# An Optimization Deployment Scheme for Static Charging Piles based on Dynamic of Shared E-Bikes

Ping Zhong Aikun Xu Yuanming Chen Feng Gao Guihua Duan *School of Computer Science and Engineering Central South University*  ChangSha, China ping.zhong@csu.edu.cn

*Abstract***—Shared e-bikes are popular because of their green, eco-friendly and efficient features. Due to the limited battery capacity of the e-bikes, the energy problem has become one of the main factors limiting its further development. The energy problem can be solved by using static charging piles (SCP) to replenish the batteries of shared e-bike. The location of the shared e-bike is time-varying, resulting in the optimal deployment of SCP as a complex location problem. In this paper, we propose an optimal Deployment algorithm for Maximum Coverage combined the Dynamic Changes of nodes (max-DCDC) based on the known number of SCP. This method first quantitatively analyzes the dynamic change process of the shared e-bike to reduce the deployment scope of the SCP. Then, according to the geometric characteristics of the e-bike distribution within the deployment scope to optimizes the deployment location of the SCP. Simulation experiments show that max-DCDC has better performance in terms of deployment stability and e-bike coverage compared with the other algorithms.** 

## *Keywords—WRSN, Shared E-Bike*,*Maximum Coverage*, *Static Charging Piles*

## I. INTRODUCTION

 Since 2009, the public bicycle transportation system has grown at an average annual rate of 37% especially in China [1]. The quantity sales of e-bike exceed other vehicles [2,3]. Compared with other modes of transportation, e-bike is more energy efficient and emits less greenhouse gas (GHG) [4]. The shared e-bike is another vehicle catalyzed by the era of shared operations after sharing bicycles. Since shared e-bike rely mainly on rechargeable batteries to maintain operation, the remaining energy of the battery is the main reason for limiting its normal operation. This also poses a challenge for the operation of the e-bike rental company. The static charging piles (SCP) is deployed at the fixed e-bike spot to charge the e-bike with little energy, and it can fundamentally solve the problem of energy limitation of the shared e-bike.

The development of shared e-bike systems have gradually matured. There has been a lot of research on sharing e-bike. Ji et al. [5] designed a shared system during finished the shared e-bike pilot project at the Knoxville (UTK) campus in Tennessee. Simulation result shown that in the case of high flow density, it is necessary to equip each e-bike with a plurality of replaceable batteries to meet the maximum demand of users. Fyhri et al. [6] proved that the use of shared e-bike will increase the number of short trips, and sharing ebike has different benefits for different groups of people. At present, the research on shared e-bike mainly focuses on shared system design [7,8], shared e-bike structure design [9,10], battery pack optimization [11,12], etc. There are few

studies on the charging mode of shared e-bike in the stage of operation. However, energy scarcity is the main problem faced by the limited development of shared e-bike. This problem also leads to an increase in operating costs for operators.

We regard the shared e-bike as a sensor node in the Wireless Rechargeable Sensor Network (WRSN) and conduct research based on the related work in the WRSN[13,14]. Shared e-bikes have high fluidity and their location are constantly changing, which is different from the static topology of sensor nodes. Therefore, the research proposes the corresponding SCP optimization deployment method based on the dynamic change characteristics of e-bike. This research brings extremely important value and practical significance to the operation of urban shared e-bike.

In order to solve the problems of low stability and low utilization of SCP deployment, and take the dynamic characteristics of shared e-bike into account, the optimal Deployment algorithm for Maximum Coverage based on Dynamic Changes of nodes (max-DCDC) is designed. The main contributions of our work are as follows:

- We studies the optimal deployment of SCP in the actual urban environment. Since shared e-bikes are frequently used, the location of shared e-bike with time-varying characteristics are constantly changing. This feature determines that the static energy source optimization deployment method for the initial node topology design is no longer applicable to the shared e-bike application scenario with dynamic variation characteristics.
- We use variance as the main measure to describe the dynamic process of shared e-bike in different time. In order to achieve stable coverage of the SCP deployment area and maximize the number of e-bike in the area, we exclude a small number of meshes with high data stability. The distribution variance  $S_i^2$  of the remaining grids is sorted from small to large, and the grid corresponding to the first *L* variances is selected as the deployment area of the SCP. After determining the SCP deployment area, an optimization method based on the distributed geometrical location characteristics of the shared e-bike is used to determine the specific deployment location of the SCP.

 The rest of the paper is organized as follows. In section 2, we present an overview of existing studies related to static charger placement. Section 3 introduces the system model. Solution is described in section 4. Section 5 presents the performance analysis. Finally, we conclude the paper in section 6.

#### II. RELATED WORK

In recent research work on static energy sources, the main research goal is to minimize the charging cost of static energy sources or maximize network utility while ensuring the lifetime of the WRSN. Facing the problem of optimal deployment of static energy sources in WRSN, the existing research mainly considers the optimal deployment location of static energy sources. And these research always use Wireless Power Technology (WPT) for energy supplementation in 2D or 3D space to meet specific optimization objectives.

#### *A. Minimize charging costs - Deployment costs*

He et al. [15] used a wireless charging model with a bounded square inverse ratio to consider how to minimize the number of static energy sources to ensure that all nodes in the WRSN can be supplemented enough energy. This problem is similar to the node coverage problem in the WSN. According to the different perception models, the node coverage problem in WSN is mainly divided into two methods. The first is the ideal perceptual model, which mainly considers that each location is covered by at least one node's perceptual domain. Another is the probabilistic perceptual model, which mainly considers that a geographical location is covered by the sensing domain of many nodes. When the perceptual domain joint perceptual information of these nodes exceeds a certain threshold, the geographic location would be chosen. Liao et al. [16] considered the static energy source deployed in the subgrid intersection in the two-dimensional plane, and the nodes are deployed under the grid. The static energy source forms a cone map with the sensor nodes in the scene. The study designs an approximation algorithm with assume the node has an "active-sleep" mode of operation, which goal is to achieve the number of static energy sources required to minimize and the node without dying.

# *B. Maximize network utility - Specific goals*

Xu et al. [17] considered using WPT to solve the smartphones energy limitation, and proposed a method of deploying static energy sources to charge smart phones in public places (e.g., the subway), so that users can charge mobile phones while riding the subway. In addition, since the remaining and required energy of each mobile phone were different, the research defined a Charging Satisfaction Problem as an optimization problem, and dispatched a limited static energy source to serve users on the subway to achieve maximum charging satisfaction. Dai et al [18] designed an approximation algorithm to determine the position and direction of the static energy source in the two-dimensional plane, which can maximize the charging efficiency. In addition, they proposed an approximation algorithm to ensure uniform distribution of static energy sources in the sensor nodes  $[0, 2\pi]$  in static topology, and the deployment of static energy source can maximize charging efficiency [19].

The deployment of static energy sources in previous studies are mainly based on static node topology in WRSN. In the real world, the location of the shared e-bikes are dynamic change constantly during the movement. The deployment position of the SCP is closely to the shared e-bike. This determines that static energy source deployment solutions for static node topologies cannot be directly applied to SCP optimized deployment.

# III. SYSTEM MODEL

## *A. Problem Description*

In real environment, the location of shared e-bike is timevarying as it is frequently used. And the static energy source optimization deployment method for the initial node topology design is no longer applicable to the shared e-bike application scenario with dynamic variation characteristics. We will propose a SCP optimization deployment scheme, which is based on the dynamic change characteristics of e-bike. And we use the deployed SCP to supplement the electric bicycles in the charging coverage. The main purpose of this part is following:

*1)* Quantitative analysis of the dynamic location changes in large-scale shared e-bike

In the actual world, the large-scale of shared e-bike is constantly changing, so the static energy source deployment method cannot be directly applied in WRSN. It is necessary to obtain the densely distributed area of shared e-bike from the shared e-bike's location. Through the quantitative analysis, the deployment scope of the SCP can be reduced, and is useful for the subsequent optimization of the specific deployment position of the SCP.

*2)* Optimize SCP deployment location based on location geometry of shared e-bike

After reducing the deployment area of the SCP, once we just simply deploy SCP in the density center of the e-bike, we will find it not be able to adapt to the dynamic distribution characteristics of the shared e-bike. Because it is impossible to balance the diversity of distribution from the single shared e-bike distribution map. By analyzing the position characteristics in the SCP deployment area of multiple e-bike distribution maps, the overall distribution characteristics of the e-bike in the deployment area are obtained. Based on the distribution feature, the specific location of the SCP is optimized by utilizing the geometric position characteristics of the e-bike, and can improve the accuracy and adaptability of the deployment position of the SCP.

#### *B. System model*

From the actual situation, the location of the shared e-bike has a dynamic change feature. Suppose there are N shared ebikes of the same specification  $(N > 1)$  distributed in a rectangular area which without obstacles. As shown in Fig. 1, let  $N_i$  ( $i = 1,2,..., N$ ) present the *i*th e-bike. The SCP*j* will fully charge the shared e-bike within its charging range  $r_i$ , i.e. regardless of the capacity of the SCP and the number of shared e-bike that can be loaded. In addition, the SCP within the ranged<sub>i</sub> of the shared e-bike  $N_i$  can serve it and can only be served by one SCP at a time. We will discusses how to find and optimize the deployment location of the SCP in a twodimensional area in section 4. The number of SCPs deployed in each location is not discussed. The operator can get the location of the e-bike in the urban area at any time. We select the distribution map of the  $Ω/ξ$ shared electric bicycle in the inner city of the  $\Omega$  with  $\xi$  time interval.

## IV. MAX-DCDC

With the continuous development of the city and the continuous expansion of the scale of the transportation network. Large-scale deployment of SCP is difficult to meet



the needs of lower land occupation and low operator investment costs. The SCP deployment is based only on the initial distribution of shared e-bikes, the dynamic change characteristics of shared e-bikes are not well described. Therefore, we first quantitatively analyzes the dynamic process of shared e-bike to reduce the scope of SCP deployment and the amount of calculation. Then, according to the geometric position feature of the e-bike distribution to further optimized the specific deployment position of the SCP, which can ensure the SCP always meets the charging requirement with charging range, thereby improving the accuracy and adaptability of the deployment method.

#### *A. Make sure SCP is responsible for charging area*

Assuming that there are *L* identical specifications, and the SCP with one-to-many charging mode is deployed in the twodimensional area, not consider the capacity of the SCP and the number of shared e-bike that can be loaded. In this paper, the scope of the SCP deployment area is reduced by gridding. And the square grid of length *d* is used to mesh the  $\Omega/\xi$  electric ebike distribution map. As shown in the Equation (1), the average value  $E(i)$  of the number of e-bike included in the  $Ω/ξ$  shared e-bike distribution map of the grid *i*:

$$
E(i) = \frac{\sum_{j=1}^{k} a_{ij}}{k} \tag{1}
$$

Where  $a_{ij}$  is the number of e-bike included in grid *i* in the distribution diagram of the  $j$ th e-bike.  $k$  is the number of distribution maps of shared e-bike,  $k = \Omega/\xi$ .

This chapter uses variance as the main measure to describe the dynamic change process of shared e-bike in different time. The goal of this paper is to find areas which cover as many ebike deployments as possible to improve the utilization of SCP after deployment. This means that the selected deployment area can not only achieve large-scale coverage, but also the number of e-bike has data stability. Therefore, a grid with a small number of data and high data stability needs to be excluded. For the  $\Omega/\xi$  electric bicycle distribution map, the average  $E_{mean}$  of the number of e-bike included in the grid  $i$  is as shown in the Equation  $(2)$ .

$$
E_{mean} = \frac{\sum_{i=1}^{I} E(i)}{I} \tag{2}
$$

Where *I* is the total number of grids. In the distribution map of each e-bike, the grid with  $E(i) < E_{mean}$  is excluded, and the variance of the number of e-bike in the remaining grid *i* is  $S_i^2$  as shown in the Equation (3).

$$
S_i^2 = \frac{(E(i) - a_{i1})^2 + (E(i) - a_{i2})^2 + \dots + (E(i) - a_{ik})^2}{k} \tag{3}
$$

Algorithm 1: charging pile deployment area determination

- 1: **Input**:*L* (Number of deployment locations ), *k* shared E-Bike distribution map ;
- **Output:** Charging pile deployment area number ;
- 3: Divide the two-dimensional area with length and width *d* to obtain *I* sub-grid;
- 4:  $i = 1$ ;
- 5: **While**  $(i \leq I)$
- 6: *k*th shared E-Bike distribution map , *i*th grid contains the set of shared e-bike  $Q = \{a_{i1}, a_{i2}, \ldots a_{ik}\};$

9: 
$$
E(i) = \frac{\sum_{j=1}^{k} a_{ij}}{k};
$$

$$
10: \qquad E_{all} = \frac{1}{I} \sum_{i}^{I} E(i);
$$

11: If 
$$
E(i) \leq E_{all}
$$

$$
12: \qquad S_i^2 = Inf;
$$

13: **Else**

14: 
$$
S_i^2 = \frac{(E(i) - a_{i1})^2 + (E(i) - a_{i2})^2 + (E(i) - a_{i3})^2 + \ldots + (E(i) - a_{ik})^2}{k};
$$

- 15: **End If**
- 16: **End While**
- 17: Sorting  $S_i^2$  of *I* sub-grid in increasing order;
- 18: Output the first *L* grid corresponding numbers after
- sorting; 19: **End While**

Where  $E(i)$  is the average number of e-bike included in the grid  $i$ ,  $a_{ij}$  is the number of e-bike included in the grid  $i$  in the distribution map of the *j*th shared e-bike, and  $j =$  $1, 2, \ldots, k.$ 

As described in Algorithm 1, the distribution variance  $S_i^2$  of the remaining meshes is sorted from small to large, and the mesh corresponding to the first *L* variances is selected as the deployment area of the SCP, because the data volume included in the grid with small variances is relatively stable, and this kind of grid is more suitable for deployment of SCP.

# *B. Optimize the deployment location of SCP based on geometric location*

In order to determine the specific distribution characteristics of electric bicycles in the deployment area, this chapter calculates the linear regression equation and correlation coefficient ε of the distribution position of the electric bicycles contained in the selected *L* grids for each ebike distribution map. If the correlation coefficient  $\varepsilon_i$  of the grid *i* is larger than a specific parameter (the parameter is generally 0.8), it determines that the grid *i* is dense distribution on the distribution map of the electric bicycle, otherwise the distribution of the grid *i* in the electric bicycle is uniform distribution. If the number of dense distributions of the selected grid *i* is greater than the number of uniform distributions in the  $\Omega/\xi$  electric bicycle distribution map, it means determined that the grid *i* is a dense distributed grid, otherwise the grid *i* is considered to be a uniform distribution grid.

Based on the distribution characteristics of the e-bike in the L deployment grids, the final SCP deployment location is determined according to the following rules:

*1)* If the grid *i* is a uniform distribution grid, the SCP will be deployed in a central area of the grid;

*2)* As shown in Fig. 2(a), if two adjacent grids are dense distribution and the dense distribution areas (80% of e-bikes



Fig. 2 SCP Optimization Based on Geometric Position Characteristics of Shared E-bike

are distributed on the 1/2 side of the grid) are adjacent, we will select the central location of the dense area as the final SCP deployment location, and select the grid with the smallest distribution variance of the e-bike from the remaining unselected grids as the new SCP deployment grid;

*3)* As shown in Fig. 2(b), if the adjacent three meshes are dense distribution, and the first mesh is adjacent to the second mesh, the second mesh is adjacent to the third mesh, we will select the density center position of the dense area composed of the first grid and the second grid is selected as the final SCP deployment position, and the density center positions of the second grid and the third grid dense area are selected as the final SCP deployment position, where The dense area is the same as in the case of 2) above. At the same time, the grid with the smallest distribution variance of the e-bike selected from the remaining unselected grids to deploy new SCP;

*4)* As shown in Fig. 2(c), if both meshes are dense distribution and the dense distribution area (80% of the ebikes are distributed on the 1/4 side of the mesh) is diagonally distributed, then we directly select the intersection position of the grids as the final SCP deployment location, and the grid with the smallest distribution variance of the ebike is selected from the remaining unselected grids as the new SCP deployment grid;

*5)* As shown in Fig. 2(d), if the three meshes are dense distribution and each has a diagonal distribution, then directly select intersection positions of the three meshes as the final SCP deployment position, and from the remaining unselected grid, the grid with the smallest distribution variance of the ebike is selected as the new SCP deployment grid.

In the above case, if the newly selected SCP deployment grid and the originally selected grid in the grid still meet the conditions described in 2)-5), then continue to optimize the SCP deployment location according to the above method until the final location of *L* SCP deployments is found.

# V. PERFORMANCE EVALUTION

This paper assumes that 4000 shared e-bike are randomly distributed in the area of  $2000m \times 2000m$ . Using MATLAB to generate 10 node topological maps, as the estimated duration of the Ω evaluation in the total length of the ξ evaluation to extracted e-bike distribution map, in which different data is represented by the different data ID. In this paper, the two-dimensional area is divided into an integer number of grids, and the length and width of the unit grid are set to *d*=100*m* in each map. Both the range of shared e-bike  $d_i$  and SCP charge range  $r_i$  are 50√2*m*. And we assumed that 6 locations are selected for SCP deployment, i.e., *L*=6.

# *A. Feasibility of quantitative analysis of dynamic changes of shared e-bike*

Maximizing of Deployments Area Selection Algorithm Based on Mean of Node Dynamics (max-DSMD) consider the grid with the largest mean value in the distribution map of shared e-bike after gridding as the deployment area of the SCP. Wang et al. in [20] proposed an algorithm is called Maximum Coverage Rate Based on Equilateral Triangle (max-CRBET). As shown in Fig. 3, the deployment location coverage value selected by max-DSMD is not as stable as max-DCDC. This is because variance can describe the degree of dispersion and stability of the data, while the mean can only describe the trend of the data. In addition, as shown in Fig. 3, the max-CRBET method can't allow the data to be in a stable state. This is because the equilateral triangle division achieved by the max-CRBET method does not take the dynamic variation characteristics of the shared e-bike into account, which also determines that the max-CRBET scheme cannot be directly applied to the actual world.

## *B. Feasibility analysis of optimization methods under SCP*

After determining the SCP deployment area, this paper uses the optimization scheme which is based on the geometric location characteristics of the shared e-bike to determine the specific deployment location of the SCP. As shown in Fig. 4, when the data obeying the Gaussian distribution and the Poisson distribution, the optimized SCP covers more shared e-bike than before (i.e., deployed in the center of the grid). However, when the data obeying uniform distribution, there is no change. This is because the number of the deployed SCPs too small to meet the prerequisites for optimization, i.e., there is an adjacent situations in the selected deployment area. For the data of Gaussian distribution and Poisson distribution, the correlation between elements is strong and aggregated. The probability that the selected SCP deployment grids are adjacent to each other is larger than the uniformly distributed data, which satisfies the preconditions of optimization. In addition, the deployment area of the SCP can be increased compared to before, thereby increasing the number of shared e-bike in the coverage area of the SCP.

# VI. CONCLUSION

In this paper, we studied the corresponding SCP optimized method based on the characteristics of e-bike movement in the actual sharing of e-bike operating. We divided the optimization SCP deployment scheme (max-DCDC) into two steps. Firstly, according to the results of quantitative analysis, we reduced the scope of deployment of SCP to reduce the calculation. Secondly, we use the geometric location characteristics of the shared e-bike



Fig. 3 SCP coverage under different deployment methods



Fig. 4 Comparison of the number of SCP coverage nodes before and after optimization

within the narrowed scope of the SCP deployment to optimize the specific deployment. Then, according to detailed simulation, the feasibility of the proposed optimization scheme based on the known number of SCP was verified. The result showed that compared with the comparison algorithm, max-DCDC has better performance in terms of deployment stability and e-bike coverage.

#### ACKNOWLEDGMENT

The work described in this paper was supported by the grant from the National Science Foundation of Hunan Province (No. 2018JJ3692) and the National Natural Science Foundation of China (No. 61402542).

#### **REFERENCES**

- [1] Meddin, R. The bike-sharing world map, http://www.bikesharingmap. com, 2019.
- [2] CAAM, Chinese association of automobile manufacturers-automotive statistics, http://www.caam.org.cn/english/newslist/a101-1.html, 2015a.
- [3] CAAM, Chinese association of automobile manufacturers-motocycle statistics, http://www.caam.org.cn/english/newslist/a104-1.html, 2015b.
- [4] Bai L, Liu P, Chen Y, Zhang X, and Wang W. Comparative analysis of the safety effects of electric bikes at signalized intersections[J]. Transportation Research Part D: Transport and Environment, 2013, 20(Complete):48-54.
- [5] Campbell A, Cherry C, Ryerson M, and Yang X. Factors influencing the choice of shared bicycles and shared electric bikes in Beijing[J]. Transportation Research Part C, 2016, 67:399-414.
- [6] Ji S, Cherry C R, Han L D, and Jordan D. Electric bike sharing: simulation of user demand and system availability[J]. Journal of Cleaner Production, 2014, 85:250-257.
- [7] Fyhri A and Fearnley N. Effects of e-bikes on bicycle use and mode share[J]. Transportation Research Part D: Transport and Environment, 2015, 36:45-52.
- [8] Florez D, Carrillo H, Gonzalez R, et al. Development of a bike-sharing system based on pedal-assisted electric bicycles for bogota city[J]. Electronics, 2018, 7(11): 1-31.
- [9] Datner S, Raviv T, Tzur M, and Chemla D. Setting inventory levels in a bike sharing network[J]. Transportation Science, 2019, 53(1): 62-76.
- [10] Zhao Y, Su Y, Chang Y. A real-time bicycle record system of ground conditions based on Internet of Things[J]. IEEE Access, 2017, 5: 17525-17533.
- [11] Guanetti J, Formentin S, Corno M, Savaresi S. Optimal energy management in series hybrid electric bicycles[J]. Automatica, 2017, 81: 96-106.
- [12] Lin J, Schofield N, Emadi A, External-rotor 6-10 switched reluctance motor for an electric bicycle[J]. IEEE Transactions on Transportation Electrification, 2015, 1(4):348-356.
- [13] Lin J, Yu W, Zhang N, *et al*. A survey on Internet of Things: architecture, enabling technologies, security and privacy, and applications[J], IEEE Internet of Things Journal, 2017, 4(5):1125-1142.
- [14] Deng X, Jiang P, Peng X, Mi C. An Intelligent outlier detection method with one class support tucker machine and genetic algorithm towards big sensor data in Internet of Things[J]. IEEE Transactions on Industrial Electronics, 2019, 66(6):4672-4683.
- [15] He S, Chen F, Jiang F, Yau D, Xing G, and Sun Y. Energy provisioning in wireless rechargeable sensor networks[C], IEEE Conference on Computer Communications (INFOCOM), 2011, 1-9.
- [16] Liao J, So W, and Jiang J. Optimized charger deployment for wireless rechargeable sensor networks[C]. The 9th Workshop on Wireless, Ad Hoc, and Sensor Networks (WASN), 2013.
- [17] Xu W, Liang W, Peng J, Liu Y, and Wang Y. Maximizing charging satisfaction of smartphone users via wireless energy transfer[J]. IEEE Transactions on Mobile Computing, 2017, 16(4): 990-1004.
- [18] Dai H, Wang X, Liu A, Ma H, Chen G. Optimizing wireless charger placement for directional charging[C]. IEEE Conference on Computer Communications (INFOCOM), 2017, 1-9.
- [19] Dai H, Wang X, Liu A X, *et al*. Wireless charger placement for directional charging[J]. IEEE/ACM Transactions on Networking, 2018, 26(4): 1865-1878.
- [20] Wang C, Li J, Ye F, Yang Y. A mobile data gathering framework for wireless rechargeable sensor networks with vehicle movement costs and capacity constraints[J]. IEEE Transactions on Computers, 2016, 65(8):2411-2427.