

Effective Taxi with Charge Recommendation System for Road Network using Refine Routing Model

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Abstract— Data mining supported large-scale taxi traces has become a hot analysis topic. A vital direction for analyzing taxi GPS dataset is to counsel cruising areas for taxi drivers. Most of the existing researches merely focus on how to maximize drivers' profits while overlooking the profit of the passengers. Such imbalance makes the prevailing solutions don't work well in a very real-world surroundings. This paper constructs a recommendation system by jointly considering the profits of both drivers and passengers. The work 1st investigates the period of time demand-supply level for taxis, and then makes an adaptive tradeoff between the utilities of drivers and passengers for different hotspots. At last, the qualified candidates square measure recommended to drivers supported analysis. Results indicate that constructed suggestion system achieves a remarkable improvement on the global utility and make equilibrium between the utilities of drivers and passengers at the same time. It also considers a driver's utility with four factors, i.e, expected revenue, searching time for next passenger, travel distance and preference. The work also provides a real-time charging station recommendation system for EV taxis via large-scale GPS data mining. In addition, the proposed system providing the solutions and recommendation for the minimal time as well as for the minimal recharging cost for the Electronic Vehicle taxi drivers.

Keywords—*Vehicular Social Networks, Hotspot location, Trajectory data mining, Supply-demand level.*

I. INTRODUCTION

A social networking service (SNS) is a platform to build social networks or social relations among people who 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 range of further services. Social network sites are web-based services that permit people to make a public profile, produce an inventory of users with whom to share connections, read and cross the connections within the system.

The most social network services are web-based and supply means that for users to act over the web, like e-mail and instant electronic communication. Social network sites are varied and that they incorporate new data and communication tools like mobile property, photo, video, sharing. The online community services are typically thought-about a social network service, though' during a broader sense, social network service sometimes means that AN individual-centered service whereas on-line community services are group-centered. Social networking sites permit users to share ideas, pictures, posts, activities, events, and interests with individuals in their network.

Social Networking has become the subsequent feature, Social networking are the favored trend in trendy days. With its vast quality, little business homes have additionally started mistreatment social networking websites for whole promotion .Today's age is AN age of advanced technology. With boon of net reaching nearly each corner of the globe, there has been AN vast transformation in every and each field. Be it setting up a better platform of communication or connecting the globe under a common network, Internet has truly contributed in making world much a smaller place to live in. From video chats to Video conferencing, from on-line promoting to socializing via social media, net has actually and sure as shooting blessing for the world societies. Social media marketing is (SMM) referred to define certain websites that facilitate interpersonal communication through certain websites where in people can create their own profile page and communicate with friends and associates through online messages or scraps. A user will produce a network of friends, produce a bunch, initiate or participate during a conference. These Social Media websites became a tool that sealed the method for advanced mode of communication between all the networks and net users.

The social media sites not only remained a platform to initiate informal dialogues and a facilitator of live messages, but became an integral part of marketing strategies of many a business houses. The application of these sites has spread to business houses that started using the Social Networking sites as a platform to promote their services and create brand awareness. Social Networking

before long became the way for complete selling and promotion on social sphere, whereby, the enterprises started using these online communities or websites for developing contacts and driving traffic to their respective websites. These social networking websites kind the most tool of social media selling. The most commonly used websites Twitter and Facebook. Facebook could be a Social Networking website that helps friends and colleagues to share dialogues with one another through Wall Posts, Messages and Comments. Social Networking site, Facebook has more than 350 million members and still counting. This site experiences more than two million clicks per day. Statistics state that users pay a mean of 20minutes per day in Facebook. Facebook is one of the lethal tools in SMM and SMO.

Twitter could be a social media platform wherever the users 'tweet' to stay up-to-date with friends and his 'followers' inside his/her circle. Twitter allows posting "tweets" to all the people in their online network. Twitter also became a tool for social media marketing, the business posting a Tweet button on every post on its blog, makes it easy for anyone who reads the post to Tweet it to their followers. This helps channelize the information to spread from one end to another, creating proper brand awareness. Tweeting the up to date information of the business can be a great source of reaching a mass of audience. Linked In is a professional social media website where a stream of professional gets the chance to review and interact with their counterparts. Linked In offers a solid platform for establishing new business relationships. Linked In by facilitating more of a personal communication between the business professionals can help the business.

My space also a massive impact in the social networking world, Once registered with MySpace, a user can not only inform the entire networking circle about their likes and dislikes but can also submit videos. This enables in building complete awareness and might be of vast facilitate to tiny business homes. Social Media networking Sites is not only contributed to take inter-personal communication to a different level, but also a great marketing tool for the small businesses. Planned approach to social media marketing. This is the feature in social media marketing The main objectives of the Taxi Recommendation are

- To focus on how to maximize drivers' profits while overlooking the profit of passengers.
- To evaluate two different levels of Demand Supply which are suitable for busy (peak) days and normal working days
- To provides a real-time charging station recommendation system for taxis.
- To calculate waiting time along with the distance for the recharging stations.

II.RELATED WORKS

Zhaolong Ning and Feng Xia [1] It emphasized the importance of high- efficiency and reliable transmissions in VSNs for smart cities. Particularly, we study a case on traffic anomaly detection for VSNs by trajectory data analysis. Although VSNs can be regarded as the integration of social networks and IoVs to improve the quality of life for citizens, the avenues of VSN studies are not flat, and many open issues are still ahead. They believed that VSNs will draw extensive attentions and research efforts in the near future as the integrations of information technology and social network services become more compacted.

Azizur Rahim and Xiangjie Kong [2] It considered social networking in a vehicular environment; the authors investigated the prospective applications of VSNs and communication architecture. VSNs benefit from the social behaviors and mobility of nodes to develop novel recommendation systems and route planning. They presented a state-of-the-art literature review on socially-aware applications of VSNs, data dissemination, and mobility modeling. Further, they gave an overview of different recommendation systems and path planning protocols based on crowd sourcing and cloud-computing with future research directions. Further, they discussed the different communication protocols design and data dissemination techniques to address the existing gap between VSNs and traditional ad-hoc networks which is the very first issue to be considered by the research community to realize the concept of VSNs publicly accepted. Finally, they presented some open research issue for future direction. From the intensive literature review, they concluded that VSNs are still in their infancy level. However, a diverse range of novel applications, socializing vehicular networks, exploiting mobility pattern, socially aware recommendation systems along the roads are some of the factors towards whom the research community has shown concrete interest.

Weigang Hou and Zhaolong Ning [3] It have designed a novel temporal, functional and spatial big data computing framework for a large-scale smart grid. In spatial dimension, a novel heuristic has been proposed to place the least number of PNs in a subset of candidate locations that have high computing resources. After determining the final location of PNs, in functional dimension, a classic K-means matrix clustering algorithm has been utilized to divide every dataset into several smaller groups, each of which is called as info. Thus, one sub-group of data items instead of a dataset (chunk) is switched out from the current PN to a specific DN, leading to the improvement of computing efficiency in temporal dimension. Simulation results have demonstrated that: 1) a promising computing efficiency has been close to the upper bound with 95 percent convergence ratio; 2) the improvement ratio of saving the in-path bandwidth has been 81 percent; 3) the switching functionality between chunk and info has been achieved with a quick response. In summary, the proposed big data computing framework is effective on improving the computing efficiency and saving the in-path bandwidth,

especially for the large-scale smart grid that includes plentiful datasets. In the future work, they would further evaluate the effectiveness of their temporal, functional and spatial big data computing framework in a more realistic environment.

Jiao Zhang and Xiping Hu [4] The single and multi-cell MEC network scenarios are considered at the same time. The residual energy of smart devices' battery is introduced into the definition of the weighting factor of energy consumption and latency. In terms of the mixed integer nonlinear problem (MINLP) for computation offloading and resource allocation, we propose an iterative search algorithm combining interior penalty function with D.C. (the difference of two convex functions/sets) programming (IPDC) to find the optimal solution. Numerical results show that the proposed algorithm can obtain lower total cost (i.e., the weighted sum of energy consumption and execution latency) comparing with the baseline algorithms and the energy-aware weighting factor is of great significance to maintain the lifetime of smart mobile devices.

Zhaolong Ning and Jun Huang [6] The authors stated that Fog computing extends the facility of cloud computing from the center to edge networks. Although fog computing has the benefits of location awareness and low latency, the rising needs of present property and ultra-low latency challenge the traffic management for good cities. As Associate in nursing integration of fog computing and conveyance networks, Vehicular Fog Computing (VFC) is promising to achieve real-time and location-aware network responses. Since the concept and use case of VFC unit at intervals the initial half, this text initial created a three-layer VFC model for distributed traffic management, in order to minimize the time interval of wide events collected and rumored by vehicles.

III. METHODOLOGY

A. Existing Work

This works makes a tradeoff between a drivers' utility and a passenger's waiting time. The score expression of each hotspot is given for recommendation. In this way, high utilities for drivers can be achieved and save a mass of waiting time for passengers meanwhile. 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.

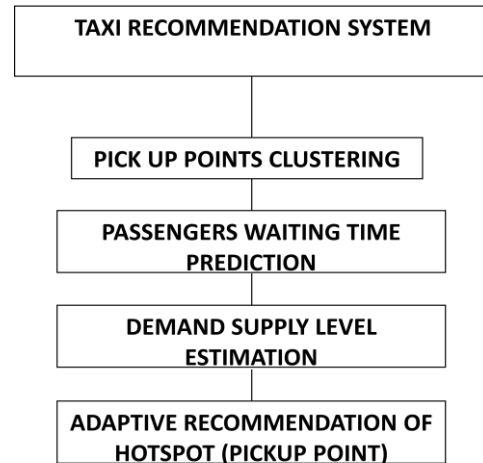


Fig 1: Taxi recommendation system

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. The essential knowledge of each hotspot is calculated for online recommendation. 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. Then the driver's utility can be calculated based on the knowledge. After evaluating the real-time demand-supply level of the whole area, we can make a tradeoff between the driver's and passengers' utilities. The recommendation score is defined according to the abovementioned idea. Finally, the hotspot with the highest value is recommended to the driver.

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. However, the parameter, Eps is required to be input manually.

First, the distance distribution matrix is calculated, denoted by $Dist_{n \times n}$.

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

where n is the number of pick-up points we extract, and $dist(i, j)$ is the Manhattan distance between GPS point p_i and p_j . The value of each element is obtained before sorting them in an ascending order line by line.

When the value of i increases, the number of clusters and noise both decrease. When they reach the convergence, the corresponding $epsi$ is the optimal estimation of parameter Eps.

Algorithm: I-DBSCAN Clustering

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

- 1: for p_i, p_j in P do
- 2: $\text{Dist}[i][j] \leftarrow \text{getManhattandis}(p_i, p_j)$;
- 3: end for
- 4: Sort Dist in an ascending order line by line;
- 5: for the i -th column vector in Dist do
- 6: get average value as epsi ;
- 7: end for
- 8: DBSCAN (epsi , fixed MinPts);
- 9: Select optimal Eps by the number of cluster and noise;
- 10: $N \leftarrow 0$;
- 11: for p in P do
- 12: $N + \text{getEpsNeighbourNum}(p)$;
- 13: end for
- 14: $\text{MinPts} \leftarrow N/P$;
- 15: Perform DBSCAN with optimal Eps and MinPts;
- 16: return clustering results C.

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.

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 $R = \{r_1, r_2, \dots, r_n\}$
Output: The real-time demand-supply level α

- 1: $S \leftarrow \emptyset$;
- 2: for each R do
- 3: for r in R do
- 4: if r .location in area and r .state was FREE then
- 5: get r .timestamp as t_a ;
- 6: while FREE IN THIS AREA do
- 7: get next record;
- 8: end while
- 9: get r .timestamp as t_b ;
- 10: get r .state as m ;
- 11: $\Delta t \leftarrow (t_b - t_a + 1 - m)$;
- 12: $S \cup (\Delta t, m)$;
- 13: end if
- 14: end for
- 15: end for
- 16: $\text{sum1} \leftarrow 0, \text{sum2} \leftarrow 0$;
- 17: for $(\Delta t_i, m_i)$ in S do
- 18: $\text{sum1} + \Delta t_i$;
- 19: $\text{sum2} + m_i$;
- 20: end for
- 21: $\alpha \leftarrow \text{sum2}/(\text{sum1} + \text{sum2})$;
- 22: return real-time demand-supply level α .

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. Tracing trajectory and computing the driver's recent spent time on each hotspot is found out. 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.

B. PROPOSED WORK

The models a road network as an undirected weighted graph $G = (V, E)$ where V and E represent the set of nodes and the set of edges of G, respectively. The existing system contains a new query named minimum path pair (MPP) query, denoted as $q = \{(v1s, v1t), (v2s, v2t)\}$, which is composed of two source/destination pairs, with an α to balance the needs of going to the destinations fast and the needs to meet. The MPP query addresses the issue of finding the shortest paths with meeting uncertainty i.e., both paths need not meet each other. All the existing system aspects are worked out in proposed system. In addition, the proposed system finds shortest path between multiple pairs of source and destination. It proposes a time-dependent landmark graph to provide a user with the practically fastest route to a given destination at a given departure time.

Minimum Path Pair (MPP) Query For Shortest Path Finding

It contains a new query named minimum path pair (MPP) query, denoted as $q = \{(v1s, v1t), (v2s, v2t)\}$, which is composed of two source/destination pairs, with an α to balance the needs of going to the destinations fast and the needs to meet. The MPP query addresses the issue of finding the shortest paths with meeting uncertainty i.e., both paths need not meet each other.

Add Terminal

Terminal details are added and saved to 'Terminal' table. X Position and Y Position in the graph details are added. The details are viewed using data grid view control.

Add Neighbor Terminal

Terminal id, Neighbor Terminal id and Distance details are added and saved to 'NeighborTerminals' table. This distance information will assist the route calculation.

Graph Construction

A graph is being constructed. To view the graph, click the Create Graph From table button. It displays a graph with nodes in round shape with arrows as edges. click on the node and drag it. It will move to new location. All the lines will be redrawn. The 'nodes' table and 'links' table records are used to create the graph. [Note: During Add Terminal 'Nodes' record is created. During Add Neighbor Terminal 'Links' record is created.]. It denotes the terminals and road segment details for the entire connected path.

Graph Propagation With Out Edge Failure

A text box is provided to find the path between two terminals. In textbox, enter from terminal, to terminal. For example (1,5). Click 'Path' button. The entire path from terminal 1 to 5 will be displayed. First all the terminals connected to 'from terminal' are found out. Then from all the terminals, the next links up to the 'to terminal' is found out.

For example, {1,3,5}, {1,4,5}, {1,3,4,5}, {1,3,6,5} are the path for 1,5. When you click the first listbox (left side), the total distance will be displayed in the bottom label. The distance for all the paths is calculated inside the coding. Of which the shortest distance is also calculated. For example 30 is the shortest distance and (Both the path 1, 4, 5 and 1, 3, 6 and 5 are having distance as 30, then the two paths are listed in second list box. The hop count is displayed in the third list box control. For example Hop count is 3 for [1,4,5] and 4 for [1,3,6,5]. One of the shortest path distances can be chosen to travel.

Graph Propagation with Edge Failure

In addition, failed path is displayed in 'failed path' listbox (left side bottom). For example, in created network menu option's form If you click create graph from table button, the graph is displayed. If you right click the node label in the graph, then the node is set as Inactive. 'Node' table's record is having a field with name Status. It changes to Inactive. If the paths (listed in first list box) contains that failed node (In real time, the road segment is failed/block due to accident or meeting like that) then the path will not be displayed (in fourth list box – left side bottom list box). Fifth and sixth list boxes show the path values and hop counts. So the entire path as well as failed path can be viewed, so that one can omit the failed path during traveling.

Time-Dependent Landmark Graph

The first describes the construction of the time dependent landmark graph, and then details the travel time estimation of landmark edges. In practice, to save energy and communication loads, taxis usually report on their locations in a very low frequency, like 2-5 minutes per point. This increases the uncertainty of the routes traversed by a taxi [3], [4].

Meanwhile, we cannot guarantee there are sufficient taxis traversing on each road segment anytime even if we have a large number of taxis. That is, we cannot directly estimate the speed pattern of each road segment based on taxi trajectories. In our method, we first partition the GPS log of a taxi into some taxi trajectories representing individual trips according to the taximeter's transaction records. There is a tag associated with a taxi's reporting when the taximeter is turn on or off, i.e., a passenger get on or off the taxi. Then, we employ our IVMM algorithm [4], which has better performance than existing map-matching algorithms when dealing with the low-sampling rate trajectories.

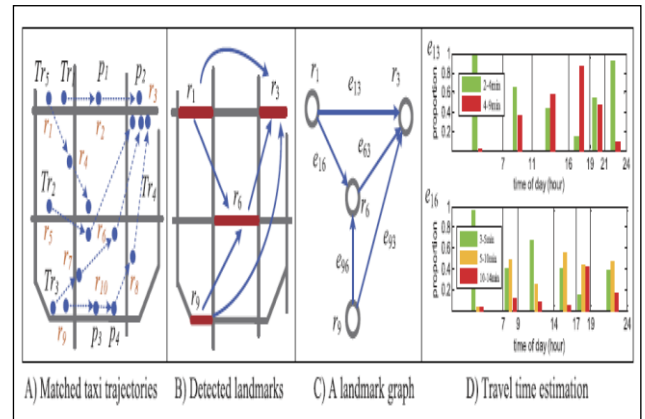


Fig 3.1 Landmark graph Construction

Therefore, they are build two different landmark graphs for weekdays and weekends, respectively. That is, we paper all the weekday trajectories (from different weeks and months) into one weekday landmark graph, and put all the weekend trajectories into the weekend landmark graph. We also find that the traffic pattern varies in weather conditions. Therefore, we, respectively, build different landmark graphs for weekday and weekend, and for normal and severe weather conditions, like storm, heavy rain, and snow. In total, 2 * 2 * 4 landmark graphs are built.

Figs. 3.1.A, 3.1B, and 3.1C illustrate an example of building the landmark graph. If we set k = 4, the top-4 road segments (r1, r3, r6, r9) with more paperions are detected as landmarks. Note that the consecutive points (likep4) from a single trajectory (Tr4) can only be counted once for a road segment (although the taxi driver only traversed the segment once), as shown in Fig. 3C. After the detection of landmarks, we convert each taxi trajectory from a sequence of road segments to a landmark sequence, and then connect two landmarks with an edge if the transitions between these two landmarks conform to Definition 3.4 (supposing 1/4 1 in this example).

Rough Route Smoothing

In Rough Route Smoothing, Given a rough route Rrough : q_s □ l₁ □ l₂ □ l₃ □ ..., □ l_{n-1} □ l_n □ q_d, we say Rrough satisfies

- Source-Farther Principle if □□i = 1, 2, ... n-1, dist(l_{i+1};q_s) > dist(l_i;q_s)
- Destination-Closer Principle if □□i = 1, 2, ... n-1, dist(l_{i+1};q_d) > dist(l_i;q_d)
- Dist(l_i;q_d) < dist(l_i;q_d), and
- Next-Nearest Principle if □□i = 1, 2, ... n-1, dist(l_i;l_{i+1}) = min_{j>i}{dist(l_i;l_j)},
- Where dist(l_i;l_j) is the road network distance from l_i to l_j.

The source-farther principles states that the distance from each landmark to the source should be farther than its previous one. The destination-closer principles state that each landmark should be closer than its previous landmark to the destination. The next-nearest principle (also

termed as “non turn-back” principle) states that the next landmark l_{i+1} should be the nearest landmark of l_i among all the landmarks after l_i . Local smoothing and Global smoothing is carried out in this module.

Local smoothing. This step aims to find the longest subsequence from the resulting sequence of the global smoothing so as to satisfy the next-nearest principle. It’s clear that the brute-force algorithm which checks all the subsequences takes exponential time.

Refined Routing

In refined routing, Suppose after the smoothing, we get a rough route Rough: $qs \rightarrow l_1 \rightarrow l_2 \rightarrow \dots \rightarrow l_n \rightarrow q_d$. This stage finds in the real road network a detailed fastest route that sequentially passes the landmarks of a rough route by dynamic programming. Assume r_1, r_2, \dots, r_n are the corresponding road segments of l_1, l_2, \dots, l_n , i.e., $r_i = l_i$. Using these notations, we have the initial states $fs(1)$ and $fe(1)$ as follows:

$$fs(1) = T(q_s, r_1, e, r_1, s) + t_{es}(1)$$

$$fe(1) = T(q_s, r_1, s, r_1, e) + t_{se}(1)$$

Let $T_{se}^i = T(r_i, s, r_{i+1}, e, r_{i+1}, s)$ denote the time of the fastest route (using speed constraint in real road network) which starts from point r_i, s and ends at point r_{i+1}, e without crossing r_{i+1}, s in road network G_r . Then, T_{ee}^i, T_{ss}^i , and T_{es}^i can be similarly defined. Now, we have the state transition equations.

$$f_g(i+1) = \min\{f_g(i) + T_{ge}^i, f_e(i) + T_{ee}^i\} + t_{eg}(i+1)$$

$$f_e(i+1) = \min\{f_g(i) + T_{gg}^i, f_e(i) + T_{eg}^i\} + t_{ge}(i+1)$$

After $f_s(n)$ and $f_e(n)$ are computed, the total travel time for the optimal route in the real road network is

$$\text{Min}\{f_g(n) + T(r_n, s, q_d, r_n, e), f_e(n) + T(r_n, e, q_d, r_n, s)\}$$

For the proposed refined routing, the following processes are carried out. In addition with the above mentioned rough routing algorithm, we enhance the methodology. It helps for finding peak hour affected path (A) and finding path with road failure occurred in the intermediate hops (B). For that, during the road segment data collection, whether it is affected by heavy traffic during peak hour is also gathered to find (A). In addition, the terminal failed data is also collected during finding (B). The above said rough route smoothing algorithm is applicable to both the algorithms discussed below. The algorithm for (A) to list the peak hour affected paths details is listed below.

Input:
 Nodes List **NL**, Edges List **EL**, Peak Hour Affected Edges **E'**, Starting Node **SN**, Ending Node **EN**
Output:List of Path available **L** and **Peak Hour Affected Path PHL**
 1. **N'** <- Starting Node **SN** 2. Find All Nodes **N** that is neighbors to the **N'** 3. **P** <- **N'** 4. For each $n \in \mathbf{N}$
 5. Propagate the next hop nodes such that 'n' as “from node in Edge” and next hop node **EN'** as “to node in Edge” until the **EN** is found out. Add the Node **EN'** to **P** 6. Add the Path **P** to **L**
 7. If **P** contains **E'** Add the Path **P** to **PHL** 8. Next
 9. Return **L** and **PHL**

For (A), all the road terminals (nodes list), road segments (edges list), road segments affected in peak hours (peak hour affected edges) are given. Source and destination terminal is given to find all the available paths.

The algorithm in addition with finding all the paths, path disturbed during heavy traffic is also found out. So, using the above said algorithm, for the given source and destination road terminal, all the available routes as well as road segments which are affected by heavy traffic in peak hour schedule is listed out.

IV. EXPERIMENTAL RESULTS

The following **Table 4.1** describes experimental result for number of node participate routing process in existing and proposed system analysis. The table contains number of travel node with in time interval (60 km/hour), existing routing travel node path count and proposed routing node path count details are shown.

S.NO	Number of Node Travel	Existing Routing Travel Path (Count)	Proposing Routing Travel Path (Count)
1	100	78	87
2	200	166	179
3	300	259	265
4	400	338	356
5	500	452	485
6	600	569	586
7	700	644	663
8	800	743	768

Table 4.1 Number of Node Participate Routing Process

The following **Table 4.2** describes experimental result for number of node participate routing process in existing and proposed accuracy analysis. The table contains number of travel node with in time interval (60 km/hour), existing routing travel node path accuracy and proposed routing node path accuracy details are shown.

S.NO	Number of Node Travel	Existing Routing Path Accuracy [%]	Proposing Routing Path Accuracy [%]
1	100	78.0	87.0
2	200	83.0	89.5
3	300	86.3	88.3
4	400	84.5	89.0
5	500	90.4	97.0
6	600	94.8	97.66
7	700	92.0	94.7
8	800	92.8	96.0

Table 4.2 Accuracy Analysis

The following **Figure 5.1** describes experimental result for number of node participate routing process in existing and proposed accuracy analysis. The table contains number of travel node with in time interval (60 km/hour),

existing routing travel node path accuracy and proposed routing node path accuracy details are shown.

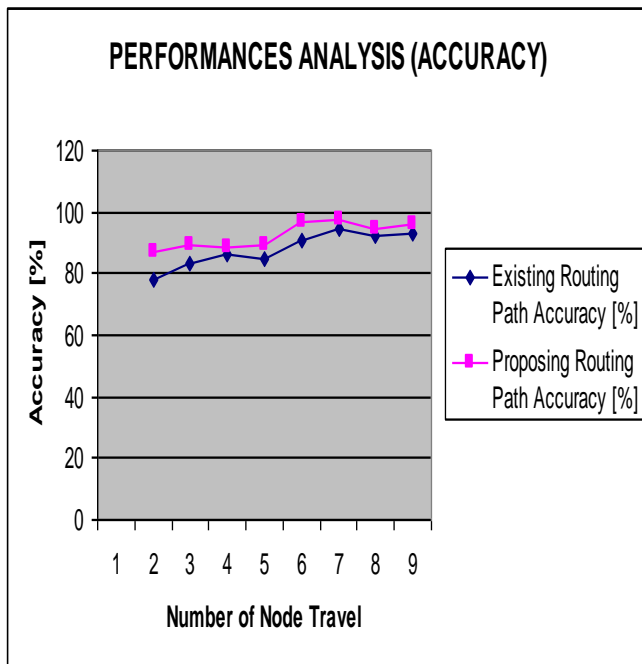


Figure 5.1 Existing and Proposed Accuracy Analysis

The following **Table 4.2** describes experimental result for number of node participate routing process in existing and proposed failure rate analysis. The table contains number of travel node with in time interval (60 km/hour), existing routing travel node failure rate and proposed routing node failure rate details are shown.

V CONCLUSION

In this paper, proposed a framework for adaptive recommendation system. The work 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. By mining the taxi trajectory data, drivers' utility calculation and passengers' waiting time prediction can be fulfilled. Then, the real-time demand-supply level for the whole area is evaluated, and a tradeoff between drivers' and passengers' utilities is made off, by which the score function of each hotspot can be calculated. The hotspot with the highest value is recommended to the driver. At last, the experiment is conducted in two different areas based on real-world taxi trajectory data.

The future work, we plan to consider more metrics. For drivers, they may pick up a passenger halfway. Thus, the influence of middle source cannot be ignored. For passengers, tolerance threshold of waiting time deserves to be considered. In addition, some external metrics, such as road network and traffic controlling, are important. For the

second phase work, real time charging system of vehicles is to be carried out.

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