Assessing Micro-Mobility Services in Pandemics for Studying the 10-Minutes Cities Concept in India Using Geospatial Data Analysis: an Application

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ABSTRACT

Active micro-mobility decreases traffic, bolsters personal health, and helps communities thrive by protecting the environment. Moreover, sustainable micro-mobility demand is expected to get boosted in the present and post-COVID society. In this work we highlight the micro-mobility modes of walkability and bicycling to city administrators controlling urban city-space, by adapting the mobility parameters and their use cases through a map-based interface. Software tools and web-based applications are introduced for easy policy decisions by city managers. Present study scope is circumscribed by exploration of different parameters in traditional and state of art data science models, for resource planning like cycle usage prediction and planning. These parameters show hazard safe-distance pedestrian flow, optimal resource planning, amenity reach (10 min cycling and walking distance) and mobility using walking and cycling modes. Parameters of the traditional Social Force Model for Pedestrian Dynamics are also inspected, according to COVID social norms, to capture safe pedestrian flow density. Finally, the analysis of two case studies, of Bhubaneshwar city and New Delhi, in India, are discussed for policy suggestions to enhance mobility via sustainable micro-mobility modes. The developed system assists managers in decisions based on urban data intelligence, and at user end eases commute related mental tension, anxiety and dependencies. The developed application is running live on our server maintained at Edinburgh University.

CCS CONCEPTS

• Spatial Analysis and Integration • Spatio-Temporal Data Management • Spatial Information and Society

KEYWORDS

micro-mobility, bike-ability, walkability, 10 minutes cities, social force model, amenity reach, safe-distance pedestrian flow, mobility parameters.

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1 Introduction

A walkable city that encourages micro-mobility modes such as walking and cycling, is a desirable solution to multiple complexities linked to both daily routines of an individual as well as the economy and environment of societal urban space. Walking and cycling balance mental stability, improve physical health, diminish vehicular jams, may lead to more reliable trip duration due to reduced traffic, generate cost savings, and aids social distancing [1][2]. In a typical city where people prefer to drive cars - they will prefer to walk only if the walk offered is as good as to drive or even better[3]. While the present study does not claim to be offering aesthetics of a city, what it does is to provide micro-mobility information for ease of reachability of resources within short-duration of travel. This is validated in a spatial context of emergent situations such a pandemic, and is equally applicable and valuable in case of other such civic disturbances.

In addition to walkability, another practical micro-mobility mode is cycling, which as a micro-mobility service provides effective solution to the first-mile/ last-mile problems, diminishing transit voids, and reaching out to traditionally remote communities [4]. Further, amid COVID 19 pandemic, after the lockdown, the micro-mobility services have been promoted worldwide by introducing new citywide policies. New cycling infrastructure as well as converting the motor drive lanes to cycle lanes are proposed. Cities like Seattle are considering permanently closing some lanes of driveways to provide more walk space [5,6].

Cycle as a resource needs to be managed for availability across usage areas. To manage and facilitate micro-mobility, city managers face various problems linked to pedestrian dynamics as well as bike mobility. Accessibility to the whole city is essential because otherwise, pedestrians would prefer cars, eventually, the city would reshape around peoples' needs - widening of streets and allocating space for ample parking lots. Hence every transit is requisite, but every transit begins and ends with a walk; walkability around transit stations should be built. Other parameters that are to be considered are such as the block size, the number of lanes, and the skinny or wide streets. A block size, which is inversely proportional to the usage of micro-mobility modes, if increased then the fatal accidents grows exponentially [7,8].

Regarding pedestrians, complications about the bottleneck flow can be improved by implementing walkable proven designs [9]. Crowd management while improving the safety and comfort of pedestrians at mass crowd ingress and egress points needs to be addressed [10]. Further, there is a need to implement adequate plans for optimal evacuation at all the pedestrian facilities [11]. These decisions before implementation require human commute behavior simulations for proof study. However, human behavior is considered to be irregular - a person's independent commute behavior as compared to within a group is different. The ideology of maintaining distance from others while walking is an add-on behavior to the people's commute amidst COVID 19 pandemic. Cognitive models such as social force models (SFM) inspired by Newtonian mechanics transpire their utility in realistic modeling of allied social commuting behavior. In SFM, a social force estimates the internal motivations of an individual to act as catalyst for certain actions and should be revisited considering COVID 19 behavioral change.

For assisting mobility there have been development of new tools and business models. Previous studies have highlighted that high-quality infrastructures and management can boost local cycling rates - thereby making software tools and methods a necessity for the effectiveness of infrastructure and cycling measures [15]. The Propensity to Cycle Tool (PCT) was developed for assisting transport planners, operators and policy makers. It is an online strategic planning tool, an interactive map-based driven support system, that aims to achieve sustainable transport via informed transport decisions and helps prioritize strategic investment in active travel [14]. Like PCT, to facilitate urban sustainability miscellaneous other tools are being used. Among them are policy oriented tools and policy implementation tools [16]. Transit oriented development like zoning, and budget controlled land acquisition for road infrastructure are facilitated using policy implementation tools [16]. These tools are designed using high end knowledge of data science. However, every city requires its own calibrated model for city developers' use cases.

The contributions of this paper lie in the following:

1. Highlighting micro-mobility modes of walkability or bikeability via map-based interface.

2. Different assessment methods that provide helpful information about micro-mobility services.

3. A predictive model that assesses the micro-mobility services, both walking and cycling, using software tools and data collected from urban mobility services.

4. The analytical and visualization components showcased in our study are integrated into a planning support system for serving the users and managers in a better way for informed decisions.

The remainder of the paper is organized as follows. Section 2 provides details of existing literature, challenges, and micro mobility accessibility and related solutions. Section 3 highlights geospatial analysis and data gathering methodology. Section 4 provides details on accessibility mapping for different micro mobility modes. Section 5 outlines the prediction models studied for cycle usage in different areas of a city. Further, in Section 6, policy-based discussion about the case study is presented. Finally, a conclusion is put forth from the study with policy recommendations.

2 Background

2.1 Problem scoping

Embracing walking and cycling campaigns relay the benefits that physical activities bring. Yet little heed has been given to bikeable and walkable city design, specifically in developing countries. The pertinent issues there include mixed traffic, poor planning processes, security frailties, and sidewalk invasion. Analysis by continent specifies that micro-mobility accessibility has been a critical research topic in North America (56.6%), Asia (22.6%), and Europe (15.1%) [17]. Primarily city managers should keep a good hold on bike-related planning like BSSPs (bike-sharing service planning problems) and related city design as it is complex and incorporates multiple stages of interlinked managerial decisions [18]. As shown in Fig.1, Primary level involves strategic level, that includes long term decisions correlated to bicycle sharing service infrastructure. Second is the tactical level, which involves medium-term decisions which may help to sustain the performance of a bicycle-sharing service if existing resources are properly used. And third is the operational level, which focuses on short-term decisions, taken frequently, to respond to the daily operation of a BSS. Measuring bikeability in terms of bicycle comfort, suitability, compatibility, accessibility, and friendliness helps in assessing the communities. However, there is no universal definition for bikeability and it can be assessed via variety of tools [19]. Further, city managers need to observe mass events for efficient flow such as marathons, festival celebrations like bullfighting, pilgrimage-related transits, and fairs. All these use cases require data intelligence and related tools for assisting optimal decisions by city managers.

2.1.1 Challenges for assisting Biking as Micro-mobility service.

According to a survey, approximately 2,110 Bike sharing programs (BSP) and 17,792,000 bicycles are in service worldwide [18]. Analysis done in 2019 projected the $300 billion worth of micro-mobility industry to see an increase to $500 billion by 2030 [6]. The e-scooters, first introduced in 2017, have been booming from city to city. The capital investment for commencing a BSP approximately ranges between $4,000 to $5,000 per e-bike, including the cost of kiosks or docking stations [20]. However, space constraints and municipal budgets hinder the plan of providing station-based micro-mobility services [21]. The dockless bike sharing systems overcome these limitations as it combines digital payments and Global Positioning System tracking. Therefore, since 2016, demand for dockless systems has increased around the globe [22].

Bikeability is also influenced by frailties linked with user experience and their expectation. Internal factors include personal preferences, personality traits, and social support. Users' perception toward and usefulness of BSS is linked to green intentions [23]. Environmental consciousness being another influential factor affecting peoples' intention to opt for a bicycle for commuting [24,25]. Usually riders may be categorized in terms of bike-streets, parks-street and mixed traffic streets. To map these city-specific behavioral parameters we have collected data using different user surveys.

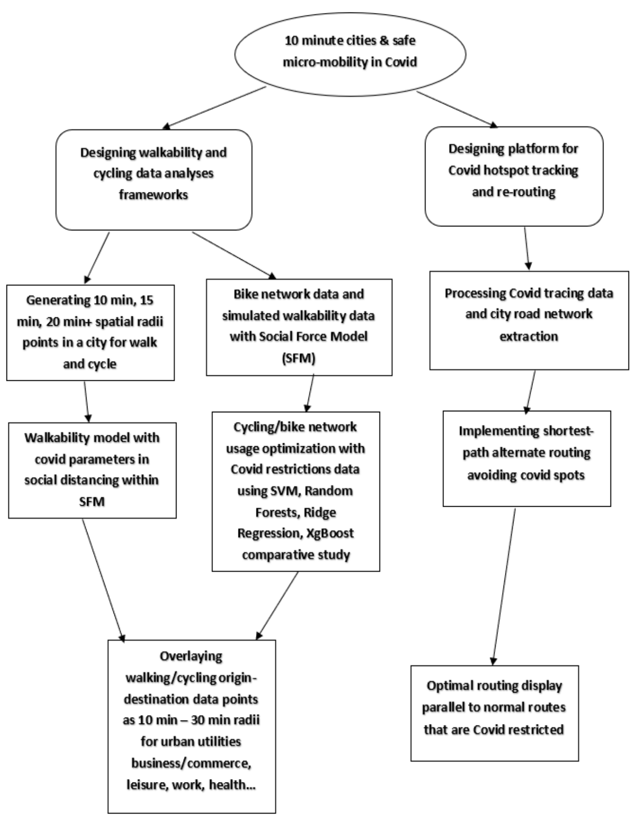

Figure 1: Workflow diagram showing the various levels of system design and functionality with sequential steps.

In addition to safety, tourists who are using micro-mobility modes and are unaware of the structure of the city may face navigational challenges. Further, during heavy traffic hours, BSPs tend to be congested, which means bicycles might not be available for use. Fricker & Gast highlighted the problem of fleet sizing - estimating the requirement of bicycles needed in the entire BSS as well as at each station [26]. Discovering locations for bicycle stations and bikeways is a mixed design problem covered in two studies [27, 28]. Further, with the rise of e-scooter new challenges are emerging like vandalism, theft and inappropriate e-scooter parking like dropping off in the middle of the sidewalks. Considering these management challenges, planning, balancing the fleet, pricing, and retrieving the off-station parked vehicles may demand vigorous labor exercise which tantamount to a great expense. Thus managers need to observe city or area-specific related parameters which will be helpful in decision-taking stage.

External factors that influence bike-sharing involve factors such as traffic, network connectivity, bike's usability, profession, age, income, and weather conditions. In studies, a positive relationship between average household income and cycling activity is noted [29, 30]. However, it was contradicted by other studies [31] [32]. The neighborhood with a higher percentage of college-educated residents shows positive relation with cycle usage [31, 30]. Taking age into account, residents younger than six or older than sixty-four indicated lower levels of cycling activity [30]. An interesting negative relation is noted for strong street network connectivity as the cycling demand is replaced by walking [33]. However, connectivity correlation may vary based on place and user behavior. The network indicators - directness and linearity show positive relation with bike commuting [34]. Given the variation in correlation, a tool subsumed with network indicators provides analysis beneficial for network planners. Thus, these parameters are valuable for informed decisions and so collected by managers.

2.1.2 Challenges for assisting Walking as Micro-mobility service.

Walking-related policies also need data to examine pedestrian walkability and flow dynamics. However, collecting such sample data involves a large number of people, and detecting their walking behavior is complex and challenging. The complexities include various factors such as psychological factors that influence human behavior, external factors, such as the layout of pedestrian facilities. Also, the behavior of the nonlinear interactions of pedestrians makes it more complex. Literature has established some models for modeling pedestrian behavior. Helbing et al. established by modeling that a horde moves in waves rather than moving continuously [35]. The other important phenomena include the land formation and the stripe formation - the land formation includes a pattern in which a pedestrian forms several lanes of different widths and moves in the same direction. The stripe formation briefly describes a pattern in which pedestrians try to diminish the friction towards the pedestrian moving in the opposite direction. A pedestrian moves forward and sidewards, both in stripes. However, this is only applicable when two pedestrian flows interact and there is no stable pattern for three or more intersecting flows [9]. Using this knowledge some models are established for pedestrian dynamics. However, with the emerging COVID pandemic, crowd behavior is prone to change amidst distancing from alien groups or entities. Considering these pedestrian behaviors changes, behavior simulation models need to be revisited for calibrating the model parameters to sustain the new changes. These calibrated models are vital to establishing flow dynamics policies on bottlenecks i.e. on the micro-level.

2.2 Accessibility analysis of different micro-mobility modes

Accessibility evaluates the number of different places such as schools, hospitals, etc. a person can reach within a given timeframe in their locality. It measures what people could do using micro-mobility modes within a circumscribed area and transit schedules. Accessibility flow analysis helps a city manager to perceive the ongoing transportation systems - the major challenges include congestion, urban sprawl, and public transportation pricing. Also, it helps to juxtapose the impacts of varied probable projects and changes. Visualizations and metrics for access lead to a viewpoint for contemplating connectivity, for all the micro-mobility modes and transportation.

Bikeways and walkways consist of three major hierarchies i.e. lane, path, and route links. Various factors at different levels, such as accident risks, usage comfort, road widths, construction, and maintenance are considered while evaluating accessibility. Further parameters that govern cycling accessibility consist of locations of bike lanes relative to its level of service based on the modal share of cycling, widths of the bike path, and overall bike route between hotspots [35-39]. There are different quantitative measures and indexes for each of the walking and cycling micro-mobility modes. Pedestrian Environment Factor (PEF), a subjective index of walkability constitutes all the climate, cultural, economic, and geographical aspects that may have an effect on walkability. Walkability Index (WI) by Frank et al., elucidate less subjective measures of physical objectives. It was computed as a weighted sum of z scores of net residential density, street connectivity, and land use mix within a buffer. Further, the Bikeability Index (BI) and Bicycle Level of Service (BLOS) are the trite metrics, whereas the other metrics including Interaction Hazard Score (IHS) [40], Bicycle Level Of Traffic Stress (BLTS) [41], and Bicycle Compatibility Index (BCI) [42] specifies safety and cycling quality after examining different attributes of the built environment. There is no specific definition for bikeability as it has been summarized in a number of ways and data scientists and city managers can formalize a function based on data availability and specific needs, as has been done in this study. Similar to bikeability, walkability is used to assess walking ease. These quantitative parameters are mainly used to establish macro and meso-level policies.

3 Use cases and solutions linked to mode and users

Software tools, help in dealing with micro-mobility frailties and policy making. Personalized knowledge, along with traditional knowledge, emerges from city-specific surveys and parameters as collected by city managers. This personalized knowledge, points to issues faced by users in given city which are known to city managers. However, a data scientist equipped with data indicators knowledge can analyze the specific problems more prudently with the personalized data. Similarly, for use cases like vehicular-resource planning and pedestrian flow prediction, data scientists can solve these issues given the personalized knowledge of the city as a system, which is known to city managers. Also, not the same model is applicable to every city, and according to data and use case different models need to be tested. So, in order to develop a personalized model and software tools, understanding between the city manager and a data scientist is needed; which warrants that the toolkit needs to be structuralized and if possible standardized too.

3.1 Bottleneck flow for micro and meso-level decisions

In the literature to facilitate micro-level decisions for bottleneck flow, physics-based simulation is used for agents. As an interaction behavioral rule Social force models (SFM) is used by Agent Based Model (ABM) that models individuals' behavior to highlight pedestrians' choice for their decisions. Further, based on ABM, a high-level framework of integrated, multimodal representations of transportation can be made for an area [43]. Helbing et al. closely scrutinized the problem of finding designs that improve the bottleneck flow [9]. Design factors like a barrier placed in front of the exit can reduce congestion; it is also studied in relation to flow. In literature, to determine the configuration that maximizes the outflow, genetic algorithms have been used [44].

The traditional approach depends on reliable baseline indicators about how much traffic is on the network, where, at what time, and by what mode. Hence, traditional models [46] consider aggregate groups of people and assume that they have the same behavior. These models look at each mode as discrete systems [11]. Further, these micro-mobility transport demand models are used to understand transport networks and plan for changes in infrastructure and policy. However, the COVID-19 pandemic has led to an unprecedented challenge to transport planners and operators. As the behavior of pedestrians is changed along with the ratio of personal to public vehicle usage. So, these traditional existing microsimulation behavioral models are struggling due to rapid new changes in interaction behavior. As a consequence, our traditional assumptions about how our networks will function are null and void. To calibrate, in this study, we study the SFM parameters and related use cases of pedestrian behavior modeling in the COVID era, as shown in Fig 2.

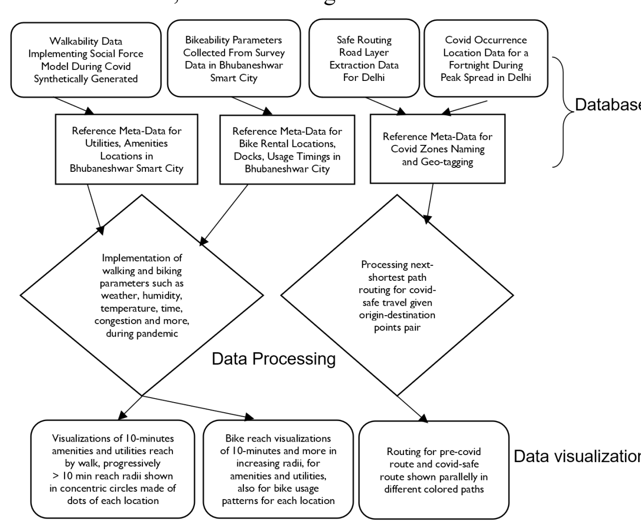

Figure 2: System architecture describing the data and output.

3.2 Visualization for macro and meso-level mobility policies

Micro-mobility accessibility for a given place can be calculated as the sum of reachable jobs via cycling and walking modes within a given reach out, in terms of time limit say 10 minutes. Areas having accessibility for more jobs are likely to be positively associated with cycling activity. In the present study, we outlined how to visualize mobility accessibilities using a case study and thus leveraging its usage in the optimal handling of last-mile travel problems. The database structure, data processing and visualization structure is shown in the system design architecture in Fig 2.

3.3 Resource prediction for optimal usage

A typical problem at the manager's end is availing bikes at the required location. A resource prediction model that could help resolve this problem will prove to be useful and should be deployed. Mostly, system operators scheme bike redistribution logistics via static models calibrated to historical demand averages. However, these models fail to examine users' information gathered from online queries and the intelligence of other factors. When the bike stations are either full or about to get empty, periodic and reactive bike redistribution are proposed; nevertheless not guided by predictive models which indicate the bike shortage [47]. [48] presented a population continuous-time Markov chain model, which helps analyze movement with the time-dependent rates to predict the future availability of bikes at stations. [49] used dynamic linear models to envisage bike counts in a BSS. [50] proposed an assignment strategy focusing on eliminating flapping and balancing demand at each station based on actual availability. Given the wide literature of prediction techniques still, some features are missing while modeling. So, considering a wide span of features, in the present study, we have deployed and tested the traditional models for prediction problems. This could highlight the usability of traditional models which is appreciated by both data scientists as well as the city managers for a better consortium.

4 Geospatial Analysis

Geospatial analysis is process of expressing information and complex relationships in terms of geographic coordinates or addresses to build maps, graphs, statistics, and cartograms. Majorly available free geographic data source: OpenStreetMap is used for mapping as well as for acquiring spatial data. To leverage the potential of geospatial analysis there are several packages like OSMnx [45] - a python package to model, project, visualize, and analyze real-world street networks, geemap, etc.

4.1 Data

In addition to road network data other temporal and spatial data are of prime importance to facilitate data-assisted decisions. Temporal data can be real-time as well as historical whereas spatial data are historical only. For accessibility visualization purposes spatial data are sufficient. However, both temporal and spatial data are essential requirements for demand forecasting. For providing a use-case as an example we have analyzed Bhubaneswar - the city in Odisha as a study area for micro-mobility assessment.

4.1.1 Location. 250+ Locations of cycle stands spread around the city are taken. In some feature-based prediction algorithms location might not be of much use as it is represented by a specific station name as ID. For our use case, we made a square grid of 1 Km around the center as a station point.

4.1.2 Time period. While analyzing any cyclic or seasonal behavioral pattern in data, time becomes an important factor. The sampling period however may vary as per the use case. For cycling usage prediction, we took a sample time of two hours given a balance between data availability and resolution. Partitioning day time into twelve features according to the slot of the day will help to assert a pattern for a given slot.

4.1.3 Calendar feature. Human behavioral usage for urban infrastructure is highly based on weekdays and declared leaves. Hence tagging the time period, with weekdays and if there is a holiday, will only make the model more accurate.

4.1.4 Road network. For spatial analysis, city-wide road network data are leveraged from OSMnx and is used as square grid of 1 Km^2.

4.1.5 Average traffic speed. As tempo-spatial data, i.e. which change as per time, as well as location, typical traffic color ratio of four different colors, is used as presented by Google map typical traffic layer. Typical traffic layer reports four colors according to average speed with five-minute resolution on a spatial basis. The color ratio is calculated as per the technique lined out in [52]. So, we averaged four samples to get a single sample for a grid area.

4.1.6 Local road network characteristics. As a spatial feature, road network characteristics are proven to be major features for determining bicycle activity. For calculating standard features OSMNx is a very useful python library. It reports on graph parameters like number of nodes; edges; intersections, average node degree, Average number of streets per node etc. We chose non-redundant parameters from tabulated feature in [45].

4.1.7 Point of Interest. All the urban infrastructure constitutes the spatial demography that is directly linked with micro-mobility usage. These consist of Bus Route terminals; stop and depot, Airport, Railway Station, Bank, Hotel/ Restaurant, Petrol Pump, Community Centre, Culture facilities- Art Centre; Library; Museum, Health-related facilities- private as well as government hospitals and clinic on different levels, Shopping Places, ATM, Post Offices, Government Offices, Police Station and post, Fire Station, Telephone Exchange, Educational- University; College; School; Training Institutes; Anganwadi Centre; Learning Point, Heritage Monuments, Youth Service and Recreational, Religious Places- Temple, Church, Gurudwara, Masjid. All the enlisted infrastructures' locations are taken from [58] for Bhubaneswar.

4.1.8 Land Use Patterns. Apart from point location, the ratio of the usage-wise areal land cover helps to weigh the usability of a total area accordingly. Different land-use patterns can be Agriculture, Forest, Retail Commercial and Business Use Zone, Wholesale Commercial Use Zone, Environmentally Sensitive Zone, Industrial Use Zone, Open Space Use Zone, Public, and Semi-public Use Zone, Residential Use Zone, Protected Monuments and Precincts, Commercial within Special Heritage Zone, Public and Semipublic within Special Heritage Zone, Residential within Special Heritage Zone, Road, Railways, Airport, Bus Depots Truck Terminals, Utility, and Services Use Zone, Rivers Canals and Streams, Ponds Lakes and Lagoons, Park, Building Footprints, Green Spaces, and playground. For each grid, we have calculated these spatial features. This data is leveraged from [58].

4.1.9 Populace revenue diversity. Populace living in an area is major spatial factor that affects internal features for micro-mobility usage. The major features related to this are ward-wise revenue, which we took from [58].

4.1.10 Weather. Features including humidity, temperature, precipitation, and environmental conditions like cloudy, sunny, rainy, etc. are major drivers for user intention to choose micro-mobility modes or a car. These features can be spatio-temporal if spatial resolution is good in the case of multiple weather stations in a city. In our use case, for Bhubaneswar, we had single station data for the whole city and thus for our usage, it is a temporal feature only.

4.1.11 Transit. For cycling usage prediction, we accumulated eight months of spatio-temporal shared cycle transit data from 15 April 2020 to 15 Dec 2020. It consists of a departure and arrival station along with a date and time stamp. For further usage of the timestamp as a feature, we converted it to a slot of the day.

4.2 Cycle Usage from station

In the undertaken study, we modeled usage prediction using almost all the necessary features linked with societal travel patterns. Standard data science algorithms such as Linear regression along with non-linear models such as Random Forest, SVR, XG-Boost available in SKLearn [59] python library are explored for modeling. Result for 30 percent test data along with hyperparameters are enlisted in Table 1.

Table 1 Standard model in SKlearn python library along with hyperparameter and the result.

	Random Forest	SVM	Ridge Regression	Xgboost
a.	max_depth = 10	kernel = linear	alpha = 0.1	colsample_bytree = 0.87
b.	n_estimators = 300	degree = 2	fit_intercept = True	gamma = 7.76
c.	max_depth = 10	gamma = auto	solver = cholesky	max_depth = 10.0
d.	min_samples_leaf = 6	decision_function_shape = ovr	mean_squared_error = 3.47	min_child_weight = 2.0
e.	min_samples_split = 7	accuracy score = 0.75		reg_alpha = 163.0
f.	criterion = entropy	mean_squared_error = 0.75		reg_lambda = 0.85
g.	accuracy score = 0.77			accuracy score = 0.78
h.	mean_squared_error =3.64			

The independent features such as humidity, temp, rain, and more are non-linearly correlated to the dependent feature ‘number of trips’. In our case study, Bhubaneswar is a tourist city; internal factors such as personality traits might also influence the target variable. Hence non-linearity is certain. Also, the dataset comprises intermingled categorical and continuous features. Linear regression did not perform well as the basic assumptions such as, multivariate normality is not fulfilled. The other reason being, Bhubaneswar city is a developing city of India where usability is dynamic due to business hubs, tourism, and local populace usage. An ‘ensemble learning method’ such as random forests or random decision forests is suitable for our study. If compared to a decision tree, random forest is considered to be more robust - the reason being it gives a low bias and low variance result. A supervised learning method such as support vector machines (SVM) has been used by us as it is a notable approach to solve both classification and regression problem statements. The SVM uses SVM kernels; a kernel function reduces the complexity of finding a mapping function that maps the non-linear separable data into a higher dimensional space where a hyperplane separates the samples. Different sets of mathematical functions termed kernels include linear, non-linear, polynomial, radial bias function (RBF), and sigmoid. Being localized and providing a finite response all along the x-axis makes RBF most used. The basic requirements for SVM effectiveness that maximizes efficiency, reduce error, and overfitting includes a selection of kernel, and kernel parameters. Xg-Boost is incorporated under boosting ensemble technique and is decision-tree based. In the problems involving unstructured data, Xg-Boost outperforms compared to the other algorithms as it solves problems in a fast and much more accurate way.

5 Walking Flow : Social Force Model

Using a simulator for a pedestrian flow estimation will help to avoid potential conflicts beforehand while making policies involving social distancing and ease transit. This model expresses the pedestrian motion by a summation of attractive, driving, fluctuating and repulsive forces contemplating external forces and internal motivations [12] [13]. The ability of the social force model to predict crowd behavior for distinct situations makes it popular. We performed three simulations to predict crowd behavior for three different situations - walking on a street, ingress and egress through the gate, and in a heavy crowd in setup shown in Fig. 3.

The SFM model comprises five forces - desired force, obstacle force, social force, pedestrian repulsive force, and space repulsive force. The desired force or the goal attractive force is the force that attracts the person towards an objective, obstacle force repels the person from the obstacles, social force is the force that repels the person from other people present in the same scene, pedestrian repulsive force is the pedestrian to pedestrian repulsive force and space repulsive force is the obstacles to a pedestrian repulsive force. We calculated the time to end the simulation using the different forces parameters mentioned in the Table 2 for both pre and post COVID situations. The time to end increases in post COVID situations for all the mentioned situations (Table 3).

Table 2 SFM force parameters for Pre and Post COVID situation

	Goal Attractive Force	Pedestrian Repulsive Force	Space Repulsive Force	Social Force	Obstacle Force
Normal	factor= 1	factor = 1.5	factor= 1	factor = 5.1	factor = 10.0
During Covid-19	factor = 0.7	factor = 3.0	factor = 2.1	factor = 6.6	factor = 18

Table 3 Time to end different simulation scenario in Pre and post

	Time (in sec) to end Pre-COVID	Time (in sec) to end Post-COVID
Simulation 1 (Gate)	67	88
Simulation 2 (Street)	42	51
Simulation 3 (Heavy Crowd)	50	55

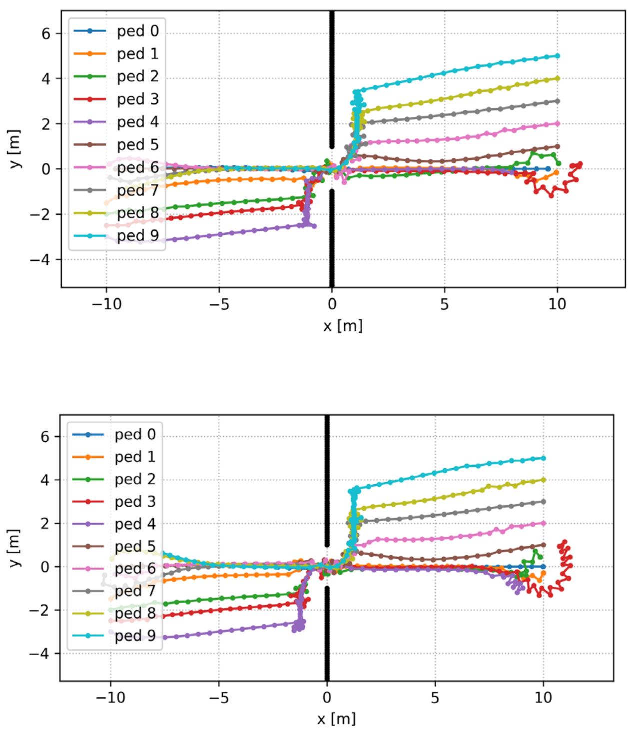

Figure 3: Pedestrian traced trajectory, top showing normal circumstances and bottom showing COVID effects on pedestrian behavior. In COVID effected trajectory agents try maintaining some distance by stopping or slowing down to let other pass away, even though trajectory trace is similar.

6 Accessibility Visualization: Static and interactive maps

Different visualization libraries such as folium, OSMnx not only make static maps but also interactive maps that portray pleasing graphics and provide additional features that allow direct interaction with the users. Folium caters to the needs of the user by visualizing geospatial data and creating a map to simplify underlying hidden patterns in data. Using python, Matplotlib can generate very customizable and high-quality output, creating reproducible figures. Other than recounting information, interactive maps have proved to be a huge asset in geo-tagging, digital mapping technologies, and in the reinforcement of a look of a website.

6.1 Cycling usage density maps

The historical average of cycle usage from a given station is a great estimation for the level of service. Density maps that show the net departure or arrival of a given station give interactive visualization to policymakers. It can be constructed based on the day or period of the day. In the case of day averaging or summation of the available data is done for each day type however for the period of a day, averaging or summation done is as per the period type. Further, some statistical and empirical estimations can be derived using data that add to the knowledge. For example, to differentiate cycle trip types we adopted the empirical bracket of 0 to 10 min, 10 to 40 min, and more than 40 min for Type 1, 2, and 3 respectively. Using this we estimated the average cycle traveling time and coverage distance of a given cycle station. Further 12 interactive maps each for a 2 hours period of the day are made using the Folium package and can be found at [53]. Dynamic radius as shown in Fig. 4 represents the total trips of 8 months.

Coverage (in terms of time in minutes) = (10*type1+20*type2+30*type3) / Total number of trips

Coverage (in terms of distance in meters) = [(10*typ1+20*typ2+30*typ3) / Total trip] *60*Avg_cycle_speed

where,

type1= Total number of trips less than 10 min, for 8 months, in a given 2 hours period of the day. The weighting factor, '10' is used as a multiplier because in short trips users just ride without stopping in the way.

type2= Total number of trips more than 10 min but less than 40 min, for 8 months, in a given 2 hours period of the day. The weighting factor, '20' is used as in a medium trip, users may stop for a while so an empirical value between 10 and 40 i.e. 20 is taken.

type3= Total number of trips greater than 40 min, for 8 months, in a given 2 hours period of the day. The weighting factor, '30' is used as in long trips users ride by stopping so an empirical value of 30 is taken.

Avg_cycle_speed = 7 m/s

Total number of trips= Total number of trips, for 8 months, in a given 2 hours period of day.

6.2 Bikeability index per station

As stated earlier, for calculating and representing the bikeability index many methods are available. For fitting the calculation to the Bhubaneswar use case, customized importance weight of amenities for each station is needed. For that we took the random forest usage prediction model features importance weights of spatial features. Weight personalization is achieved as the importance of the features gets adjusted to the stations' usage while random forest model training. Further for standardization, we applied min-max scalar to importance weight and features' magnitude. Finally, to get the bikeability index for a given station, a weighted summation by feature importance of magnitude for each amenity is taken. An interactive map is drawn to present the index for each bike station in Bhubaneswar [54].

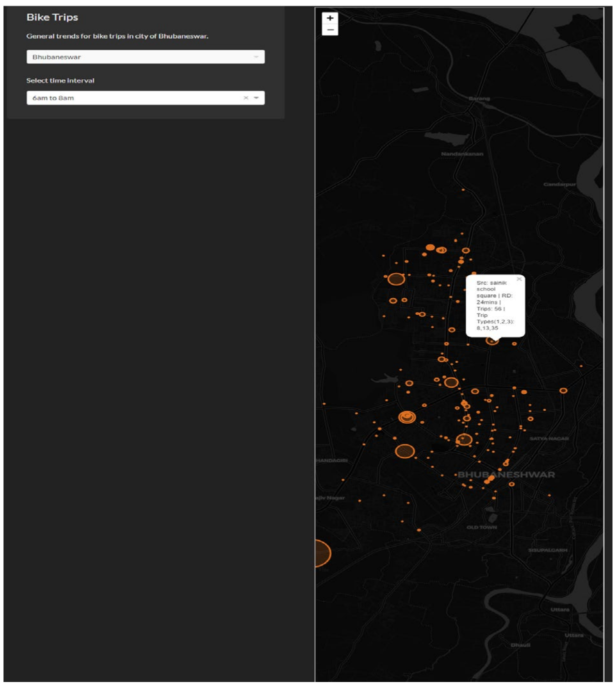

Figure 4: Cycle usage coverage for different cycle stands are shown for a time period in Bhubaneshwar, app live at [53-55].

6.3 Accessibility visualization and COVID hotspot avoiding navigation

Accessibility visualization is done to visualize the reach out of the populace to accomplish different jobs in a given time frame. To get granular level intelligence, analysis of job reach out has to be done for every intersection. For our use case, we analyzed 10 minutes of reach out to different amenities of necessity such as shopping complex, park, hospital, bank, ATM, school, and college. To represent accessibility of necessary amenities, for all the nodes, we summed up every job type with equal weight within the square region centered at that node. Using the Bhubaneswar data, we visualized accessibility for every node for different use case maps for cycling as well as walking. The only difference being that for analyzing 10 min accessibility in case of cycle the square bounding box centered at every node is of 4200 meters side, however for walking it is of 900 meters side. The color bands so formed while visualizing, known as isochrones, represent areas with access to equal numbers (or range) of jobs (Fig. 5). Further to reach out to different amenities a dashboard for users is deployed showing route avoiding COVID hotspots as shown in Fig. 6 [56, 57].

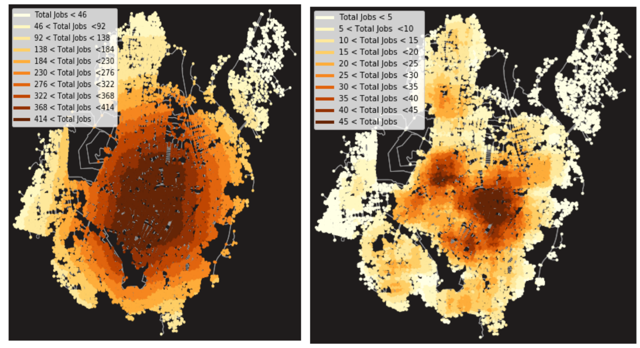

Figure 5: Cycling and walking accessibility for various purposes of undertaking micro mobility travel to reach utilities like schools, banks, ATMs, hospitals, colleges, shopping, parks and more, as seen in our app available at [53-55].

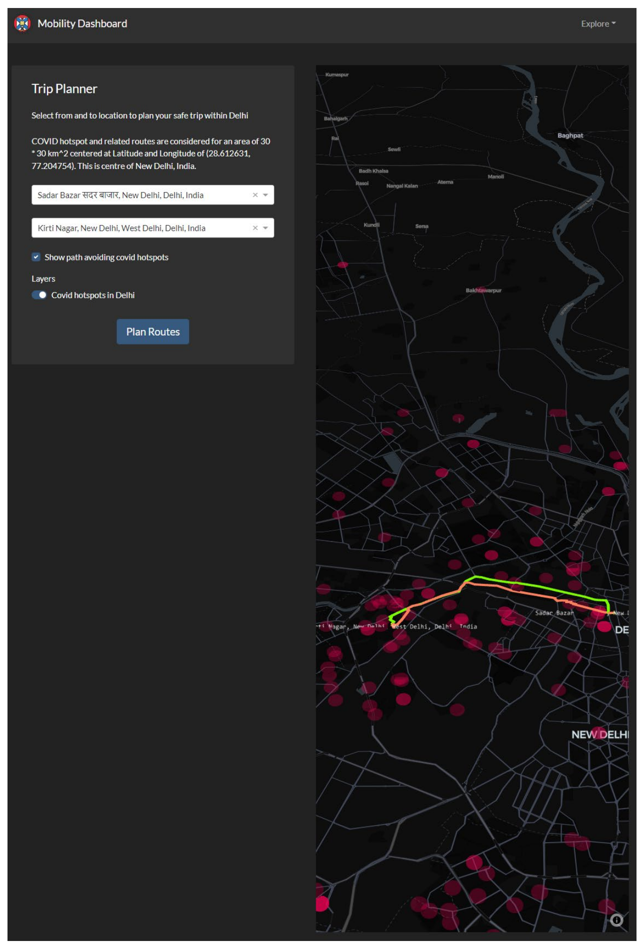

Figure 6: Safe routing through Covid19 hotspots as visualized in default zoom, at locations in Delhi. Green route shows COVID spots avoided, access live app at [57].

7 Results, Discussions and Future Scope

The deployed systems app can be openly accessed and tried with existing datasets fed in the system [53-54]. The non-availability of data for the same place for both 10-minute cities and pandemic spread necessitated data collection from two different cities in India – Bhubaneshwar and New Delhi where we validated the system on 10-minutes amenities reach estimation in Bhubaneshwar [55] and validated the Covid19 safe mobility routing parameters in New Delhi [56, 57]. There are other similar apps that offer micro-mobility solutions for example, the shared and mixed micro-mobility solutions developed by SUMC app [60] aims to fill the gaps in this direction by providing users with multiple short commute options. This is a very good example of utilizing more than one micro-mobility modes. As a future project we are planning to setup a research on merging data from such multi-mode options when available, and also the impact of pandemic spread or civil disturbances on 10-minutes reach of amenities in cities. Witnessing the social and economic disruption that novel coronavirus caused, gives us a clear indication that we should foresee such a malady and the unprecedented challenge it imposes on public health, transportation, and economy. Cities like Paris, Milan, and Barcelona have put forward provincial measures focusing on improving cycle routes - considering it as an essential element to sustain social distancing. With the increased demand for micro-mobility services, the development of tools to oversee these has been continuously suggested. We carried out this study with the sole motive to emphasize the use of micro-mobility services through a map-based interface to help assuage any tension due to information mismatch between the city manager and the tech-savvy.

The tool which we proposed may prove to be useful to city managers for managing BSS, for making decisions regarding infrastructure investments, to understand pedestrian dynamics and accessibility analysis. The existing traditional models were challenged by the sudden COVID 19 lockdown and turned out to be null and void. Second, we conducted our study on the dataset from the city of Bhubaneswar, Odisha and we explored parameters using the road-network graph features. Introduced interactive maps in our study that will assist city managers to interpret data for apt decisions. We leveraged folium, OSMnx to achieve our objective. Third, we promoted the idea of adopting the two forms of active travel - walking and cycling for innumerable benefits it offers. We examined all the factors that have an effect on micro-mobility mode and also predicted the number of trips in an area in order to meet the bike demand of the users.

Cycling measures to formulate a policy include intermodality, connectivity, awareness raising, and promotion. The purpose of a policy is to promote solutions to mobility problems and is aimed at maintaining and increasing the participation of collective public transport and the non-polluting individual. Intermodality structures three perspectives. First, the improved conditions for the use of bicycles at intermodal points. Second, the construction of safe and supervised bicycle storage infrastructure at major intermodal points. Third, the introduction of e-bicycle rental: railway stations, selected O/D points. New parameters were calculated using road-network graph features could be introduced for policy planning.

Connectivity encapsulates outlining safe national/regional cycling connections and coordination of inter-municipal cycling infrastructure. The key measures to ensure connectivity - establishment of political regional committee for sustainable mobility, preparation of the spatial documentation for prioritized cycling connections (agreement of development of regions), common regional working body for coordination of inter-municipal projects and increase effective communication on cycling, strengthening the cooperation among municipalities and state: cycling services and infrastructure.

Participation and education play a vital role in providing momentum to cycling activity. Campaigns can be carried out in two aspects: campaigns through brochures and/ or media, reinforcement campaigns in teaching centers. The vulnerability of pedestrians and bike riders towards rain is visible when they stand under the flyovers. The weather conditions as an external factor have an influence on walking and cycling behavior. In our study, data revealed that the cycling activity is inversely proportional to the rain. It is extremely risky for riders to drive in rain as already slippery roads, metal stripes and white lines and markings become more slippery. Raising awareness of cyclists to respect road regulations, adopting safety measures, improving the acceptance as well as the respect of the non-cyclist towards the bicycle would lead to considering cycling as one mode of transport.

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REFERENCES

[1] Hatfield, J., & Boufous, S. (2016). The effect of non-recreational transport cycling on use of other transport modes: A cross-sectional on-line survey. Transportation Research Part A: Policy and Practice, 92, 220-231.

[2] Osama, A., Sayed, T., & Bigazzi, A. Y. (2017). Models for estimating zone-level bike kilometers traveled using bike network, land use, and road facility variables. Transportation Research Part A: Policy and Practice, 96, 14-28.

[3] Popova, M. (2015, September 18). What Makes a Great City: A General Theory of Walkability. Brain Pickings. https://www.brainpickings.org/2012/11/15/walkable-city-jeff-speck/

[4] Zarif, R., Pankratz, D., & Kelman, B. (2019). Small is beautiful Making micromobility work for citizens, cities, and service providers. Https://Www2.Deloitte.Com/. https://www2.deloitte.com/us/en/insights/focus/future-of-mobility/micro-mobility-is-the-future-of-urban-transportation.html

[5] Pojani, D., Chen, J., Mateo-Babiano, I., Bean, R., & Corcoran, J. (2020). Docked and dockless public bike-sharing schemes: research, practice and discourse. In Handbook of Sustainable Transport. Edward Elgar Publishing.

[6] Heineke, K., Kloss, B., & Scurtu, D. (2020, July 16). The future of micromobility: Ridership and revenue after a crisis. McKinsey & Company.

https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/the-future-of-micromobility-ridership-and-revenue-after-a-crisis
[7] Bradshaw, R., & Kitchin, R. (2021). Charting the design and implementation of the smart city: the case of citizen-centric bikeshare in Hamilton, Ontario. Urban Geography, 1-23.
[8] MacDonald, E., Sanders, R., & Supawanich, P. (2008). The Effects of Transportation Corridors' Roadside Design Features on User Behavior and Safety, and Their Contributions to Health, Environmental Quality, and Community Economic Vitality: a Literature Review.
[9] Helbing, D., Buzna, L., Johansson, A., & Werner, T. (2005). Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. Transportation science, 39(1), 1-24.
[10] Selim, S. Z., & Al-Rabeh, A. H. (1991). On the modeling of pedestrian flow on the Jamarat bridge. Transportation science, 25(4), 257-263.
[11] Vermuyten, H., Beliën, J., De Boeck, L., Reniers, G., & Wauters, T. (2016). A review of optimisation models for pedestrian evacuation and design problems. Safety science, 87, 167-178.
[12] Helbing, D., & Molnar, P. (1995). Social force model for pedestrian dynamics. Physical review E, 51(5), 4282.
[13] Moussaïd, M., Helbing, D., & Theraulaz, G. (2011). How simple rules determine pedestrian behavior and crowd disasters. Proceedings of the National Academy of Sciences, 108(17), 6884-6888.
[14] Geertman, S., & Stillwell, J. (Eds.). (2009). Planning support systems best practice and new methods (Vol. 95). Springer Science & Business Media.
[15] Lovelace, R., Goodman, A., Aldred, R., Berkoff, N., Abbas, A., & Woodcock, J. (2017). The Propensity to Cycle Tool: An open source online system for sustainable transport planning. Journal of transport and land use, 10(1), 505-528.
[16] Talukdar, M. H., & Hossain, Z. (2011). PLANNING TOOLS THAT CAN BE USED TO FACILITATE URBAN SUSTAINABILITY. Management Research & Practice, 3(4).
[17] Arellana, J., Saltarín, M., Larrañaga, A. M., González, V. I., & Henao, C. A. (2020). Developing an urban bikeability index for different types of cyclists as a tool to prioritise bicycle infrastructure investments. Transportation Research Part A: Policy and Practice, 139, 310-334.
[18] Shui, C. S., & Szeto, W. Y. (2020). A review of bicycle-sharing service planning problems. Transportation Research Part C: Emerging Technologies, 117, 102648.
[19] Kellstedt, D. K., Spengler, J. O., Foster, M., Lee, C., & Maddock, J. E. (2020). A scoping review of bikeability assessment methods. Journal of community health, 1-14.
[20] Despite Popularity, Bike Share Programs Often Need Subsidies. (2016, March 24). Https://Www.Pewtrusts.Org/. https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2016/03/24/despite-popularity-bike-share-programs-often-need-subsidies
[21] Fishman, E., Washington, S., Haworth, N., & Mazzei, A. (2014). Barriers to bikesharing: an analysis from Melbourne and Brisbane. Journal of Transport Geography, 41, 325-337.
[22] Shen, Y., Zhang, X., & Zhao, J. (2018). Understanding the usage of dockless bike sharing in Singapore. International Journal of Sustainable Transportation, 12(9), 686–700.
[23] Chen, S. Y., & Lu, C. C. (2016). A model of green acceptance and intentions to use bike-sharing: YouBike users in Taiwan. Networks and Spatial Economics, 16(4), 1103-1124.
[24] Te Pai, J., & Pai, S. Y. (2015). User behaviour analysis of the public bike system in Taipei. International review for spatial planning and sustainable development, 3(2), 39-52.
[25] Kass & Moses. (2020, November 16). Bike Sharing Benefits and Disadvantages. Kass & Moses. https://kassandmoses.com/bicycle/blog/bike-sharing-benefits-and-disadvantages
[26] Fricker, C., & Gast, N. (2016). Incentives and redistribution in homogeneous bike-sharing systems with stations of finite capacity. Euro journal on transportation and logistics, 5(3), 261-291.
[27] Lin, J. R., & Yang, T. H. (2011). Strategic design of public bicycle sharing systems with service level constraints. Transportation research part E: logistics and transportation review, 47(2), 284-294.
[28] Lin, J.J., Yu, C.J., 2013. A bikeway network design model for urban areas. Transportation 40 (1), 1–24.
[29] Strauss, J., Miranda-Moreno, L. F., & Morency, P. (2013). Cyclist activity and injury risk analysis at signalized intersections: A Bayesian modelling approach. Accident Analysis & Prevention, 59, 9-17.
[30] Wang, X., Lindsey, G., Hankey, S., & Hoff, K. (2014). Estimating mixed-mode urban trail traffic using negative binomial regression models. Journal of Urban Planning and Development, 140(1), 04013006.
[31] Hankey, S., Lindsey, G., Wang, X., Borah, J., Hoff, K., Utecht, B., & Xu, Z. (2012). Estimating use of non-motorized infrastructure: Models of bicycle and pedestrian traffic in Minneapolis, MN. Landscape and Urban Planning, 107(3), 307-316.
[32] Hankey, S., Lu, T., Mondschein, A., & Buehler, R. (2017). Spatial models of active travel in small communities: merging the goals of traffic monitoring and direct-demand modeling. Journal of Transport & Health, 7, 149-159.
[33] Gehrke, S. R., & Reardon, T. G. (2020). Direct demand modelling approach to forecast cycling activity for a proposed bike facility. Transportation Planning and Technology, 1-15.
[34] Kamel, M. B., & Sayed, T. (2020). The impact of bike network indicators on bike kilometers traveled and bike safety: A network theory approach. Environment and Planning B: Urban Analytics and City Science, 2399808320964469.
[35] Smith, H. (2011). A mathematical optimization model for a bicycle network design considering bicycle level of service (Doctoral dissertation).
[36] Duthie, J., Unnikrishnan, A., 2014. Optimization framework for bicycle sharing service design. J. Transp. Eng. 140 (7), 04014028.
[37] Sohn, K., 2011. Multi-objective optimization of a road diet network design. Transport. Res. A: Pol Pract. 45 (6), 499–511.
[38] Mesbah, M., Thompson, R., Moridpour, S., 2012. Bilevel optimization approach to design of network of bike lanes. Transport. Res. Rec.: J. Transport. Res. Board 2284, 21–28.
[39] Lin, J.J., Yu, C.J., 2013. A bikeway network design model for urban areas. Transportation 40 (1), 1–24.
[40] Landis, B. W. (1994). Bicycle interaction hazard score: a theoretical model (No. HS-042 006).
[41] Kent, M., & Karner, A. (2019). Prioritizing low-stress and equitable bicycle networks using neighborhood-based accessibility measures. International journal of sustainable transportation, 13(2), 100-110.
[42] Harkey, D. L., Reinfurt, D. W., & Knuiman, M. (1998). Development of the bicycle compatibility index. Transportation research record, 1636(1), 13-20.
[43] Wagner, N., & Agrawal, V. (2014). An agent-based simulation system for concert venue crowd evacuation modeling in the presence of a fire disaster. Expert Systems with Applications, 41(6), 2807-2815.
[44] Antonini, G., Bierlaire, M., & Weber, M. (2006). Discrete choice models of pedestrian walking behavior. Transportation Research Part B: Methodological, 40(8), 667-687.
[45] Boeing, G. (2017). OSMnx: New methods for acquiring, constructing, analyzing, and visualizing complex street networks. Computers, Environment and Urban Systems, 65, 126-139.
[46] Jose, W. (2018). Improving the Service Quality of Bike Sharing Systems via the Analysis of Real-Time User Data.
[47] Feng, C., Hillston, J., & Reijsbergen, D. (2017). Moment-based availability prediction for bike-sharing systems. Performance Evaluation, 117, 58-74.
[48] Almannaa, M. H., Elhenawy, M., & Rakha, H. A. (2020). Dynamic linear models to predict bike availability in a bike sharing system. International journal of sustainable transportation, 14(3), 232-242.
[49] Schlote, A., Chen, B., & Shorten, R. (2014). On closed-loop bicycle availability prediction. IEEE Transactions on Intelligent Transportation Systems, 16(3), 1449-1455.
[51] Jenkins, P., Farag, A., Wang, S., & Li, Z. (2019, November). Unsupervised representation learning of spatial data via multimodal embedding. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (pp. 1993-2002).
[52] Mishra, S., Kushwaha, A., Aggrawal, D., & Gupta, A. (2019). Comparative emission study by real-time congestion monitoring for stable pollution policy on temporal and meso-spatial regions in Delhi. Journal of Cleaner Production, 224, 465-478.
[53] Bike trip https://peacetech.epcc.ed.ac.uk/bike-trips
[54] Bikeability App On Different Stations https://peacetech.epcc.ed.ac.uk/bike-index
[55] General trends for bike trips and walkablity in city of Bhubaneswar. https://peacetech.epcc.ed.ac.uk/jobs
[56] Mishra, S., Singh, N., & Bhattacharya, D. (2021). Application-based COVID-19 micro-mobility solution for safe and smart navigation in pandemics. ISPRS International Journal of Geo-Information, 10(8), 571, https://www.mdpi.com/2220-9964/10/8/571/htm
[57] Trip planner https://peacetech.epcc.ed.ac.uk/trip-planner
[58] BhubaneshwarOne https://bhubaneswarone.in/home/
[59] SCIKIT-LEARN https://scikit-learn.org/stable/
[60] Shared use mobility center SUMC, http://maps.sharedusemobilitycenter.org/sumc/