Vanpool trip planning based on evolutionary multiple objective optimization

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Abstract. Carpool and vanpool draw a lot of researchers’ attention, which is the emphasis of this paper. A concrete vanpool operation definition is given, based on the given definition, this paper tackles vanpool operation optimization using user experience decline index (UEDI). This paper is focused on making each user having identical UEDI and the system having minimum sum of all users’ UEDI. Three contributions are made, the first contribution is a vanpool operation scheme diagram, each component of the scheme is explained in detail. The second contribution is getting all customer’s UEDI as a set, standard deviation and sum of all users’ UEDI set are used as objectives in multiple objective optimization to decide trip start address, trip start time and trip destination address. The third contribution is a trip planning algorithm, which tries to minimize the sum of all users’ UEDI. Geographical distribution of the charging stations and utilization rate of the charging stations are considered in the trip planning process.

1 Introduction

There are already 1.2 billion vehicles on the road by July 29, 2014 and it is estimated to have 2 billion of cars in 2035\textsuperscript{[1]}. The enormous number of vehicles brings convenience to consumers, however, it also causes severe environmental burden, such as energy crisis and environmental pollution. Data shows that in 2014, 28\% of total U.S. energy was used for transportation\textsuperscript{[2]}. Transport accounts for nearly one-quarter of global energy-related CO\textsubscript{2} emissions\textsuperscript{[3]}. It is predicted that without strong global action, car ownership worldwide is set to triple to over two billion by 2050. Due to heavy transport usage, transport related energy usage and CO\textsubscript{2} emission are expected to have higher growth rate.

There is numerous action taken by different parties to make transport greener, including individuals, different communities and the government. Carpool and public transportation are encouraged to be used as often as possible by individuals to reduce burden borne by the environment. Electricity generated by solar power, wind power or nuclear power does not consume fossil fuels and also emit less greenhouse gases and other poison particles. Electric vehicle is also more efficient in energy conversion. The vehicle industry is doing an amazing job to produce vehicles with higher mile per gallon and longer travelling range\textsuperscript{[4]}. From the point of the government, as of 2012, there are about 126 HOV facilities on freeways in 127 metropolitan areas in the United States, which includes over 1000 corridor miles (1600 km)\textsuperscript{[5]}. Carpool combined with electric vehicle is a suitable solution of the combination of individuals’ contribution and governments’ efforts. Due to lack of administration of the vehicles, gang-rape and assaults are reported in websites\textsuperscript{[6, 7]}. Security is considered to be an obstacle for carpool, the same goes for vanpool. Vanpool with higher transport efficiency and better security surveillance system to ensure safety is adopted\textsuperscript{[8, 9]}. 
This paper proposes a vanpool operation schema based on UEDI. Two assumptions are made about the vanpool operation system.

- Each consumer is equal, each consumer’s UEDI should be as similar as possible.
- Sum of every consumer’s UEDI should be minimized for system efficiency.

Two functions expressing these two assumptions, based on travel time and travel distance, are given in this paper. Trip start address, trip end address and trip start time are decided based on the evolutionary multiple objective algorithm given in this paper. After trip start address and trip end address being decided, a routing method ensuring these two assumptions is given. The routing method considers the geographical distribution and utilization rate of charging stations. Our main contributions are summarized as follows.

- We integrate routing algorithm into the vanpool operation schema, a workflow is given for the vanpool operation schema.
- Genome representation, objective representation functions are given in this paper to compose the evolutionary multiple objective algorithm.

A trip planning algorithm, aiming to minimize sum of every user’s UEDI, embodied with geographical distribution and utilization rate of charging stations is proposed, real charging stations data is used to evaluate the trip planning algorithm. The remainder of this paper is organized as follows. Related work is given in Section 2. We then state our problem in Section 3. The vanpool management model is built in Section 4. In Section 5, evaluation and discussions of the proposed algorithm are given. Section 6 summarizes the whole paper.

2 Related work
This paper is composed of three subjects, carpool, multiple objective optimization and route search for EV. 2.1 is mainly about the state of art about carpool. 2.2 summarizes how different methods tackling multiple objective optimization problems. 2.3 talks about the state of art of electric vehicle route searching method with consideration of charging stations.

2.1 Carpool
Wen He uses data mining technique with the Geolife dataset provided by MSRA[10] to find similarities in different persons’ tracks. Using the information dug up, users with similar tracks are found to constitute a carpool system. Researchers also highlight society’s concern for carpool using social survey. Shih-Chia Huang uses evolutionary algorithm and fuzzy logic to build a carpool system[11], the paper is mainly focused on the algorithm’s processing time. Cools, Mario gives out a social survey about reasons public want to be a part of carpool system[12]. Reasons about public participation in carpool are given. Sheng-Kai Chou focuses on carpool system’s establishment[13], the proposed system gathers users’ different information and then uses the gathered data to form a carpool system using particle swarm optimization. The matching and routing result show statistical advantage. Similarly, Shih-Chia Huang is focused on carpool’s establishment[14]. The only difference is that Shih-Chia uses genetic optimization method[14]. The approach considers multiple objective optimization and is superior to other literature in multiple objective optimization. Ming-Kai Jiau gives a carpool establishment method using evolutionary multiple objective method[15], too. Carpool and vanpool have a lot in common when it comes to user behavior matching and system establishment. Related research in carpool can be used to help establish the vanpool system. Currently, all related literature focused on carpool system establishment and no attention is paid to system management and operation. This paper mainly focuses on vanpool system operation, which would be helpful to run vanpool system in real life.

2.2 Multiple objective optimization
C.-L Hwang points out system needs to have a preference between different objectives before the optimization[16], this kind of research focused on what can be done before the optimization. J. Branke’s method do not have any preference between different objectives[17]. Algorithms having a
preference between different objectives can be categorized into two different kinds. One is mathematical, usually it requires lots of iterations, each iteration brings one pareto optimal solution,[18], the other kind simulates the evolutionary process and each iteration produces a set of pareto optimal solutions. The method introduced by K. Miettinen requires preference between different solutions after each iteration [19]. For vanpool system operation, there is no good reason deciding priority beforehand between customer fairness and system efficiency, a solution giving out a pareto set would be more suitable for vanpool system management.

2.3 Route search for EV
Hua Qin guides EV’s charging behavior to minimize waiting time in a network of electric vehicles and charging stations, a theoretical study is given to provide a practical distributed schema [20]. MN Mariyasagayam uses location and reachability information of other electric vehicles along the route in order to estimate charging spot occupancy ratio at the charging stations [21]. Using occupancy ratio at the charging stations, vehicle drivers can be opportunistically advised to take appropriate routes with less crowded charging stations. The paper fails to mention the importance of vehicle to vehicle communication in the proposed schema, as a result the proposed system may not be suitable for real traffic flow. Tingting Mu uses past related data to predict travel time and energy cost of electric vehicles [22]. For its superior usage of past data, effectiveness of the proposed method for both short-term and long-term prediction of travel time and energy cost is proved. René Schönfelder proposes a highly efficient solution for energy-efficient profile routing, different initial energy status of EV is considered [23]. In paper [24], a framework for energy-driven and context-aware route planning for EV is proposed. It considers negative energy cost and real-time traffic data. In paper [25], a route search method is proposed in consideration of range and location of charging stations. Yuhe Zhang first gives out a rough range estimation, when necessary, a precise range estimation method is proposed, calculation complexity is reduced for this approach [26]. The method we proposed in this paper considers the utilization ratio of the charging station, and advises drivers to avoid the busy charging stations and does embody the real life traffic flow into the model.

3 Problem Statement
Currently existing vanpool operation approaches are different in how the van pick up customers, how the customers get off, and how every customer pay for the vanpool system. Figure 1 gives a most frequently used and representative vanpool definition. Different customers use different travel style (Bike, Walking or Driving) to get to start address before trip start time, then all customers use vanpool to get to their common trip end address. After arriving, different customers choose their preferred travel style to get to their destination. Real life examples using Figure 1 is given as follows.

![Figure 1: Vanpool Operation Definition](image-url)
Table 1: Signs used in this paper

| Sign   | Meaning                                      |
|--------|----------------------------------------------|
| $CD_i^1$ | Customer’s original Lon/Lat coordinate      |
| $CD_i^2$ | Customer’s destination Lon/Lat coordinate   |
| $CD_{te}$ | Optimized trip start Lon/Lat coordinate    |
| $T_{te}$  | Optimized trip end time                     |
| $CD_{te}$ | Optimized trip end Lon/Lat coordinate       |
| $TS_i^1$  | Customer’s travel style to trip start coordinate |
| $TS_i^2$  | Customer’s travel style to trip end coordinate |
| $T_{te}^0$ | Customer’s expected to arrive time         |
| $CD_{cs}$ | Charging station j’s Lon/Lat coordinate     |
| $RoU_i^j$ | Charging station j’s utilization rate        |
| $UEDI_i$  | Customer’s user experience decline index    |
| $int_i^k$ | Customer’s travelling interval lasted for trip start part |
| $int_e^k$ | Customer’s travelling interval lasted for trip end part |
| $d_i^c$   | Customer’s travelling distance for trip start part |
| $d_i^e$   | Customer’s travelling distance for trip end part |

- College students and faculty members use vanpool to travel from one campus to another located one.
- Different group of people share same residential and working region, vanpool can be used by them to communicate between their home and their office.

For every user i, the vanpool program collects user’s $CD_i, CD_d, T_{tea}, TS_i^1$ and $TS_i^2$. The vanpool operation using evolutionary objective optimization algorithm to get $D_{ts}, T_{ts}$ and $CD_{te}$. Using $CD_{ts}, CD_{te}, CD_{cs}^i$ and $RoU_i^j$, a route for electric van can be obtained based on UEDI. Table I shows symbols and their corresponding meanings.

3.1 User Experience Decline Index ($UEDI$)

There are mainly two reasons for customer’s experience to suffer, time spent on road($int$) and travelling distance on road($d$).

- $(int) > 0, (d) > 0$
- $\forall (int) \in R, \forall d \in R, UEDI(int, d) = UEDI_{int}(int) + UEDI_d(d)$
  * $(int) = 0, UEDI_{int}(int) = 0, \forall int_1 \in R, \forall int_2 \in R, if int_1 < int_2, then UEDI_{int}(int_1) < UEDI_{int}(int_2)$
  * $d = 0, UEDI_d(d) = 0, \forall d_1 \in R, \forall d_2 \in R, if d_1 < d_2, then UEDI_d(d_1) < UEDI_d(d_2)$
- If $int_m + int_n = int_k, then UEDI_{int}(int_m) + UEDI_{int}(int_n) = UEDI_{int}(int_k)$
- If $d_m + d_n = d_k, then UEDI_d(d_m) + UEDI_d(d_n) = UEDI_d(d_k)$
- If $\forall (int_m < int_n), then UEDI_{int}(int_m) < UEDI_{int}(int_n)$

Any function satisfying above constraints can be used to represent UEDI.

$$UEDI(int, d) = k_1 \times (int) + k_2 \times (d)$$ (1)

In (1), k1 and k2 are parameters used to represent time interval and travelling distance of customers’ UEDI.

User Experience Decline Index Definition

There are three factors contributing to UEDI, $CD_{ts}, T_{te}$ and $CD_{te}$.

Firstly, for choosing of $T_{ts}$, customer with smallest $T_{tea}$ must be satisfied, which will lead other customers waiting certain time before their expected to arrive time. The corresponding $UEDI_{tst}$ can be defined as (2).

$$UEDI_{tst}^i = k_1 \times (T_{exp}^i - T_{dest}^i)$$ (2)
Secondly, after CD_{ts} is decided. Customer i use TS_{ts} to get to CD_{ts}. (3) can be used to describe the influence of CD_{ts}.

\[ UEDI_{c\, dts}^i = k_1 \cdot (int_{ts}^i) + k_2 \cdot (d_{ts}^i) \quad (3) \]

Finally, after CD_{te} is chosen, customer i choose TS_{te} to reach CD_{te}. (4) can be used to represent CD_{te}’s influence.

\[ UEDI_{c\, dte}^i = k_1 \cdot (int_{te}^i) + k_2 \cdot (d_{te}^i) \quad (4) \]

For customer, UEDI of customer i can be represented as (5).

\[ UEDI^i = UEDI_{c\, dst}^i + UEDI_{c\, dts}^i + UEDI_{c\, dte}^i \quad (5) \]

User Fairness) The interested vanpool system consists of N customers, \{UEDI_i, i \in \{1,2,3,\ldots,N\}\} is a set containing N user experience decline index.

\[ \sigma_N = SD(UEDI_1, UEDI_2, UEDI_3, \ldots, UEDI_N) \quad (6) \]

In (6), \( \sigma_N \) is the standard deviation of \{\{UEDI_i, i \in \{1,2,3,\ldots,N\}\}\} and can be used to represent fairness between customers.

System UEDI minimization

\[ \sum_{i=1}^{N} (UEDI_i) , i \in \{1,2,3,\ldots,N\} \quad (7) \]

\[ \sum_{i=1}^{N} (UEDI_i) \] in (7) represents system efficiency, the objective is to minimize \( \sum_{i=1}^{N} (UEDI_i) \).

3.2 Evolutionary Multiple Objective Optimization

Three factors, CD_{ts}, T_{te} and CD_{te}, constitute a solution for the vanpool operation problem. When searching for such solutions, the goal is minimizing \( \sigma_N \) and \( \sum_{i=1}^{N} (UEDI_i) \) at the same time, which defines an evolutionary multiple objective optimization problem.

3.3 Vanpool Route

The van used here is assumed to be electric for EV popularity. 3.2 has already given CD_{ts}, CD_{te} and T_{ts}. Using these, the emphasis is to consider CD_{cs} and RoU_{cs} to find the most suitable route.

![Vanpool Operation Schema](image)

Figure 2: Vanpool Operation Schema

4 Vanpool operation management system

This section talks about our approach to solve the vanpool management problem. Firstly, 4.1 gives out a diagram showing the vanpool operation management schema. Secondly, 4.2 gives out an evolutionary multiple objective approach to tackle the proposed problem. Lastly, 4.3 presents a plan about how to search for a suitable route.
4.1 Vanpool Operation Management Schema

The whole vanpool management system consists of three parts. Figure 2 is about the proposed vanpool operation system and typically consists of three parts. This section is mainly focused on how different parts of the system could be used together for the whole system to work.

**System Input** System input part is mainly about collecting customers’ $T_{s_i}, CD_{s_i}, T_{eta_i}, TS_{e_i}$ and $CD_{d_i}$. Robert Geiberger provides an implementation of the CH algorithm to find suitable route [27]. Provided travel styles (walking, biking and driving), also known as $T_{s_i}$ and $TS_{e_i}$ are given, expected to arrive time and expected to travel distance $int_{s_i}, int_{e_i}, d_{s_i}, d_{e_i}$ can be calculated [27]. Using (2), (3), (4) and (5), every customer i’s UEDI can be attained.

**Evolutionary Multiple Objective Optimization** For every $T_{s_i}, CD_{s_i}, T_{eta_i}, TS_{e_i}$ and $CD_{d_i}$ combination, each customer i’s UEDI can be attained using (5). For a specific vanpool system with N customers, $\sigma_N$ and $\sum_{i=1}^{N}(UEDI_i)$ can be calculated.

We use $S_{s_i}, CD_{s_i}, T_{eta_i}, TS_{e_i}$ and $CD_{d_i}$ to form a row vector. k can be used as objectives in an evolutionary multiple objective optimization algorithm to find suitable solutions. One thing need to keep in mind is that multiple objective optimization algorithms can only be used to search for the pareto front, which is a set of solutions. We need to find one solution in the pareto front set which can be used by route search method, the solution then can be used to search for a suitable route.

**Route Search** For everyone that is on the van, fairness between customers is ensured for everybody sharing the same route. The only objective is to minimum $\sum_{i=1}^{N}(UEDI_i)$. For

![Figure 3: Evolution Process](image)

single objective optimization problem, there are already many mature algorithms, such as A* and CH to find suitable route for electric vehicles. Considering the limited driving range of electric vehicles, finding appropriate charging stations is an important area. What can be done here is a two step work, firstly, finding suitable charging stations for electric vehicles and then using existing route search method to provide route advice between charging stations.

4.2 Evolutionary Multiple Objective Optimization

Figure 4 shows the evolutionary multiple objective optimization process. The whole process consists of two main parts, evolution initialization and evolution process. The evolution part is consisted of chromosome representation and setting chromosome boundaries. chromosome initialization should be done in this part to finish initialization. Evolution process part is mainly going to be about getting optimal results using iteration. Elite retention, chromosome crossover and chromosome mutation is included in this part.
**Chromosome Representation**} Figure 4.a is the process of encoding every related variable into a row vector.

To find eligible range for $T_{eta}$, $CD_{ts}$ and $CD_{te}$, extreme cases are considered.

$$T_{eta}^{min} = \min\{T_{eta}^1, T_{eta}^2, \ldots, T_{eta}^N\} \quad (8)$$

Firstly, for $T_{te}$’s range, $T_{eta}^{min}$ belongs to a customer $j$, when $CD_{te}$ is chosen as $CD_{d}^j$, which means customer $j$’s destination coordinate is the same as trip end coordinate, $T_{te}$ is the biggest and is equal to $T_{eta}^{min}$. When $CD_{te}$ is chosen the same as $CD_{s}^j$, $T_{te}$ is the smallest and is equal to customer $j$’s time to leave $T_{tol}^j$. In order to keep $T_{tol}^j$ smallest, we make customer $j$ walking all the way to his destination.

Secondly, for $CD_{ts}$’s range, Figure 4b is a diagram about how to find eligible range. (10) finds the range of latitude.

$$range(T_{te}) = (T_{eta}^{min} - \text{int}_{walking}^{j} T_{eta}^{min}) \quad (9)$$

In (10), lat function is used to get the latitude of the input coordinate, min and max function are used to get minimum and maximum of the corresponding set. In the similar way, (11) finds longitude set. (12) finds the range of Lon/Lat called CRS.

$$DWS = \left( \min\{\{\text{lat}(CD_d^j)\}\}, \max\{\{\text{lat}(CD_d^j)\}\} \right), j \in \{1,2,3,\ldots, N\} \quad (10)$$

$$DHS = \left( \min\{\{\text{lon}(CD_d^j)\}\}, \max\{\{\text{lon}(CD_d^j)\}\} \right), j \in \{1,2,3,\ldots, N\} \quad (11)$$

$$CRS = \max(DWS, DHS) \quad (12)$$

Finally, the same goes for deciding the range of $CD_{te}$ and $D_{ts}$, (13), (14) and (15) decide CRD.

$$DWD = \left( \min\{\{\text{lat}(CD_d^j)\}\}, \max\{\{\text{lat}(CD_d^j)\}\} \right), j \in \{1,2,3,\ldots, N\} \quad (13)$$

$$DHD = \left( \min\{\{\text{lon}(CD_d^j)\}\}, \max\{\{\text{lon}(CD_d^j)\}\} \right), j \in \{1,2,3,\ldots, N\} \quad (14)$$

$$CRD = \max(DWD, DHD) \quad (15)$$

Related time is normally represented in military format first and then converted into seconds to be used in the model.

**Population Initialization** The first generation seeds are composed of two parts, one part is designed to make faster convergence and the other part is randomly assigned to emphasize the diversity of the population.
The population of each generation is defined as follows:

\[ \text{Population}_{g} = \{ C_1, C_2, \cdots, C_{ps} \} \]  \hspace{1cm} (16)

where \( g \) denotes the number of generations and \( ps \) represents the population size.

For \( CD_{ts} \), related customer i’s UEDI is related with the distance between \( CD_{ts} \) and \( CD_{si} \). Fairness between customers can be expressed as finding the center of the square containing all \( CD_{si}, i \in \{1,2,3,\cdots,N\} \). Efficiency can be expressed as the geometric median \[^{28}\]\], which can be solved efficiently, and the same goes for \( CD_{te} \).

**Evolutionary Process** After proper solutions are initiated, SPEA2 is used to search for the non-dominated set \[^{29}\]\). Procedure 1 is the main part to do evolutionary process using SPEA2. Figure 5 is a diagram showing how to implement the algorithm using elitism. Procedure 1 is based on Figure 5, \( P_g \) is short for Populationg and the main idea in the procedure is using archive to store non-dominated set of each iteration. As generation grows, solutions in archive become more accurate when comparing with the pareto front. After algorithm termination, \( A^* \) is the non-dominated set (the pareto front).

To make individuals dominated by the same archive members have different fitness values, both dominating and dominated solutions are considered. Each individual \( m \) in archive \( A_g \) and the population \( P_g \) is assigned a strength value \( S_m \), which is an index of solutions it dominates:

\[ S(m) = | \{ n \in P_g + A_g \land n \succ m \} | \] \hspace{1cm} (17)

In (17), \( || \) represents the carnality of a set, \( + \) stands for multiple set union and \( \succ \) represents pareto dominance relation (\( n \succ m \) means decision caused by \( n \) dominates decision caused by \( m \)). Raw fitness value \( R(m) \) is calculated by (18).

\[ R(m) = \sum_{n \in P_g + A_g \land n \succ m} S_n \] \hspace{1cm} (18)
To avoid algorithm got stuck when most solutions do not dominate each other, density is incorporated to set apart individuals having identical raw fitness value. Density technique used here is an adaption of the k-th nearest neighbor method \cite{[30]}. For each individual m, the distances (in objective space) to all individuals n in archive and population are calculated and stored in a list. After sorting the list in increasing order, the k-th element gives the distance sought, denoted as $\delta_m^k$. $k = 1$ is used for efficiency. (19) represents how to get corresponding density.

$D(m) = \frac{1}{\delta_m^k + 2}$ \hspace{1cm} (19)

In (20), fitness is calculated and ready to be used.

$F(m) = R(m) + D(m)$ \hspace{1cm} (20)

As for the environmental selection, there are mainly two things setting SPEA2 apart from other algorithms.

- The number of solutions in the archive is fixed over time.
- The truncation method prevents boundary solutions being removed.

There are mainly two steps involved in environment selection. The first step is copy all non-dominated solutions from archive.
and population to next generation archive, which ensures convergence of the algorithm. (21) shows how to produce next generation’s archive.

\[ A_{g+1} = \{ m | m \in P_g + A_g \land F_m < 1 \} \]  

(21)

The second step is dealing with situation where the non-dominated front does not fit into the archive (\(|A_{g+1}| \neq N\)). If \(A_{g+1} < N\), we sort the multiple set \(P_g + A_g\) according to the fitness values and copy the first \(N - |A_{g+1}|\) solutions with \(F(m) \geq 1\) from the sorting order list to \(v\). If \(A_{g+1} > N\), the solution which has the minimum distance to another solution is removed to preserve diversity. By considering the second smallest distance and so forth a tie can be broken. This process is performed until \(A_{g+1} = N\). The solution \(m\) chosen to remove meets the following standards. \(m \leq n\) and \(n \in A_{g+1}\), (22) shows the mathematical description.

\[
m \leq n : \leftrightarrow \forall 0 < k < |A_{g+1}|: \delta^k_m = \delta^k_n \land \exists 0 < k < |A_{g+1}|: [(\forall 0 < l < k: \delta^l_m = \delta^l_n) \land \delta^k_m < \delta^k_n]
\]

(22)

4.3 Vanpool Routing with Consideration of Charging Stations

Charging station utilization ratio and related charging station parameters are assumed to be the same as last month’s corresponding data for vanpool routing procedure. Table 2 shows the symbols used for vanpool route searching procedure. 4.3 outlines the vanpool route search idea, focusing on how to find suitable charging stations.

**Charging station characteristic** Figure 6 is the usage of charging stations in April, 1, 2016. Charging stations in Beijing now have two characteristics, capacity and charging efficiency. There are different kinds of outlets for each charging station. For every charging station, some outlets are slow while others are fast. In Figure 6, capacity means how many outlets a charging station has and utilization ratio means how many outlets are used. In vanpool routing problem, we emphasized

![Figure 6: Charging Station Utilization](image-url)
Table 2: Symbols used for charging stations selection

| Symbols | Meaning |
|---------|---------|
| $CS_k$  | Charging station k |
| $T_{pos}^k$ | Expected arrival time at $CS_k$ |
| $D_r$  | Remaining driving distance at $CS_i$ |
| $D_f$  | Van driving distance for full electricity |
| $D_{se}$ | Distance between $CD_{ts}$ and $CD_{te}$ |
| $C_s$  | Circle has $CD_{ts}$ as the center and $D_r$ as radius |
| $C_c$  | Circle has $CD_{te}$ as the center and $D_f$ as radius |
| $CW_k$ | Waiting time spent at $CS_k$ |
| $CT_k$ | Charging time spent at $CS_k$ |
| $t_{int_{m-n}}$ | Time interval spent travel from $CS_m$ to $CS_n$ |
| $d_{m-n}$ | Travel distance of $CS_m$ to $CS_n$ |
| $\mu^t_k$ | Usage ratio of $CS_k$ at t |
| $CAP_k$ | Capacity of $CS_k$ |
| $n_k$ | Proportion of fast charging outlets to slow outlets in $CS_k$ |
| $CFT$ | Fast charging time for interested van |
| $CST$ | Slow charging time for interested van |
| $\sigma^i_k$ | Customer $i$’s accelerated travel distance |
| $int^i_{ts}$ | Customer $i$’s accelerated travel time interval |

on finding appropriate charging stations. After suitable charging stations are found, vanpool route problem between charging stations becomes the traditional single objective route problem.

As (1) points out, mainly $int$ and $D$ are connected with UEDI. For every customer in the same van, $int$ and $D$ between customers is the same, which make every customer fair between this journey. Since every customer use the same van to communicate between $CD_{ts}$ and $CD_{te}$. Now (7) becomes the only left objective. Three things can be summarized as below about vanpool route search.

- Different charging stations have different capacity, utilization ratio, and percentage of fast charging outlet, which would lead to very different charging related time.
- UEDI introduced by charging time need to be multiplied by customer number $N$ to be ready for usage.
- Route Search between charging stations, which is a single objective optimization problem, can be solved by traditional A* or CH methods.

We are mainly focused on finding suitable charging stations to minimize $\sum_{i=1}^{N}(UEDI_i)$.

Vanpool charging station selection) There are mainly four cases about finding suitable charging stations.

The first case is when the van gets to $CD_{te}$ from $CD_{ts}$ without need to recharge, it is not necessary to consider charging stations is this case.

The second case is $D_r < D_{se}$ and what Figure 7.a describes. In Figure 7.a, when no charging station exists, there does not exist a method for the electric van to travel from $CD_{ts}$ to $CD_{te}$.

$$CW_k = t_1 - t_0 + \frac{\beta}{CAP_k} \{\mu^t_0 = 1 \land \mu^t_1 < 1\}$$ (23)

The third case is presented in Figure 7.b, there exists several charging stations in the overlapping area. In (23), $t_0$ refers the time the van gets to $CS_k$ and $\beta$ is used to represent the waiting time. $g$ can be used to estimate $CW_k$, (24) can be used to decide $CT_k$.

Suppose customer $i$ go through $CS_1$ to get to $CD_{te}$, (25), (26) and (7) can be used together to calculate UEDI, after multiplying customer number $N$, we get UEDI$_{CS1}$ related with using $CS_1$.

$$CT_k = \kappa_k * CFT + (1 - \kappa_k) * CST$$ (24)

$$d^i_a = d_{s_{a+1}} + d_{1_{a+e}}$$ (25)
\[ \text{int}_{d}^{i} = \text{int}_{s} + (C W_{i} + C T_{d})d + \text{int}_{e} \quad (26) \]

Similarly, we can get UED\text{I}_{CS2}. After comparing UED\text{I}_{CS1} and UED\text{I}_{CS2}, the charging stations to minimize UEDI can be picked out.

Finally, we would like to talk about the fourth case, as presented in Figure 7.c. We use CD_{ts} and CD_{te} as centers and \( \frac{D_{se}}{2} \) as the radius to draw half circles, two common tangential lines of those circles are drawn. Charging stations surrounded by two half circles and two common tangential lines are selected as potential charging stations. Figure 7.d shows the search direction, suppose the van is at CS_{i} at the moment, using CS_{i} as the center and D_{i} as the radius, we can draw the circle. A line perpendicular to the line connecting CS_{i} and CD_{te} can divide the circle in Figure 7.d into two halves, the half on CD_{te} side is the area to find the next charging station.

Using the same idea in (25), (26) and (7), we can get UEDI for different charging station selection plan. The plan minimizing \( \sum_{i=1}^{N} (UEDI)_{i} \) is the chosen plan. Thus, we have chosen the suitable charging stations.

5. Experimental results

Table 3: Units used and parameter values

| \( k_{1} \) | \( k_{2} \) | Interval Unit | Distance Unit |
|----------|----------|---------------|---------------|
| 5        | 1        | Second        | Meter         |

The vanpool scenario is suitable for users sharing nearly common departure place and destination. We chose Beijing as the experimental city to conduct the simulation experiment. The simulation is conducted on a 2015 MacBook Pro Laptop, with a 2.5GHz Intel i5 Chip and 8 GB random access memory.

Table 3 is the parameter values, and units used in this simulation.

Table 4 is the data used to conduct the vanpool experiment, the departure has a lot of people rent houses there and the destination has a lot of corporations, which would be a good simulation of the real application of vanpool definition given in this paper.
In Table 3 we chose $k_1$ as 5 and $k_2$ as 1, for normally a person can move 5 meters in one second, such the relationship between time internal and distance. Figure 8 is the result of running multiple objective optimization vanpool problem using evolutionary algorithm. Fig.8a is the pareto front got, which is just a solution set, there is contradiction between fairness and system efficiency. The administrator can pick suitable solution from the pareto front according to the real world situation. Different solutions nearly uniformly distribute on the pareto front, a quality sign for a good solution set. Figure 8.b is a plot of average spread as a function of iteration number, average spread becomes more steady as generation increases, which is shown by the decrease of range of average spread as generation increases. Figure 8.c plots a bar chart of the distance of each individual from its neighbors. As what is shown from Fig.8c, the distance of each individuals from its neighbor is quite identical, which means standard deviation of these distance is small and these solutions is nearly uniformly distributed. Figure 8.d plots a histogram of the ranks of the individuals. Individuals of rank 1 are on the Pareto frontier. Individuals of rank 2 are lower than at least one rank 1 individual, but are not lower than any individuals from other ranks, and so on. As Figure 8.d points out, most of the population of the last generation is in the first rank (the pareto front), which can also be thought as a factor of convergence. Population of other rank is quite similar as a result of population leading to convergence.

Table V is the evaluation of the proposed routing method. For electric vehicles, the only difference in routing method is to find the suitable charging stations. In the evaluation, algorithm execution time is measured in two parts, execution time for selecting potential charging stations and search for route with some of the selected charging stations using traditional route search method (A* or CH). As Table 5 shows, route search time increases as travel distance increasing. The reason of travel distance and charging station time increasing simultaneously is that there is a bigger pool of potential charging stations to search for. The search time is acceptable for vanpool is real life.

In real life, the government or some corporation can be responsible for delivering vanpool service using this model, security can be enforced for the third party holding information about the van and the driver, which may help with society’s concern about vanpool safety.

6. Conclusion
Vanpool can be divided into three subjects, carpool, multiple objective optimization and route search method. Firstly, we express the state of art of these three subjects. UEDI definition is given. Based on UEDI, from the point of fairness and system efficiency, an evolutionary multiple objective optimization algorithm is used to calculate trip start address, trip end address and trip start time. Routing method is given considering charging station location and charging station usage ratio. At last of the paper, evaluation result and discussion is given.

The whole idea is based on user experience and more experiments and research about what factor would contribute to customer’s experience is needed. Also the model built in this paper considers distance travelled and duration lasted, $k_1$ and $k_2$ are parameters used in this paper, the relation of distance and

| No. | $T_{eta}$ | $TS_s$ | $TS_e$ | $CD_{ts}(Lon, Lat)$ | $CD_{te}(Lon, Lat)$ |
|-----|-----------|--------|--------|----------------------|----------------------|
| 1   | 08:30     | walking| riding | 116.384974,39.773012 | 116.307755,40.056856 |
| 2   | 08:45     | riding | walking| 116.386582,39.771729 | 116.310323,40.058444 |
| 3   | 08:00     | riding | driving| 116.388746,39.770698 | 116.395645,39.929986 |
| 4   | 08:30     | riding | walking| 116.389403,39.771972 | 116.352997,39.764581 |
| 5   | 09:00     | walking| riding | 116.389212,39.773787 | 116.540512,39.773673 |
| 6   | 09:30     | riding | riding | 116.652576,39.102899 | 116.35236,39.763797 |
| 7   | 09:30     | walking| driving| 116.391527,39.772837 | 116.306129,40.056703 |
| 8   | 09:00     | walking| riding | 116.390111,39.770863 | 116.395645,39.929986 |
Table 5: Evaluation result by proposed routing method

| Dr (km) | Travel Distance(Km) | Travel Time(h) | No. of CS | CS Search Time(s) | Route Search Time(s) | Total Search Time(s) |
|---------|---------------------|----------------|-----------|-------------------|----------------------|----------------------|
| 10      | 37                  | 0.8            | 1         | 3.42              | 7.06                 | 10.48                |
| 30      | 42                  | 1.1            | 1         | 2.83              | 8.34                 | 11.17                |
| 50      | 46                  | 1.2            | 0         | 0                 | 9.03                 | 9.03                 |

(a) Pareto Front

(b) Average Spread

(c) Distance of Individuals

(d) Rank Histogram

Figure 8: Multiple Objective Optimization Vanpool Problem

duration to customer’s experience is unknown and more sociological and psychological study is needed. There is paper in the community focused on using simulated annealing to solve multiple objective problems. Evidence shows simulated annealing converges faster but can stuck in local optimal solutions, efforts can be made by finding out whether using simulated annealing is suitable in this field.

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