Distribution of scarce resources based on crowd density detection and queuing theory

Tingxuan Zhang
International School, Beijing University of Posts and Telecommunications, Beijing, China
*Corresponding author e-mail: zhangtingxuan@bupt.edu.cn

Abstract. This paper makes a reasonable estimate of the number of charging stations to be set in each charging station by detecting the density of people near the charging station. Due to the shortcomings of traditional MCNNs that are currently commonly used for population density estimation, we added dilated convolution to the traditional MCNN and applied queuing theory to this problem. The population density estimation result of the MCNN incorporating the reduced convolution is used as the input of the aligned flow, so that the number of charging piles in each charging station is more reasonably set.

1. Introduction

The development speed of electric vehicles has exceeded expectations and the construction of hardware facilities has matured, it has often encountered difficulties in the product promotion stage and has never been able to replace crude oil-powered vehicles. The main reason is that the battery life of electric vehicles is not strong and the charging time is long [1]. Taking the Tesla Model S as an example, Tesla offers a variety of charging methods [2]. However, it takes 30 hours to fully charge the battery with Mobile Connecter, and 10 hours and 5 hours respectively using the regular Single Charger and Twin Charger [3]. The newly developed Super Charging has a significantly faster charging speed, but its charging device only exists in the North American market and is not universal. In addition, many consumers report that it is difficult to find available charging stations or charging piles during driving, which greatly affects the experience of remote users. Therefore, at this stage, in addition to the technical team's efforts to develop larger capacity batteries and charging reactors with higher charging efficiency, the reasonable distribution of charging stations and charging piles is very important. This paper thinks that for countries that do not build EV charging stations, initial design should be carried out. At the same time, for countries that have built EV charging stations, whether the reasonable distribution of charging stations is an important factor affecting the driving experience of consumers. In order to have a good experience for the electric car users who travel frequently and the continuous development of the electric vehicle industry, it is extremely urgent to properly arrange the charging station.

In the previous paper, we wrote the location of the charging station based on the generalized maximum coverage model. But the question of the efficiency of charging is also a problem, that we need to consider. Under the premise that the charging station has been reasonably distributed, in order to improve the charging efficiency, we can reasonably allocate the number of charging piles in the charging station.

The intelligent system proposed in this paper has the following advantages:
1. Apply the queuing theory to the rational allocation of charging piles in charging stations.
2. Combined with the idea of population density estimation issues, the series and parallel combined delayed convolution was added to the original MCNN model. The new model is used to estimate the flow of people in the EV charging station, thereby setting the appropriate number of service stations (i.e., the number of charging stations) in the charging station.

2. Background

2.1. Queuing theory
In the early 20th century, the Danish mathematician Erlang was very interested in the queuing phenomenon in telephone calls and conducted research. Thus, the queuing theory was proposed [4, 5]. The queuing theory improves the service system based on data such as waiting time and queue length to meet the needs of the service object to the greatest extent. The queuing system consists of three parts: input process, queuing rules and service organization.

First, the input process is to show the customer according to what rules to reach the service system. The total number of customers is limited or unlimited; the customers arrive at the service system separately or in batches; the time interval at which the customer arrives at the service system is deterministic or random. Second, the queuing rules are divided into loss system, waiting system and hybrid system. Finally, service organization can be divided into a single service and a batch service according to the service mode, which also can be divided into a deterministic type and a random type according to the service time.

2.2. Population density estimate
With the increase of people's social activities, dangerous events such as pedaling caused by crowds are often infrequent. The idea of the population density estimate is thus produced. If an accurate estimate of the population density at a particular location is available, it will provide a reliable basis for urban construction and risk prevention.

In the early days, a sliding window detector was used to detect the crowd in the scenes to estimate the number of people in the scene [6]; the researchers estimated the population density by extracting features such as the edge of the pedestrian [7], but such detection method only works for sparse scenes. In crowded scenes, people and people occlude each other, edges and other features cannot be accurately extracted, so the researchers found that testing specific parts of the body (such as shoulders, heads) will make the results more accurate than the overall detection [8]; Lempitsky and Zisserman proposed a method based on density estimation, which integrates saliency information and is more suitable for crowded scenarios [9]. After deep learning is proposed, convolutional neural network (CNN) is also applied to population density estimation. Shang et al. proposed an end-to-end convolutional neural network with an image as input and a direct output of the density estimate [10]; Zhang et al. proposed a multi-column convolutional neural network (MCNN), which allows the input image to be of any resolution and can adapt to different sizes of objects, greatly improving the accuracy of population density estimation [11]; Sindagi and Patel add a high-level prior to the density estimation network [12]. Li et al. proposed CSRNet, which does not blindly expand network complexity and generate higher quality density maps [13].

3. Scarce resource distribution
In this section, we use queuing theory and MCNN with series and parallel combined delayed convolution to estimate the population density near the EV charging station, directly reacting to the nearby population density and indirectly reflecting nearby vehicle density and economic conditions. Thereby an appropriate number of charging posts are placed in the charging station.

3.1. Population density estimate
In this paper, the baseline we used in population density estimation is MCNN. We add a dilated convolution between two CNNs. The output of the upper CNN and the output of the lower CNN
simultaneously enter the dilated convolution as input, and the information is fused and input into the last
CNN to obtain the output result.

Due to the large size of the images in the crowd count dataset, the greater the receptive field, the
higher the accuracy of the results. Therefore, in order to increase the receptive field of the model, we
tried to deepen the network depth and increase the size of the convolution layer filter. However, although
these methods allow the model to obtain more information, the model parameters will be greatly
increased, and the training and running speed will be greatly slowed down. Finally, we were inspired by
Li et al. [13] and chose to use dilated convolution to achieve this function.

Compared with ordinary convolution, the advantage of dilated convolution is that the receptive field
of the network can be multiplied, and the efficiency of processing large-scale images is also higher.
Compared with the pooling layer, the advantage of dilated convolution is that the output feature map
will not lose the input image details. Therefore, the dilated convolution can not only do convolution
operations, but also help to expand the receptive field.

Traditional dilated convolution networks are mostly in series [14]. At present, there are two most
popular connection modes. The first one is mainly used in transfer learning. It mainly changes the
convolution layer at the tail of the network to the void convolution by increasing the void rate. This
structure is more suitable for large-scale feature maps of population density detection. The second
structure is not suitable for transfer learning, but it usually enhances the receptive field of the network
by increasing the dilated rate. Therefore, series dilated convolution is of great help to improve the
accuracy of population density detection.

In this paper, the traditional series dilated convolution is improved by using the characteristics of
residual network "parallel expansion" to transform it into a complex structure of series and parallel,
which can obtain more spatial information and fuse feature maps of different sizes. While maintaining
the resolution of the feature map unchanged, the receptive field of the network is greatly increased.
There are five branches in the module, each of which corresponds to different network depth and field
size. The receptive field size of branch 1 is 1 and the network depth is 0 (identity mapping); the receptive
field size of branch 2 is 3 and the network depth is 1; the receptive field size of branch 3 is 7 and the
network depth is 2; the receptive field size of branch 4 is 15 and the network depth is 3; the receptive
field size of branch 5 is 31 and the network depth is 4. The updated network structure diagram is shown
in Figure 1.

![Figure 1. network structure diagram](image-url)

After training, our results have improved the accuracy of population density estimate compared to
the traditional MCNN, as shown in Table 1. We apply this technique to crowd density detection near
the charging station to predict the traffic flow and economic conditions near the charging station, and
use this data as an important parameter in the input of the queuing theory model.
3.2. Queuing theory

We introduce a queuing theory model to plan the number of charging stations at the charging station. According to the population density estimate method mentioned above, we assume that the traffic near the charging station is in accordance with the Poisson flow, and the probability distribution formula is

\[ P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}, k = 0,1, \ldots \]

In the queuing theory model established in this paper, the daily average traffic flow of the charging station is discussed. Assuming that the traffic flow rate is \( \lambda \), the corresponding departure rate is \( \mu \). Here the queuing theory M / M / n: ∞ / ∞ / FIFO model, the input rate and the departure rate are stable. We introduce the following parameters:

Average stay captain \( L_d \)

\[ L_d = \rho(1 + \frac{D}{n - \rho}) \]  

(1)

Where \( D \) is the probability of vehicle waiting in the model, \( n \) is the number of charging piles at a charging station in the model, \( \rho = \lambda / \mu \).

Average waiting captain \( L_q \)

\[ L_q = L_d - \rho \]  

(2)

Average length of stay \( W_d \)

\[ W_d = L_d / \lambda \]  

(3)

Average waiting time \( W_q \)

\[ W_q = L_q / \lambda \]  

(4)

\( W_d, W_q, L_q, L_d \) are relatively easy to obtain during the sampling process. From these values, we can get the values of \( \lambda \) and \( \mu \). Let \( A = \lambda / \mu \), where \( A \) is called system flow.

In the model presented in this paper, we can also obtain the overall utilization of the charging piles in the charging station and evaluate the entire model. The overall utilization rate of the charging pile is \( \eta \). In the formula (5), \( n \) is the number of charging piles in the entire model.

\[ \eta = \frac{\rho}{n} \]  

(5)

In the above modeling of the distribution of destination charging and super charger charging stations, based on the battery life of the Tesla electric vehicle and the population in the Irish region, this paper presents a generalized maximum coverage based on a cellular network in Dublin, Ireland. The model selected Super Charger for example analysis, according to a charging station actual sampling and population flow and traffic flow and other practical considerations, the variables obtained in Table 2.

### Table 1. Estimation errors on ShanghaiTech dataset

| ShanghaiTech Part A | MAE   | MSE   |
|---------------------|-------|-------|
|                     | 86.87 | 126.06 |
|                     | (110.2)| (173.2)|
| ShanghaiTech Part B | 18.24 | 31.47 |
|                     | (26.4) | (41.3) |

### Table 2. The distribution of Sample Variable

| S/Times | \( L_d / \text{h} \) | \( L_q / \text{h} \) | \( \lambda / \text{h} \) | \( \mu / \text{h} \) |
|---------|---------------------|---------------------|---------------------|---------------------|
| 1       | 6.0                 | 4.0                 | 50                  | 25                  |
| 2       | 4.7                 | 3.1                 | 48                  | 30                  |
| 3       | 5.1                 | 2.3                 | 56                  | 20                  |
| 4       | 4.3                 | 2.4                 | 52                  | 28                  |
| ……      | ……                  | ……                  | ……                  | ……                  |
The charging station currently has only two charging posts. The average of the above data, the use of the formula available in the sampling of the charging station, the traffic $A = \frac{\lambda}{\mu} = 2.065$. In the case of the system to ensure the loss rate $B \leq 0.2$, Charles Ireland table can be established that the number of charging piles $N = 4$.

For the reasonable distribution of scarce resources, this paper uses loop model, cellular network model combined with generalized largest coverage model, the MCNN model with a dilated convolution and queuing model. When these models are actually applied to the location problem, since the loop model is suitable for larger areas that are built with loops or roads that are diverging from the center, the loop model should be used first. After using the loop model to make the station layout in a wide range, the cellular network model combined with the generalized largest coverage model can be applied to areas where the road layout is not developed. After both models are properly applied, all demand points are covered by the station. On this basis, the MCNN model with the series and parallel combined dilated convolution and queuing model can be applied to estimate the flow of people and economic development next to the facility, and then we can determine the number of charging piles that should be set in the station.

4. Conclusion
This paper summarizes the location selection of charging stations and charging piles. When these models are actually applied to the location problem, since the loop model is suitable for larger areas that are built with loops or roads that are diverging from the center, the loop model should be used first. After using the loop model to make the station layout in a wide range, the cellular network model combined with the generalized largest coverage model can be applied to areas where the road layout is not developed. After both models are properly applied, all demand points are covered by the station. On this basis, the MCNN model with the series and parallel combined dilated convolution and queuing model can be applied to estimate the flow of people and economic development next to the facility, and then we can determine the number of charging piles that should be set in the station.

For the future development of the electric vehicle industry, the improvement of charging technology is inevitably crucial. At the same time, in order to rationally lay out scarce resources, more location models can be proposed for various road distribution areas. In addition, the crowd counting model has its advantages when estimating the number of charging piles required in each charging station, but it is still not completely accurate. Therefore, we can also estimate the population density near the charging station by analyzing people's mobile phone signals [15]. The combination of the detection of the mobile phone signal and the MCNN model can not only detect a larger geographical area, but also better reflect the mobility of the crowd, and at the same time better simulate the traffic flow.

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