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Demand Supply Oriented Taxi Suggestion System for Vehicular Social Networks with Fuel Charging Mechanism

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ABSTRACT

Data mining depends on large-scale taxi traces is an important research concepts. A vital direction for analyzing taxi GPS dataset is to suggest cruising areas for taxi drivers. The project first investigates the real-time demand-supply level for taxis, and then makes an adaptive tradeoff between the utilities of drivers and passengers for different hotspots. This project constructs a recommendation system by jointly considering the profits of both drivers and passengers. At last, the qualified candidates are suggested to drivers based on analysis. The project also provides a real-time charging station recommendation system for EV taxis via large-scale GPS data mining. By combining each EV taxi's historical recharging actions and real-time GPS trajectories, the present operational state of each taxi is predicted. Based on this information, for an EV taxi requesting a recommendation, recommend a charging station that leads to the minimal total time before its recharging starts.

Keywords : Vehicular Social Networks, Hotspot location, Trajectory data mining, Supply-demand level, Electronic Vehicle.

I. INTRODUCTION

A social networking service (SNS) may be a platform to create social networks or social relations among people that share similar interests, activities, backgrounds or real-life connections. A social network service consists of an illustration of every user usually a profile, his or her social links, and a spread of extra services. Social network sites area unit web-based services that enable people to make a public profile produce a listing of users with whom to share connections, and think about and cross the connections among the system. Social network sites area unit varied and that they incorporate new info and communication tools like mobile property, photo, video sharing. The Most social network services area unit web-based and supply suggests that for users to act over the net, like e-mail and instant electronic messaging. Social networking sites enable users to share ideas, pictures, posts, activities, events and interests with folks in their network. The web community services area unit generally thought of a social network service, although in an exceedingly broader sense, social network service sometimes suggests that associate degree individual-centered service whereas on-line community services area unit group-centered.

The social media sites not solely remained a platform to initiate informal dialogues and a supporter of live messages, however became associate integral a part of promoting ways of the many a business homes. Social Networking shortly became how for whole promoting and promotion on social sphere, whereby, the enterprises started victimization these on-line communities or websites for developing contacts and driving traffic to their several websites. The appliance of those sites has unfold to business homes that started victimization the Social Networking sites as a platform to market their services and build whole awareness. These social networking websites kind the most tool of social media promoting. The foremost ordinarily used websites Twitter and Face book. The main objectives of the Taxi Recommendation square measure

- ✓ To specialize in a way to maximize drivers' profits whereas high the profit of passengers.
- ✓ To value 2 completely different levels of Demand offer that square measure appropriate for busy (peak) days and traditional operating days.
- ✓ To provides a time period charging station recommendation system for taxis.
- ✓ To calculate waiting time beside the gap for the recharging stations.

II. RELATED WORKS

A. Vehicular Social Networks: A Survey

Considered social networking in an exceedingly transport environment; the authors investigated the possible applications of VSNs and communication design. VSNs enjoy the social behaviors and quality of nodes to develop novel recommendation systems and route coming up with. Further, they gave an outline of various recommendation systems and path coming up with protocols supported crowd sourcing and cloud-computing with future analysis directions. They bestowed a progressive literature review on socially-aware applications of VSNs, information dissemination, and quality modeling. Further, they mentioned the various communication protocols style and information dissemination techniques to deal with the present gap between VSNs and ancient ad-hoc networks that is that the terribly 1st issue to be thought-about by the analysis community to understand the construct of VSNs in public accepted. However, various vary of novel applications, coming together transport networks, exploiting quality pattern, socially aware recommendation systems on the roads area unit a number of the factors towards whom the analysis community has shown concrete interest. Finally, they bestowed some open analysis issue for future direction.

B. Vehicular Social Networks: Enabling Smart Mobility

In this article stressed the importance of high-potency and reliable transmissions in VSNs for sensible cities. Significantly, we tend to study a case on traffic anomaly detection for VSNs by mechanical phenomenon knowledge analysis. They believed that VSNs can draw in depth attentions and analysis efforts within the close to future because the integrations of data technology and social network services become additional compacted. Though VSNs will be considered the mixing of social networks and IoVs to enhance the standard of life for voters, the avenues of VSN studies aren't flat, and plenty of open problems are still ahead.

C. Energy-Latency Trade-Off For Energy-Aware Offloading In Mobile Edge Computing Networks

In this paper, single and multi-cell MEC network eventualities are thought-about at an equivalent time.. In terms of the mixed number nonlinear drawback (MINLP) for computation offloading and resource allocation, we tend to propose AN reiterative search rule combining interior penalty operate with D.C. (the distinction of 2 convex functions/sets) programming (IPDC) to search out the optimum resolution. The residual energy of good devices' battery is introduced into the definition of the coefficient issue of energy consumption and latency. Numerical results show that the projected rule will get lower total price (i.e., the weighted add of energy consumption and execution latency) examination with the baseline algorithms and also the energy-aware coefficient issue is of nice significance to keep up the life of good mobile devices.

III. METHODOLOGY

A. Existing Work

This work constructs an adaptive recommendation system based on the supply-demand level, by which a tradeoff is made between the utilities of drivers and passengers. Then the hotspot with the highest score is recommended to available taxis. It considers a passenger's utility with the waiting time for vacant taxis, which is predicted by mining the pick-up events.

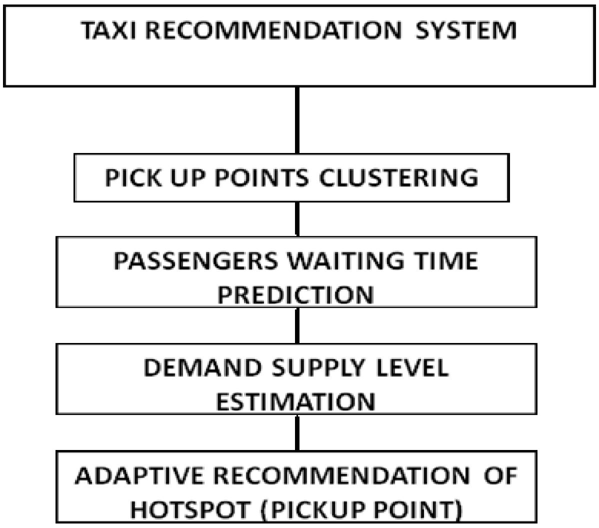


Fig 1 : Taxi Recommendation System

First pick-up points for each time segment from the taxi trajectory are extracted. Then an adaptive Density-based Spatial Clustering of Applications with Noise algorithm (I-DBSCAN) for clustering is utilized. Passengers' expected waiting time is predicted based on the information of different hotspots. For the online part, we retrieve hotspots within certain limits for the correct time segment according to the time and location of available taxis. The essential knowledge of each hotspot is calculated for online recommendation. After evaluating the real-time demand-supply level of the whole area, we can make a tradeoff between the driver's and passengers' utilities.

1) Demand Hotspots Scanning By Clustering

By clustering the pick-up points, information from taxi trajectory can be extracted to identify candidate demand hotspots. Traditional DBSCAN algorithm is a kind of density-based clustering methods, which can discover arbitrary clusters and deal with noise or outliers effectively First, the distance distribution matrix is calculated, denoted by Dist nxn.

$$Dist_{n\times n} = \{dist(i,j) | 1 \leq i \leq n, 1 \leq j \leq n\}$$

Input: The pick-up points dataset to be clustered P
Output: The final set of clusters C

```
for pi,pj in P do
Dist[i][j] ← getManhattandis(pi,pj);
end for
Sort Dist in an ascending order line by line;
for the i-th column vector in Dist do
get average value as epsi;
end for
DBSCAN (epsi , fixed MinPts) ;
Select optimal Eps by the number of cluster and noise;
N ← 0;
for p in P do
N + getEpsNeighbourNum(p);
end for
Perform DBSCAN with optimal Eps and MinPts;
return clustering results C.
```

where n is the number of pick-up points we extract, and dist(i,j) is the Manhattan distance between GPS point pi and pj. When the value of i increases, the number of clusters and noise both decrease.

2) Passenger's Waiting Time Prediction

The arrival times of passenger for a particular vehicle and actual vehicle arrival time is taken. Then the average values of waiting times are calculated and thus the passenger waiting time is predicted. The following algorithm is used to predict the waiting time. With the input of pick up events time stamp sequences, the waiting time is calculated.

Input: The pick-up events timestamp sequence
Tp = {pe1,pe2,··· ,pen}
Output: The estimated waiting time w for the hotspot

```
λ ← n−1 pen−pe1;
Initiaize the passenger arrival events timetamp sequence
Ta = {ae1,ae2,··· ,aen};
for i = 1 to n do
if i = 1 then
aei = random(0,pei);
// Uniform distribution
else
aei = aei−1 + random(0,pei −aei−1);
// Truncated exponential distribution with λ
end if
end for
w ← 0;
for i = 1 to n do
w + (pei −aei);
end for  expected waiting time w.
```

3) Demand-Supply Level Evaluation

The following algorithm is used for demand supply level evaluation. Total time intervals among the trajectories and total free/busy counts are calculated and **α** value is found out.

Input: Record of trajectory points for the taxi R = {r1,r2,··· ,rn}
Output: The real-time demand-supply level α

```
S ← ø;
for each R do
if r.location in area and r.state was FREE then
get r.timestamp as ta;
while FREE IN THIS AREA do
get next record;
end while
get r.timestamp as tb;
get r.state as m;
Δt ← (tb −ta + 1−m);
S ∪(Δt,m);
end if
end for
sum1 ← 0,sum2 ← 0;
for (Δti,mi) in S do
sum1 + Δti;
sum2 + mi;
end for
α ← sum2/(sum1 + sum2);
```

4) Adaptive Recommendation

The following Algorithm is carried out in which Input is Available taxi's current time curtime and location curloc, candidate hotspots set H and Output is the recommended hotspot. Real-time demand-supply level α is taken from previous algorithm. Max Score is found out based on revenue in various pick up points. Hotspot with max score is recommended.

Input: Available taxi's current time curtime and location curloc, candidate hotspots set H
Output: The recommended hotspot

```
MaxScore ← 0,MaxId ← 0;
U ← ø,w ← ø;
Tracing trajectory and computing the driver's recent spent time on each hotspots ST = {st1,st2,··· ,stn};
for hi in H do
d ← getManhattandis(curloc,hi.core);
V ← (hi.revenue−βhi.searchingtime−γd) ;
ε ← sti ∑k stk ;
U ∪(V + ε);
w∪hi.waitingtime;
end for
Evaluate real-time demand-supply level α based on curtime using previousAlgorithm
for U∗ i , w∗ i corresponding to each hotspot do
score ← (1−α)U∗ i + αw∗ i ;
if score > MaxScore then
MaxScore ← score;
MaxId ← i;
end if
end for
return recommended hotspot hMaxId.
```

B. Proposed Work

1) State Inference Algorithm

This module is used to update the state inference of the particular vehicle. It includes vehicle id, entry time, time interval, x and y position. This module also updates vehicle state inference details every particular second. These details are stored in 'State Inference' table and viewed by using data grid view control.

Find State Inference (Algorithm)

This module is used to find the state inference of the particular vehicle by using state inference algorithm. When the vehicle id is selected it will automatically display the time interval. This algorithm has threshold value based on this value state inference of a particular vehicle such as recharging, operating or to station can be calculated. These details are updated every particular second.

```
Input: an EV taxi v, time t, time interval Ik correspond to t, v's state distribution {Pk(st),Pk(sr),Pk(so)} in Ik, travel distance d, v's real-time trajectory trj = p1,p2,...,pm
Output: predict v's state at t.
if Occupied field of pm is 1 then
v's state at t is operating;
else
if ∃sp ⊂ trj and pm = ˆpm then
v's state at t is recharging;
else {∃sp ⊂ trj and pm = ˆpm}
v's state at t is operating;
else
if Pk(st)=max{Pk(st),Pk(sr),Pk(so)} and d<τd then
v's state at t is operating;
else {Pk(st)=max{Pk(st),Pk(sr),Pk(so)} and d>τd}
v's state at t is to-station;
else {Pk(so) = max{Pk(st),Pk(sr),Pk(so)}}
v's state at t is operating;
else {Pk(sr) = max{Pk(st),Pk(sr),Pk(so)}}
v's state at t is recharging;
end if
end if
end if
```

2) Waiting Time for Fuel Charging Calculation

```
Input: A charging station s, the number of charging piles Ns, current time t, the number of EVs being recharging and waiting at s is l and n, respectively, the number of EVs arriving at s earlier than v0 is k;
Output: Wv 0 (s), i.e., v0's waiting time at s;.
if n = 0 then
if l + k < Ns then
W v 0 (s) = 0;
else {l + k > Ns}
M = l + k
when an EV taxi finishes recharging, M = M − 1
denote the time when Ns − M = 1 as t1;
W v 0 (s) = t1 − t;
end if
else {n > 0}
when an EV taxi finishes recharging, n = n − 1
denote the time when n = 0 as t2;
M = l + k
after t2, when an EV taxi finishes recharging, M =M − 1
denote the time when Ns − M = 1 as t3;
W v 0 (s) = t3 − t;
end if
```

This module is used to calculate the waiting time of a particular station. It contains information such as station id, number of outlet when the station id is selected it will automatically display the number of outlets, minimum rechargeable time, maximum rechargeable time and entry time. It also includes vehicle state details such as recharging vehicle count, waiting vehicle count and arriving vehicle count. By using these details waiting time will be calculated.

3) Vechile Optimization

Particle Swarm Optimization technique is used to achieve the result. Instead of arithmetic operators, set theory based approach is used here. The velocity and position update rules in S-PSO also have the same format as that in original PSO algorithms but, the particle's position in S-PSO is represented by a hard division, i.e., $X \subseteq S$, instead of the numerical digits in unique PSO algorithms, and the velocity is represented by a set with possibilities. And this module are not in existing system , so we used it as proposed technique. The algorithm is a very powerful optimization technique.

```
1.Initialize particles
2.Repeat for each particle do
3.Calculate the fitness value if fitness value is better than the best fitness value (pbest ) in hist
4.Set current value as the new pbest
5.end if
6.end for
7.Choose the particle with the best fitness value of all the particles a for each particle do
8.Calculate particle velocity according to velocity update equation
9.Update particle position according to position update equation
10.end for
11.until maximum iterations or minimum error criteria is attained
```

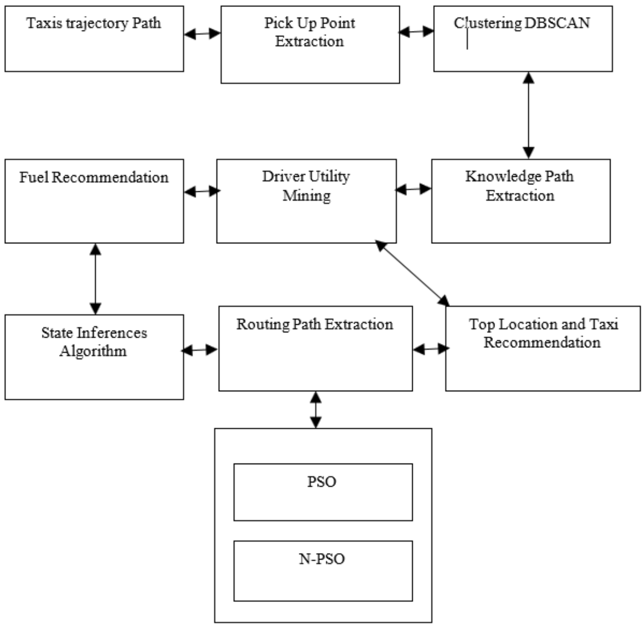
4) Node Failure Scenario

Delivering the goods in road failure as well as vehicle failure scenario is also carried out. During the vehicle routing if any of the node (vertex) in the graph is found to be failure, then alternate path is also found out from one hop before that failure node (vertex). Node failure scenario is taken in to account. Any vehicle if found to be failed in intermediate stage, then the solution works from the remaining available vehicles.

The solution that N-PSO finds for the optimization problem is thus the best position found by the swarm, represented as a set of elements. In every iteration, each element is updated by following two "greatest" values. The first one is the greatest solution (fitness) it has achieved so far. (The fitness value is and stored.) This value is call pBest. Another" greatest" value that is tracked by the particle swarm optimizer is the greatest value, obtained so far by any element in the population. This greatest value is a overall best and called gBest.

v[ ] = v[ ] + c1 * rand() * (pbest[ ] - present[ ]) + c2 * rand() * (gbest[ ] - present[ ]) + ((c3 * rand()) + a[t])) + ((c4 * rand( )) - s[t])) - **(a)**present[ ] = present[ ] + v [ ] - **(b)**
where, a[t]=v[ ]+ pbest+ gbest
a[t]=v[ ]- pbest- gbest
v[ ] is the element velocity, present[ ] is the current element (solution),
rand ( ) is a random number between (0,1); c1, c2 are learning factors usually c1 = c2 = 2.

IV. ARCHITECURE



V. EXPERIMENTAL RESULTS

Experimental results illustrate the effectiveness and efficiency of the proposed algorithm, for it provides better results than the existing results. Experimental result for comparison of PSO and N-PSO algorithm. The finding seat available between two location and average of seat counting Time details as followed:

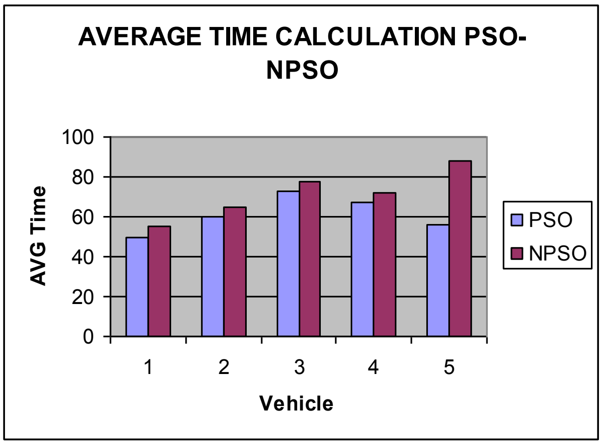


Fig 2. Average Time Calculation PSO- N-PSO

Example:
Number of Seat Count, C
Number of Distances, D
Total Number of Vehicle TV
Total Number of distances TD
N number of Iteration N

$$AVG= [(C+D) * (TV+TD)/ N] * 1000$$

VI. CONCLUSION

The project constructs an adaptive recommendation system by jointly considering the benefits of drivers and passengers. First, a spatio-temporal clustering method named I-DBSCAN is leveraged to group pick-up locations into different clusters. Second, to improve the drivers' utility, kinds of metrics including expected revenue, driving distance, searching time and preference are taken into consideration. Recent advances in designing to find the shortest path for minimum traveling costs and number of vehicles without violating the constraints and loading capacity of vehicle with Time Windows. To optimize the objective of the work, SBPSO algorithms have been found to have a global search ability, fast convergence speed, strong robustness, etc.,

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