Low Risk Covid-19 Travel Map – A Generic Solution

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Abstract- Whole world has seen the havoc created by Coronavirus disease (COVID-19), which is an infectious disease. 'CO' stands for corona, 'VI' for virus, and 'D' for disease. Formerly, this disease was referred to as '2019 novel coronavirus' or '2019-nCoV.' The COVID-19 virus is a new virus linked to the same family of viruses as Severe Acute Respiratory Syndrome (SARS) and some types of common cold. The recovery rate for someone suffering from COVID-19 varies from 92%-97% around the world, which is probably not a cause of concern. More concerning is that older people, and those with underlying medical problems like cardiovascular disease, diabetes, chronic respiratory disease, and cancer are more likely to develop serious illness and even can lead to death. The major concerns for the governments around the world was to control the transmission of this disease. The world which was known to be interconnected suddenly started closing borders. Even the states within countries sealed their borders. Flights were disrupted. Hospitality industry suffered a great financial loss. According to The World Travel and Tourism Council (WTTC), tourism generated $240 bn or 9.2% of India's GDP in 2018 and supported 42.67 mn jobs which is 8.1% of its total employment. The industry saw major job loss and contraction in its revenues. This was the biggest motivator to carry out this research. Challenge is to come up with best possible routes during Covid-19 times and this could be extended to any such pandemic we might encounter in future as well.

We propose two standard approaches to calculate risk for the travel locations in this paper. The two approaches are:

- Approach 1: Risk calculation based on main travel locations' active cases, and
- Approach 2: Risk calculation based on main travel locations and locations' immediate neighbours

In our research, Covid-19 dataset for India has been used and that has been downloaded from the government official website. Though the proposed solution can be applied in any country/area map, our experiment is mainly focus India as we have used India's Covid-19 dataset. Our proposed algorithms connects with Google Maps and suggest risk associated with all the possible routes between source and destination for the traveller and traveller can choose the low risk route for this travel. We want to make sure the world remains connected and no other such pandemic should stop the movement of goods or people.

Index Terms- Corona Virus, travel map, pandemic impact, safe travel map

I. INTRODUCTION

This paper presents a stepwise walkthrough on how to generate a relatively safe route map for travel during pandemic like Covid 19. Coronavirus disease (COVID-19) is an infectious disease which has created a havoc in the world. It is caused by a newly discovered coronavirus. Even though we have seen that most people who gets infected with the COVID-19 virus, experience mild to moderate respiratory illness and recover without requiring special treatment. The recovery rate varies from 92%-97% around the world, which is probably not a cause of concern. More concerning is that older people, and those with underlying medical problems like cardiovascular disease, diabetes, chronic respiratory disease, and cancer are more likely to develop serious illness and even can lead to death.

From the various research, we have seen that the best way to prevent and slow down transmission is be well informed about the COVID-19 virus, the disease it causes and how it spreads. One has to protect themselves and others from infection by washing your hands or using an alcohol based rub frequently and not touching your face [14]. Research also says that the COVID-19 disease spreads primarily through droplets of saliva or discharge from the nose when an infected person coughs or sneezes. It's very important that we practice respiratory etiquette (for example, by coughing into a flexed elbow) among the other etiquette we mentioned.

At the time of writing this report, there were couple of vaccines developed for the treatments for COVID-19. However, there are many more ongoing clinical trials evaluating potential treatments and organizations are also conducting trial on human for finding an effective vaccine.

In this research, we looked at the Covid-19 scenario in India. Recovery rates are higher but since the disease itself is infectious, both central and state governments have announced lockdowns in various regions. People are not encouraged to travel. This has hit the economy hard.
Covid-19 pandemic is set to impact the India growth story and the country's gross domestic product (GDP) could in fact shrink in 2020, as per a Dun & Bradstreet global report.

In 2020 fiscal year, India's growth rate could get into negative value of 4.5%. One of the reason is the travel restrictions. The hospitality industry has suffered the most. India's hotels are reimagining the hospitality industry to survive the coronavirus pandemic because how far can they go with just being creative at the time when people are reluctant to even step out of their homes. The corona virus outbreak in India and the ensuing 70-day lockdown enforced by government has crippled the hospitality industry from small restaurants to big hotel chains and travel industry. Hotels are struggling to pay salaries, and in many cases, even are laying off staff. Companies are re-calibrating and localizing supply chains, which will change the way they operate their business. But these measures are not sustainable.

According to The World Travel and Tourism Council (WTTC), tourism generated $240 bn or 9.2% of India's GDP in 2018 and supported 42.67 mn jobs which is 8.1% of its total employment. This was the biggest motivator to carry out this research. Challenge is to come up with best possible routes during Covid-19 times and this could be extended to any such pandemic we might encounter in future as well. Input that we take is the zone classification by the government into Red, Orange and Green. Red zone indicating complete lockdown of non essential goods and certain type of travel is allowed with special permissions. Orange is where the travel is allowed with certain limitation and Green zone has no travel restrictions [16]. Apart from this, even the people travelling would want to visit few or no red zones and minimal orange zones because the chances of getting infected is very high in these areas. In our research, we use four zone classifications but decide the category based on the number of active cases. However, this logic is highly customizable and additional rules can be added/modified/removed to decide the zone category. With these info in mind, the paper comes up with an efficient and low risk travel routes based on any two given points.

The generated travel plan would be the least risky of all the possible routes. The time factor is also taken into account but has very low weight. Many similar papers have been referred but none of the papers have spoken about similar situation. There are many articles which talks about coming up with route planners in emergency situation. The conditions and the attributes analyzed in this paper is different compared to similar research done in the past.

This research can be used in multiple scenarios apart from Covid-19 situations. This study can be extended to include in different situations which requires the planner to re-route the planned route for variety of reasons like, collapse of a bridge, heavy rain in certain part, etc. This research can be used by travel industry for route planner, individual people to plan their travel route to have least chances of surprise and also by supply chain planners.

II. LITERATURE REVIEW

There are many research papers which were referred to understand how the route planning is done in similar situations. A paper titled "Travel Time Forecasting and Dynamic Routes Design for Emergency Vehicles" by Giuseppe Musolino and others were published in 2013. The paper presents a framework to dynamically design routes of emergency vehicles taking into account within-day variations of link travel times on a road network presented. The framework integrates two modelling components: (i) a within-day dynamic assignment model that simulates the interaction between the time-varying network and travel demand, and (ii) a dynamic vehicle routing model that design optimal routes of emergency vehicles. The linking variable of the two modelling components is the short-term forecasted travel time, which allows to design routes of emergency vehicles based on anticipatory knowledge of traffic dynamics on the road network. Some procedures of the proposed framework are calibrated and validated in an experimental evacuation test site.

The safe operation of all highway facilities, including intersections, requires the consideration of three primary elements for safe roadway operations: the driver, the vehicle, and the roadway. Robert Layton presented the detailed analysis in a report to Oregon Department of Transportation (US) in 2012.

There was a study done by a team in Egypt on GIS-Based Network Analysis for the Roads. This study was conducted for Greater Cairo area. Sayed Ahmed, Romani Farid Ibrahim and Hesham A. Hefny, in their paper, says in a crowded city like Grater Cairo Region (GCR), Egypt, finding a desired location becomes a difficult task, especially in emergency situations. The main criteria of any emergency response system (ERS) are its readiness to solve the immediate emergency situation such as fire emergency response, police station emergency response, healthcare emergency response system,etc.

Then there are many papers which talks about the vehicle movement in crowded city. Road accidents are a serious problem in the world especially in developing countries. Travel time of Emergency Vehicle (EV) is an important parameter in emergency rescue during accidents. The situation can be improved provided the emergency information services like Web based emergency information and management systems which identifies incident, alerts emergency vehicle (EV), estimate travel time, enhance pre-emption control and route the EV. The study titled "Travel Time Estimation and Routing for Emergency Vehicles Under Indian Conditions" by R. Anil, M. Satyakumar, Jesh Jayakumar proposes a multilayer fuzzy model to determine the degree-of-priority (DOP) based on emergency vehicle pre-emption demand and impact intensity on each road section.

There are few research papers which focusses on shortest path problem. A research paper published in 2016 titled "Dynamic Path Planning of Emergency Vehicles Based on Travel Time Prediction" by Jiandong Zhao in Journal of Advanced Transportation. The dynamic paths planning problem of emergency vehicles is usually constrained by the factors including time efficiency, resources requirement, and reliability of the road network. Therefore, a two-stage model of dynamic paths planning of emergency vehicles is built with the goal of the shortest travel time and the minimum degree of traffic congestion. Firstly, according to the dynamic characteristics of road network traffic, a polyline-shaped speed function is constructed. And then, based on the real-time and historical data of travel speed, a new kernel clustering algorithm based on shuffled frog leaping algorithm is designed to predict the travel time. Secondly, combined with the expected travel time, the traffic congestion index is defined to measure the reliability of the route. Thirdly, aimed at the problem of solving two-stage target model, a two-stage shortest path algorithm is proposed, which is composed of K-paths algorithm and shuffled frog leaping algorithm.

Travel Time Forecasting and Dynamic Routes Design for Emergency Vehicles by Giuseppe Musolino published in 2013 in Science Direct, proposed a framework to dynamically design routes of emergency vehicles taking into account within-day variations of link travel times on a road network is presented. The framework integrates two modeling components: (i) a within-day dynamic assignment model that simulates the interaction between the time-varying network and travel demand, and (ii) a dynamic vehicle routing model that design optimal routes of emergency vehicles. The linking variable of the two modeling components is the short-term forecasted travel time, which allows to design routes of emergency vehicles based on anticipatory knowledge of traffic dynamics on the road network. Some procedures of the proposed framework are calibrated and validated in an experimental evacuation test site.

II. Methodology

In order to discover the safest or low risk travel map between origin and destination, risk zones have been categorised into four, namely, (i) red, (ii) amber, (iii) yellow and (iv) green. The green zone is the very safest zone, yellow is low risk zone, amber is medium risk and red is high risk zone, respectively. Further, to calculate the zone category, two parameters have been used, (i) current zone's active case count and (ii) maximum active case count from the entire zones.

$$current\ zone\ riskscore = \frac{current\ zone's\ active\ case\ count}{\text{maximum active case count from the entire zones}}$$

The figure [1] shows the coloured categories of four zones with its respective risk score range.

Fig [1] : Zone category with score

The reference range to determine the zone category can be modified based on the condition.

We use risk score matrix to store each routes' different risks count and calculate the overall risk score for all the routes between origin and destination. The risk score matrix is a N X 4 size matrix and the sample risk zone matrix prior to the calculation risk score is shown in the table[1].

	red	amber	yellow	green	risk_score
route1	23	5	1	3	
route2	6	15	111	322	

Table[1] : Sample risk zone matrix

In table [1], first four columns are named with risk zone categories and final column is used to store each routes' calculated risk score. Each row in the table has been used to store each route's risk score details. For instance, route 1 has 23 red, 5 amber, 1 yellow and 3 green zones. As our intention is to calculate only the risk associated with each route, we skip the green zone count while calculating the risk score. Further, we use zero prefix filling approach to calculate the risk score. The calculated risk score using zero prefix filled approach for the two routes is shown in the Table[2].

	red	amber	yellow	green	risk_score
route1	23	5	1	3	2305001
route2	6	15	111	322	0615111

Table[2] : Risk zone matrix with calculated risk score

The zero-filling approach is about finding the big number's length in each column and just fill prefix zero for the values in the same column if its length is less than maximum number's length and append the value with risk score column value. The technique will be applied to all the risk zone columns except green. Finally it gives the correct risk score for the decision making.

Risk Calculation Approaches

We propose two standard approaches to calculate risk for the travel locations.

Approach 1: Risk calculation based on main travel locations' active cases

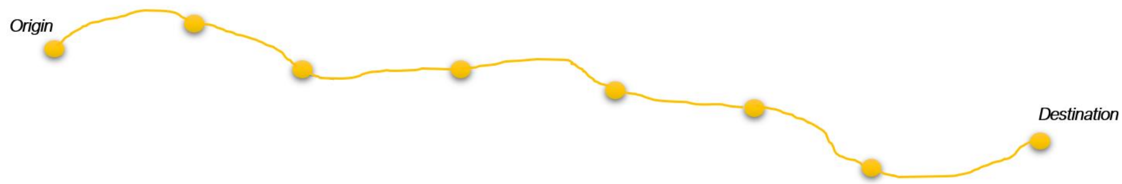

Figure [a]: Risk calculation using intermediate main locations

In figure [a], each yellow circles refers main locations, and there are eight main locations have been connected between origin and destination. While computing risk score, only the intermediate six locations (excluding origin and destination) will be considered. So all the intermediate locations' active cases count will be used.

Approach 2: Risk calculation based on main travel locations and locations' immediate neighbours

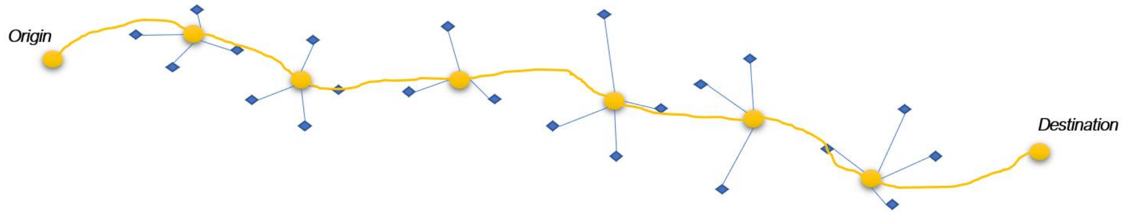

Figure [b]: Risk calculation using intermediate main locations and its neighbours

In figure [b], each yellow circles refer main locations and blue colour connected diamond shapes refer main locations' immediate neighbour locations. While computing risk score, six intermediate main locations and its neighbour locations active cases will be considered. i.e. For each intermediate locations, mean value of active case count for main as well as neighbour locations' count will be used.

The steps for discovering low risk travel map is summarized as follows:

Steps to discover low risk travel map using approach 1

1. Load the Covid-19 active cases dataset.
2. Find out the max_active_count_case from the dataset.
3. Read all the routes between origin and destination.
4. Construct the empty risk score matrix with rows count equivalent of number of routes.
5. Read each route's all the main locations' latitude and longitude.
6. Process each route's main locations' latitude and longitude:
   6.1 find out the place name from latitude and longitude.
   6.2 Read the active count from the Covid-19 dataset and find out the zone category for the current place.
   6.3 Update the risk score matrix against current route's row with zone category count.
7. Calculate risk score for each route using zero prefix fill approach and update the risk score column.
8. Rank each route's risk based on the score.

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The very first step of the algorithm loads the Covid-19 data set and the active cases for each main places exist in the dataset. The maximum active case count is about finding the place name from the list which has highest active cases comparing with others. The maximum active case value has been used to compute the zone risk score and the risk score will help to find out the zone category. The next step of the algorithm gets the list of all routes between origin and destination. In case there is only one route exist between origin and destination, the proposed algorithm cannot help user as there is no alternative route(s). So, the more possible routes exist between origin and destination, can give more risk score options to the traveler. Once the list of routes obtained, each routes data will be processed to find out the main places, zone category and its risk score.

While processing each route's main locations, proposed algorithm finds out the place name from latitude and longitude. Once the place name is identified, it finds out the zone category for the place. As and when the new place is identified, its category has been computed and the risk score matrix will be updated for the current route and zone column value will be incremented by one. Once all the routes' main place details are processed, risk score will be computed and stored in the risk score column of risk score matrix. Eventually, each routes score can be used to find out the risk involved, and the higher risk score refers the higher risk and lower score refers lower risk.

If we need to use the approach 2, Step 6.2 will use the mean value of main location and its neighbour locations' active case count. All the other steps will be same as stated.
Some code snippets are:

```python
#sample risk zone matrix
def create_sample_risk_zone_matrix(should_print):
    route_risk_zone_matrix = pd.DataFrame(columns=['red','amber','yellow','green','risk_score'],
                                          index=['route1','route2'])
    #initialize first row
    route_risk_zone_matrix.loc['route1','red'] = 23
    route_risk_zone_matrix.loc['route1','amber'] = 5
    route_risk_zone_matrix.loc['route1','yellow'] = 1
    route_risk_zone_matrix.loc['route1','green'] = 3
    #initialize second row
    route_risk_zone_matrix.loc['route2','red'] = 6
    route_risk_zone_matrix.loc['route2','amber'] = 15
    route_risk_zone_matrix.loc['route2','yellow'] = 111
    route_risk_zone_matrix.loc['route2','green'] = 322
    #assign empty to risk score
    route_risk_zone_matrix['risk_score'] = ''

    if (should_print == True):
        print(route_risk_zone_matrix)

    return route_risk_zone_matrix
```

Figure 1: Sample Risk Zone Matrix

```python
#function to calculate risk score
def calculate_risk_score(risk_zone_matrix, should_print):
    #https://queirozf.com/entries/pandas-dataframe-examples-column-operations
    max_number_length = len(np.str( np.max(risk_zone_matrix['red'])))
    risk_zone_matrix['risk_score'] = risk_zone_matrix['red'].map(lambda value: np.str(value).zfill(max_number_length))
    max_number_length = len(np.str( np.max(risk_zone_matrix['amber'])))
    risk_zone_matrix['risk_score'] += risk_zone_matrix['amber'].map(lambda value: np.str(value).zfill(max_number_length))
    max_number_length = len(np.str( np.max(risk_zone_matrix['yellow'])))
    risk_zone_matrix['risk_score'] += risk_zone_matrix['yellow'].map(lambda value: np.str(value).zfill(max_number_length))

    if (should_print):
        print(risk_zone_matrix)

    return risk_zone_matrix
```

Figure 2: Function to create risk score

```
def get_all_alternative_routes_latitude_longitude_dict(routes_json, should_print):
    #latitute and longitude : https://www.latlong.net/Show-Latitude-Longitude.html
    latitude_string='\'lat\': '
    longitude_string ='\'lng\': ';
    num = 0
    latitude_longitude_list = list()
    latitude_longitude_dict = dict()
    for single_route in routes_json:
        num += 1
        legs = single_route['legs']
        steps = legs[0]['steps']
        if(should_print == True):
            print('ROUTE : {} -- START\n'.format(num))
        #below loop will extract the latitute and longitute of single route
        for step in steps:
            #print(str(step['start_location']))
            latitude_and_longitude = str(step['start_location'])
            latitude_index = latitude_and_longitude.find('\'lat\': ') + len(latitude_string)
            comma_index = latitude_and_longitude.find(',')

            longitude_index =latitude_and_longitude.find(longitude_string)  + len(longitude_string)
            last_index = len(latitude_and_longitude) - 1

            if (should_print == True):
                print(rg.search((latitude_and_longitude[latitude_index:comma_index],
                                 latitude_and_longitude[longitude_index:last_index])))

            latitude_longitude_list.append([latitude_and_longitude[latitude_index:comma_index],
                                            latitude_and_longitude[longitude_index:last_index]])

        if(should_print == True):
            print('ROUTE : {} -- END\n'.format(num))

        latitude_longitude_dict['route_{}'.format(num)] =  latitude_longitude_list.copy()
        latitude_longitude_list.clear()
        if(should_print == True):
            print(latitude_longitude_list)
    return latitude_longitude_dict
```

Figure 3: Generate Alternate Routes

III. FINDINGS

In our research, Covid-19 dataset for India has been used and that has been downloaded from the official website [1]. It has confirmed active, recovered, and deceased cases for each state as well as districts. We use only active cases count to compute the risk score for each route, and load the active cases data and find out the district which has maximum cases for zone categorization. As the dataset has the district wise data, we compute the zone category for each district. However, this algorithm is capable for identifying zone category in small spot/location level if the dataset supports.

The google map data has been used to find out all the routes between origin and destination. Google map API gives all the main locations' latitude and longitude between origin and destination in JSON format. Further, we do not alter any existing map route but computes the risk involved in each route and advise the traveller with risk score.

Though the proposed solution can be applied in any country/area map, our experiment is mainly focus India as we have used India's Covid-19 dataset. The figure[2] shows the routes between Kanaykaumari (TamilNadu, India) and Chennai(TamilNadu, Inida), and there are three routes suggested by google map.

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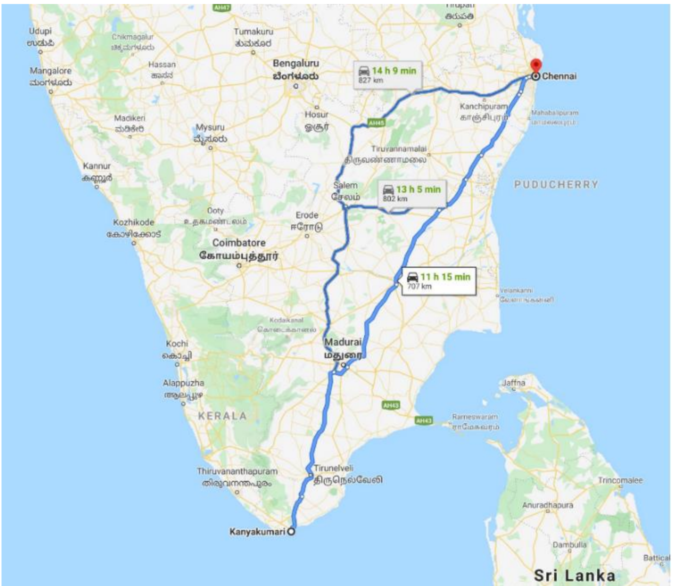

Figure[2]: Three routes between Kanyakumari and Chennai

The algorithm connects with google map and get the latitudes and longitudes for all the three routes in JSON format. The three routes' places details are processed by the algorithm and eventually it gives the risk score matrix as output. The table[3] shows the risk score matrix for routes between Kanaykaumari (Tamil Nadu, India) and Chennai (Tamil Nadu, India) using approach 1.

	red	amber	yellow	green	risk_score
route_1	1	0	7	2	107
route_2	1	0	6	6	106
route_3	1	0	6	6	106

All the three routes have only 1 red zone but route 1 has 7 yellow zones but others have 6 yellow zones each. In this experiment result, route 1 has slightly higher risk comparing with route 2 and route 3.

IV. CONCLUSION AND FUTURE ENHANCEMENT

Over two months of lockdown and caught within the same four walls—we are close to becoming a society of Schrödinger's cats (hanging somewhere between dead and alive). But we are humans, we don't stop thinking. Lockdown restricted the movement of people as the COVID 19 disease transmit rapidly. Our idea was to develop a low cost route map which people can use for emergency movement of goods or people.

The main focus of this study has been on the lowest possible risk of travelling during COVID-19. In this study Google Map API has been utilized between origin and destination and this approach can be used all over the world during any situation. A future direction of this paper will be to use during natural calamities such as flood, earthquake, and cyclone by rescue team in order to help/guide the affected people. This approach can have generic solution and can be customized according to new requirements.

It is important to note that the approach is suitable to let us know the less possible risk path for travelling from one place to another place by road. This Proposed method has been considered for the COVID-19 data of

India. It is not limited to one place or country/area/zone but can be applied to anywhere and in any situation of the world. Therefore, generalization and customization is the next step of the approach.

The result presented in the article can be used in future to guide travelers during pandemic or natural calamities. Each of these problems can bring different challenges and we believe that our model can handle these challenges with minor modifications. The algorithm we proposed in this paper will give specific low cost routes during COVID 19 pandemic and at the same time it also serves as a generic solution for finding similar routes which can be customized to handle natural calamities.

REFERENCES

[1] India Covid-19 cases data : https://api.covid19india.org/documentation/csv/
[2] https://www.researchgate.net/publication/259037953_Travel_Time_Forecasting_and_Dynamic_Routes_Design_for_Emergency_Vehicles
[3] https://cce.oregonstate.edu/sites/cce.oregonstate.edu/files/12-2-stopping-sight-distance.pdf
[4] http://ceur-ws.org/Vol-2144/paper2.pdf
[5] https://ieeexplore.ieee.org/document/8492696/references#references
[6] https://www.hindawi.com/journals/jat/2017/9184891/
[7] https://www.sciencedirect.com/science/article/pii/S1877042813040482
[8] AmrapaliDabhade, Dr. K. V. Kale, Yogesh Gedam, "Network Analysis for Finding Shortest Path in Hospital Information System", IJARCSSE, Vol.5, No.7, July 2015, pp. 618-623.
[9] Gubara, A. Amasha, Z. Ahmed and S. El Ghazali, "Decision Support System Network Analysis for Emergency Applications", Informatics and Systems (INFOS), 2014 9th International Conference on, Cairo, 2014, pp. ORDS-40-ORDS44
[10] Vineeth Kodire, Sreebha Bhaskaran and H N Vishwas, "GPS and Zig Bee based traffic signal pre-emption", Internatinal conference on Inventive Computation Technologies (ICICT) Aug 2016 published in IEEE Xplore.
[11] Satyajith Mondal, Sandip Chakrabathoy and Ankit Gupta, "Estimation of passenger car unit for heterogeneous traffic stream of urban arterials: case study of Kolkata", The International journal of Transportation Research, Feb 2017.
[12] Noraimi Azlin Mohd, Zati Aqmar Zaharudin and Nor Amalina Nordin, "Finding shortest path of the ambulance routing: Interface of A* algorithm using C# programming", IEEE kuala Lumpur Malaysia, 2012.
[13] Simmons, R.; Browning, B.; Zhang, Y.; Sadekar, V. Learning to predict driver route and destination intent. In Proceedings of the 2006 IEEE Intelligent Transportation Systems Conference, Toronto, ON, Canada, 17–20 September 2006; pp. 127–132.
[14] Froehlich, J.; Krumm, J. Route Prediction from Trip Observations; SAE Technical Paper; SAE International: Warrendale, PA, USA, 2008.
[15] Song, C.; Qu, Z.; Blumm, N.; Barabási, A.-L. Limits of predictability in human mobility. Science 2010, 327, 1018–1021.
[16] Krumm, J.A. Markov Model for Driver Turn Prediction; SAE Technical Paper; SAE International: Warrendale, PA, USA, 2008.
[17] Sun, X.; Huang, Z.; Peng, X.; Chen, Y.; Liu, Y. Building a model-based personalised recommendation approach for tourist attractions from geotagged social media data. Int. J. Digit. Earth 2018, 661–687.
[18] Kostov, V.; Ozawa, J.; Yoshioka, M.; Kudoh, T. Travel destination prediction using frequent crossing pattern from driving history. In Proceedings of the 2005 IEEE Intelligent Transportation Systems, Vienna, Austria, 13–16 September 2005
[19] Cui, G.; Luo, J.; Wang, X. Personalized travel route recommendation using collaborative filtering based on GPS trajectories. Int. J. Digit. Earth 2018, 11, 284–307.
[20] Randy L. Haupt, Sue Ellen Haupt, 2004, Practical genetic algorithms, second edition, A John Wiley Inc publication. Xiaoyu Ji, Kakuzo Iwamura,
[21] Zhen Shao, 2001, New models for shortest path problem with fuzzy arc lengths.Matti Tommiska, Jorma Skytta, 2001, Dijkstra's shortest path routing algorithm in reconfigurable hardware, springer-verlag. pages 653-657.
[22] Mitchell Melanie, 1999, An introduction to genetic algorithms, A Bradford Book the MIT Press, Fifth printing.
[23] M. Munemoto, Y. Takai, Y. Sato, 1998, A migration scheme for the genetic adaptive routing algorithm, in proc. IEEE Int. Conf. Systems.
[24] J. Inagaki, M. Haseyama, H. Kitajima, 1999,a genetic algorithm for termining multiple routes and its applications, in Proc. IEEE Int. Symp. Circuits and Systems.

[25] C. Lin, K. L. Choy, G. T. S. Ho, S. H. Chung, and H. Y. Lam, "Survey of green vehicle routing problem: past and future trends," Expert Systems with Applications, vol. 41, no. 4, pp. 1118–1138, 2014.
[26] M. Björklund, "Influence from the business environment on environmental purchasing—drivers and hinders of purchasing green transportation services," Journal of Purchasing and Supply Management, vol. 17, no. 1, pp. 11–22, 2011.
[27] J. H. Holland, Adaptation in Natural and Artificial Systems: An Introductoryanalysis with Applications to Biology, Control, and Artificial Intelligence, University of Michigan Press, Ann Arbor, Mich, USA, 1975.
[28] F. Dobslaw, "A parameter tuning framework for metaheuristics based on design of experiments and artificial neural networks," in Proceedings of the International Conference on Computer Mathematics and Natural Computing (WASET '10), 2010.
[29] E. Uchoa, D. Pecin, A. Pessoa, M. Poggi, A. Subramanian, and T. Vidal, "New benchmark instances for the capacitated vehicle routing problem," Research Report Engenharia de Produção, Universidade Federal Fluminense, 2014.
[30] https://www.who.int/news-room/articles-detail/key-considerations-for-repatriation-and-quarantine-of-travellers-in-relation-to-the-outbreak-of-novel-coronavirus-2019-ncov
[31] https://www.worldnomads.com/travel-safety/worldwide/top-tips-to-stay-safe-while-driving-in-remote-areas
[32] https://www.bbc.com/future/article/20200904-covid-19-how-to-travel-safely-on-the-bus-train-and-subway
[33] https://www.outlookindia.com/outlooktraveller/explore/story/70591/5-tips-to-keep-in-mind-for-your-next-road-trip-during-covid-19
[34] https://www.lonelyplanet.com/landing/covid-19

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