nexus of human mobility, urban planning, and energy management.

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DECLARATION OF INTEREST STATEMENT

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

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