Municipal Waste Collection Optimization using Technique of Order Preference by Similarity to Ideal Solution in IOT-Assisted Dustbins

Khyati Gaurana—Gaurav Kumar—Sanchi Singh
Department of Computer Science Engineering, Netaji Subhas University of Technology, New Delhi, India

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The collection of solid waste poses multiple challenges as the population grows at an exponential rate. With the rise of population density in urban areas, waste collection has become a huge challenge in these areas. In this paper we propose the use of a multi-criteria decision analysis method widely known as Technique of Order Preference by Similarity to Ideal Solution (TOPSIS) in this waste collection scenario to optimize bin selection by considering multiple dependant factors to create rankings for dustbins to yield optimal results in bin selection during bin collection routing to prioritize the selection of bins with optimal waste parameters. To demonstrate the selection of bins, a simulation is presented using OpenRouteService Tools map service in the densely populated city of New Delhi. A web application is presented to demonstrate the use of this model to optimize bin selection with a working prototype. **Keywords: IOT, waste collection, smart city, vehicle route optimization**

1 Introduction

The upsurge in urban population correlates with a heightened demand for municipal services, placing additional stress on waste management facilities. The increase in city residents invariably leads to a proportional rise in the generation of municipal solid waste, prompting the need for the development of supplementary waste disposal sites to accommodate the amplified volume [1]. The environmental consequences of mounting municipal solid waste (MSW) are substantial, playing a significant role in the exacerbation of climate change [2]. Inadequate waste disposal practices lead to the release of significant quantities of greenhouse gasses, particularly methane, as organic waste decomposes in landfills. Moreover, the energy-intensive processes involved in waste treatment and disposal contribute to an increased carbon footprint, intensifying the overall environmental impact. Addressing these challenges through the adoption of sustainable waste management practices is imperative to mitigate adverse environmental effects and reduce the contribution to climate change. Typical waste collection processes in metropolitan cities involve several key stages [3]. Residents generate waste through daily activities, resulting in the production of household waste comprising various materials. Waste bins or containers are strategically placed in residential areas, commercial districts, and public spaces to facilitate convenient waste disposal. Waste collection schedules are established, specifying the days and times when waste collection vehicles will visit designated areas for pickup. Specialized waste collection vehicles, such as garbage trucks, move through predetermined routes to collect waste from designated bins. In some cases, residents are required to separate their waste into different categories, such as recyclables and non-recyclables. Waste collectors may also perform additional sorting. Collected waste is transported to transfer stations or inter- mediate facilities, where it may undergo further sorting and processing. Waste is then transported to landfills or recycling facilities, depending on its nature. Recyclables are sent to recycling plants, while non-recyclables may be disposed of in landfills. The final step involves the proper disposal of waste, adhering to environmental regulations and waste management policies. Overall, an effective waste collection process in metropolitan cities integrates strategic planning, scheduled collections, sorting, and proper disposal to ensure the efficient management of diverse types of waste generated by a densely populated urban environment [4]. Advancements in sensors and wireless communications have paved the way for the integration of Internet of Things (IoT) networks in numerous smart city applications. Waste management can also harness the power of IoT to ascertain the quantity and composition of waste, transmit these data to waste collection organizations, and formulate optimized routes for efficient waste collection. Indeed, IoT can automate and improve the entire waste collection process [5].

In this paper, we focus on optimizing bin collection scheduling within the domain of waste management. In this context, given the multiple criteria to decide against, the Technique of Order Preference by Similarity to Ideal Solution is employed. This technique is useful in scenarios where multiple alternatives need to be compared against varying degrees of importance.

The proposed model has the following key factors and the major contributions of the work are presented as follows :

- An IOT-based Solution is provided along with a MCDM Model using TOPSIS algorithm to generate bin priorities by using multiple decision criteria.
- Multiple waste related metrics are collected by the use of sensors equipped on the dustbin prototype such as volume, toxicity and time since last collection.
- The TOPSIS technique is used to consider these factors to generate scores for each bin in the area to prioritize bins that are completely filled, highly toxic waste, and have not been collected for a long time.
- Simulations are performed using the ORS Tools in QGIS network analyser to show the working of this model in a real world scenario

2 Literature review

[1] presented an agent-based waste management simulation comparing traditional periodic review with IoT-enabled smart sensor bins. The simulation included waste generation, management, and validation using economic, environmental, and citizen satisfaction measures. The paper describes a model for household waste management with IoT bins, utilizing organization-based and agent-based modeling concepts. IoT bins are distributed across the city, equipped with sensors to determine their status and capacity. Economic performance is evaluated based on total distance traveled by waste collection trucks, with CO2 emissions being a key factor. Results indicate lower CO2 emissions with the IoT strategy compared to periodic review.The approach in [2] utilizes real-time data from smart waste bins to manage and maintain cleanliness in smart cities. Fuzzy logic guides the strategic placement of these bins, forming a Smart Garbage Bin Mechanism (SGBM) to enhance solid waste management. SGBM integrates real-time monitoring and a fuzzy expert system for decision-making, facilitating strategic bin deployment. Implemented in Netlogo, the system proves responsive, adaptable, and effective in diverse smart city environments. Traditional waste management systems suffer from limited data accessibility and delayed waste unloading.[3] introduces BIN for the CiTy (BINCT), a free intelligent software system designed to optimize waste collection routes using historical and forecast data. BINCT aims to reduce costs by minimizing truck travel distance and fuel usage. The system predicts waste container fill levels and generates optimal collection routes, addressing key challenges in waste collection services: determining which containers to collect and in what order to visit them to minimize costs. Historical data informs predictions for future collection scheduling.[4] introduces an IoT-based garbage management system for smart cities, where each bin is equipped with a unique ID and a gadget to monitor its condition. These devices promptly send filling level data to aid waste collectors in efficient bin cleaning. Garbage bins are interconnected via WSN, with sensors collecting data at regular intervals. When the fill threshold is reached, a Garbage Collector Agent (GCA) coordinates waste collection requests via the IoT system. Data from the sensors is transmitted to workers for capacity and preparation purposes, facilitating daily decisions on bin selection and route optimization.[5] proposes a bin monitoring and solid waste management system that uses flame sensor and temperature and humidity sensor to detect and predict fires in the bin and ultrasonic sensor to monitor waste levels in the bins. The simulation consists of 100 bins distributed in 5 areas each having 20 bins. The waste is collected only when multiple alerts from different IoT bins are received in the same area in a defined amount of time and as per defined schedule timeframe for non-IoT bins. The system also aims at predicting future waste generation. However, the sys-

tem assumes static routes for waste collection and there is no route optimization to improve efficiency.[6] introduces effective solid waste collecting methods.With escalating quantities of waste generated in urban areas researchers have increasingly turned to Geographic Information Systems (GIS) and remote sensing technologies to address the complexities of solid waste management (SWM), leveraging techniques such as network analysis to identify optimal waste collection routes and proposing transfer stations to enhance waste handling efficiency. The statistics reveal that the established collecting routes reduce travel distance by a good margin. Furthermore, Lella underscores the urgent need for holistic approaches to waste management that consider socio-economic, institutional, and environmental factors, particularly in the context of rapidly developing smart cities.

3 Methodology

In this section, the system model for this approach is presented. Our system has n bins distributed across a network and connected to the central database by GPS. These bins are equipped with sensors to collect the parameters for bin prioritization. The volume (V) of the waste collected in the bin is measured using ultrasonic sensor module, the toxicity (v) of the waste is measured using air quality sensors to detect toxic garbage gases including ammonia (NH3) , methane (CH3), and smoke to detect burning waste. The duration of trash collected in the bin is measured using the time (t) since the bin was last emptied. These sensor readings are communicated to a centralised server where the database stores these readings and uses them for further processing. Consequently, garbage collection vehicles are dispatched to routes based on selected bins on the basis of these readings.

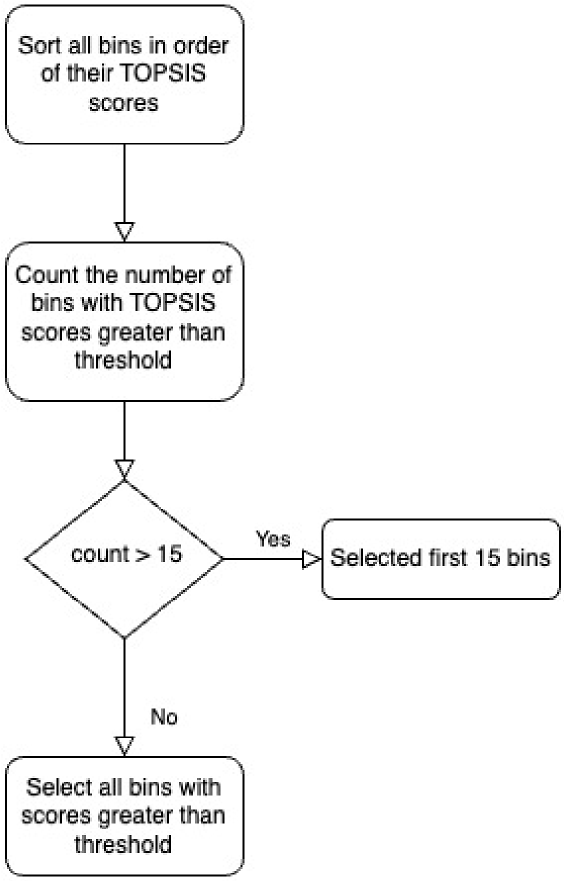

Figure 1: Methodology

3.1 Proposed Technique

In our proposed technique, we use a multi-criteria decision making model called TOPSIS (Technique of Order Preference by Similarity to Ideal Solution) . This technique is used in cases where there are multiple influencing factors that affect the decision making process to varying degrees of importance. In the context of waste collection, TOPSIS is used here to take the sensor readings of volume of waste, time duration of the garbage in the bin and the toxicity levels of the waste in the bin to calculate a score for each bin. These scores are sorted in decreasing order and the bins with the highest scores are selected for garbage collection in routing. The bins are selected such that the waste to be collected from the bins does not exceed the waste carrying capacity of the garbage truck.

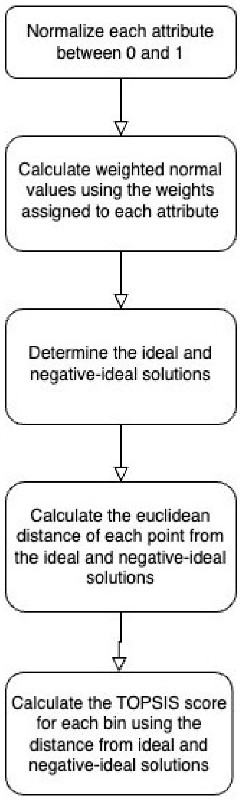

Figure 2: Algorithm

Algorithm 1: Waste Attribute Optimization Algorithm

Input: A graph G with n nodes and edges e. Data regarding waste attributes as weights of G (toxicity ν, volume V, time t)

Algorithm Steps

Step 1: Normalize the data for each waste attribute (v, V, t) between 0 and 1. The goal is to maximize ν , V and t

Step 2: Calculate the weighted normalized values for each bin attribute based on the waste attributes and the assigned weights

Step 3: Determine the ideal and negative-ideal solutions for each attribute.
Ideal solution: Maximum normalized value for toxicity, volume, and time; minimum normalized value for distance.
Negative-ideal solution: Minimum normalized value for toxicity, volume, and time; maximum normalized value for distance.

Step 4: Calculate the proximity of each bin to the ideal and negative-ideal solutions using a distance measure. Calculate the distance of each bin from the ideal solution and the negative-ideal solution

$$D_i^+ = \sqrt{\sum_{j=1}^{m}(\text{Normval}_{ij} - \text{IdealSol}_j)}$$
$$D_i^- = \sqrt{\sum_{j=1}^{m}(\text{Normval}_{ij} - \text{NegIdealSol}_j)}$$

Step 5: Compute the TOPSIS score for each bin

$$TOPSIS_i = \frac{D_i^-}{D_i^+ + D_i^-}$$

Step 6: Rank the bins based on their TOPSIS scores. The bins with higher accumulated TOPSIS scores are more favorable for waste collection as they match the criteria of higher toxicity, volume, time.

Output:
The bins are prioritised for waste collection based on TOPSIS scores. Bins with high scores and above a threshold will be added to the waypoints, for which the routes have to be generated.

3.2 Hardware Integration:

The prototype for this project is presented as a dustbin equipped with 3 sensor modules namely Neo 6M for GPS location, HC-SR04 Ultra-Sonic sensor , MQ-135 gas sensor, Arduino UNO microcontroller board, an ESP32 microcontroller with Wifi and Bluetooth connectivity and a bi-directional level shifter to connect digital I/O pins from Arduino to ESP32 board.

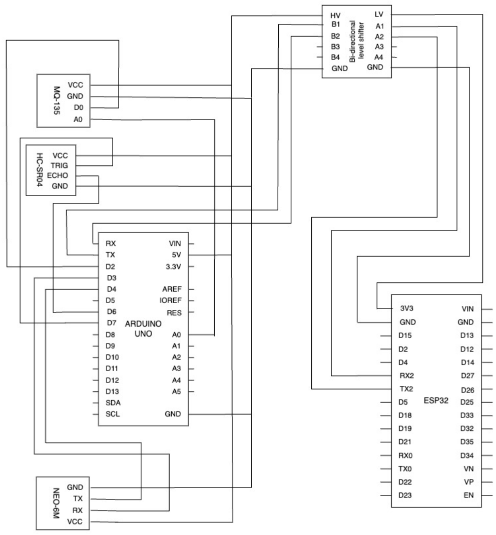

Figure 3: Circuit Diagram of Smart Dustbin

1. Arduino Uno: UNO is a microcontroller board based on the ATmega328P. It has 14 digital input/output pins (out of which 6 can be used as PWM outputs) and 6 analog inputs. We utilised Arduino to efficiently read sensor values from Ultrasonic, MQ-135 and GPS sensors. These values are then processed and sent to the Serial Port to be further processed by ESP-32.

2. Ultrasonic Sensor: The HC-SR04 ultrasonic distance sensor is capable of accurately measuring distances from 2cm up to 400cm with a precision of up to 3mm. In our project, we employed the HC-SR04 to monitor the fill levels of waste bins. This Data is then sent to Arduino which processes it to find the percentage of fill level of bins. Subsequently, this data is being transmitted to the Cloud.

$$Fill_level = \frac{Currentdistance}{Distancewhenthebinisempty} * 100$$

3. GPS Module: The NEO-6M GPS module is the navigation device utilized in our project. It is known for its accuracy and performance, the NEO-6M provides real-time positioning information with reliability. It sends the latitude and longitude to the Arduino Uno which further sends it to the Serial Port for ESP-32. By using the location coordinates we are adding the bins to the bin collection path.

4. Air-Quality Module: The MQ-135 Gas sensor is handy for detecting various gases like Ammonia(NH3), sulfur(S), Benzene(C6H6), CO2, and harmful gases and smoke. It comes with both digital and analog output pins. When the level of these gases exceeds a certain limit in the air, the digital pin signals high. This limit can be adjusted using the built-in potentiometer. The analog output pin provides a voltage that helps estimate the concentration of these gases in the air.

Operating at 5V and consuming around 150mA, the

MQ135 sensor needs a bit of pre-heating before providing accurate readings.

5. ESP-WROOM-32: The ESP-WROOM-32 is powerful microcontroller module that integrates a dual-core processor, Wi-Fi and Bluetooth connectivity, and a plethora of GPIO pins for interfacing with sensors and peripherals. With its compact size and low power consumption, the ESP-WROOM-32 is ideal for developing smart devices and connected systems. It operates at a voltage of 3.3V. It reads the data from the Serial TX port of Arduino and sends it to the cloud using its WiFi capabilities.

6. Level Shifter: The TXS0108E is a bi-directional level shifter which allows the different devices with different logic levels to communicate with each other. To connect the TX pin of Arduino to the RX pin of ESP-32 we are using a level shifter because Arduino works on 5V and ESP works on 3.3V so we have to downshift the 5V to 3.3V otherwise the ESP-32 module will fry.

7. Thing-Speak: It is an open-source IoT platform that allows users to collect, analyze, and visualize data from sensors or devices in real time. It provides an easy-to-use interface for storing and retrieving data, as well as tools for creating custom visualizations and performing analysis.

3.3 Software Integration:

The data from Hardware is sent to the cloud which is further used by our software to route the bins according to the TOPSIS algorithm. We have developed a web-app for displaying the routes to be taken by the waste collector to efficiently collect the waste from bins.

1. TOM-TOM Maps API:
TomTom Maps APIs are a set of APIs that provide real-time data, navigational assistance, and compatibility with Android Auto. To use the SDK, you need to obtain a developer account and an API key. The API key is free and authenticates you with TomTom so you can use all of the free features available in the SDK.

In our project, we leverage the routing capabilities of the TomTom API. Using the TOPSIS algorithm, we dynamically add waypoints to optimize routes. These waypoints are then transmitted to TomTom to compute the most efficient routes.

We utilize the ThingSpeak API to retrieve the coordinates of bins, which store sensor data. The bin's coordinates are added to the waypoints and an optimised route is drawn between them for the waste collector to follow. We are also optimising the routes based on traffic data and sensor data from the bins.

The prototype operates in the following way :

The web application is designed and organized in conjunction with the hardware prototype. The website features an information page where the data about all the bins is displayed along with the fill levels of these bins. For the sake of demonstrating the prototype, the bins are located around the Dwarka sub-city of New Delhi. These bins are connected to the cloud via the ESP32 module that communicates the sensor readings from these bins to the ThingSpeak IOT Cloud. The data collected in the cloud is fetched using an API key that is interfaced with a ThingSpeak database that stores all these readings. The web application fetches the data from the ThingSpeak API to display on the website. The website then uses this data queried from the bins to calculate the TOPSIS scores for all the bins. These scores are ranked in descending order with the highest TOPSIS scores given the most priority. The bin rankings are then used in the next step of the process which is routing. The locations of these bins are added on the map. These locations are used for creating routes that pass visit each bin. Furthermore, route optimization is performed after this to give the final route which gives the fastest route that visits each bin.

4 Results Analysis

4.1 Experiment Setup

In this section we present the results obtained from performing the simulation on QGIS network analyst. The data was is kept randomized for values of volume and time since pickup, to simulate a real world scenario of waste pickup. The number of bins are chosen to be 20 in this simulation. The value of toxicity ranges from 0-1 and the volume of bins V ranges from 600-1200 litres. The time since last pickup ranges from 5-15 days. The vehicle capacity of the vehicle is set to 5000L.

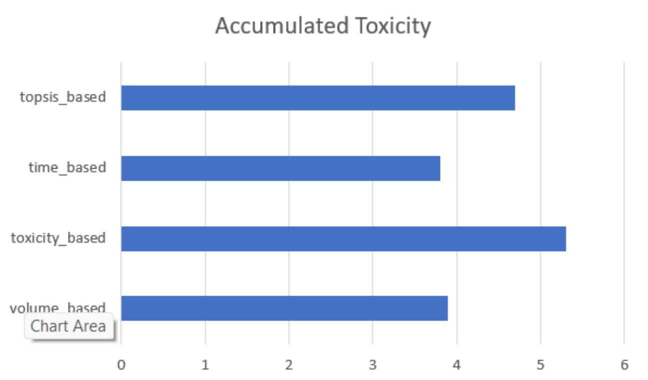

Figure 4: Accumulated toxicity of collected waste vs. different criteria

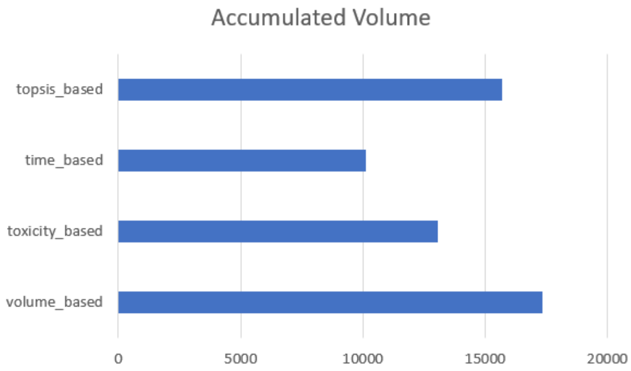

Figure 5: Accumulated volume of collected waste vs. different criteria

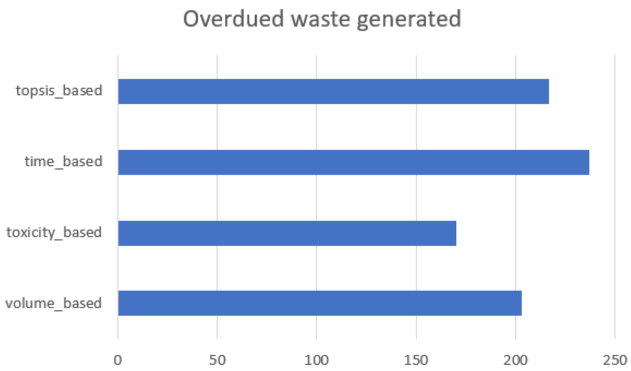

Figure 6: Accumulated waste time in bin before being collected vs. different criteria

4.2 Observation Inference

It can be seen in 4 that the results for toxicity obtained by the TOPSIS algorithm approaches the result obtained solely by considering the toxicity parameter. The time and volume based algorithms perform the worst in terms of toxicity.
In 5, our proposed scheme pefroms second to the volume based algorithm which maximizes the volume of the collected waste. The other two schemes perform worst in this case as they are aimed at optimizing the corresponding paramernters.
In 6, we see that the duration before the waste is collected is maximum in the case of time-based scheme, however our proposed scheme performs only second to the this scheme.

From the above analysis , it is clear that our proposed waste collection scheme performs at a comparable level to each of the singly-optimized schemes for each parameter demonstrating the effectiveness of our method. In each of the figure, the time based scheme sets an upper limit for the amount of waste collected that has been in the bin for the longest time, however , our scheme gives comparable results to all of these single-parameter optimized schemes because the TOPSIS based algorithm considers volume, time and toxicity as parameters and it yields the best solution in terms of all the parameters.

4.3 Routing:

Routing is done bye tom tom API which shows both the optimised route and the route by the order in which bins are added.
The Orange path is generated on the order of addition of waypoints. The Green path is the optimised path between the added waypoints .

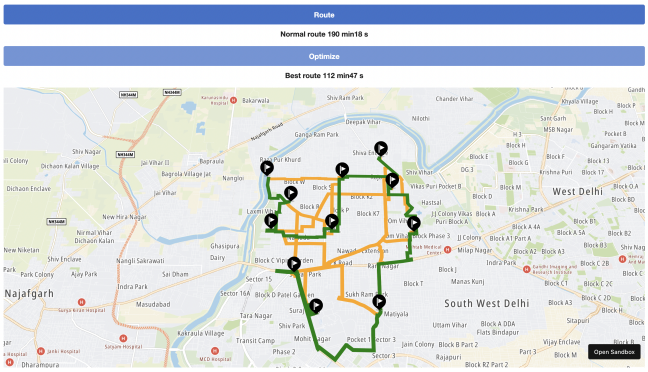

Figure 7: Route Optimisation by TomTom

4.4 Sensor Values:

Sensor values are read by Arduino and sent to the ESP 32 for transmission to cloud.

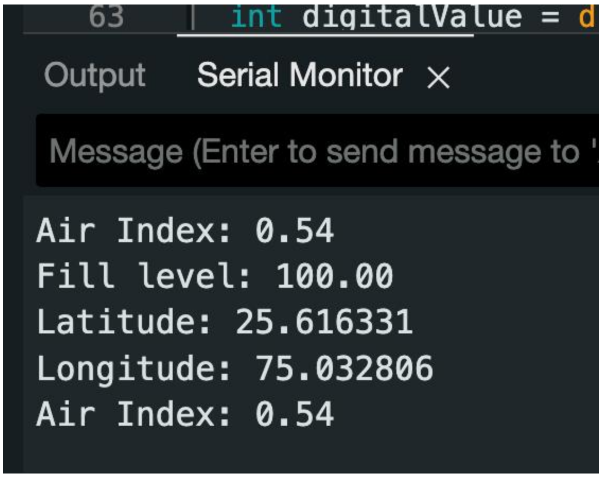

Figure 8: Sensor Readings

4.5 ESP-32 Transmission:

Sensore values from Arduino are sent to Thinkspeak Cloud.

4.6 Topsis Simulation:

Waypoints added are processed using TOPSIS Algorithm and then routing is done on the preference order.

Figure 9: ESP sending data to thinkspeak

The black nodes are not selected by the TOPSIS Algo and the red ones are selected by the TOPSIS.

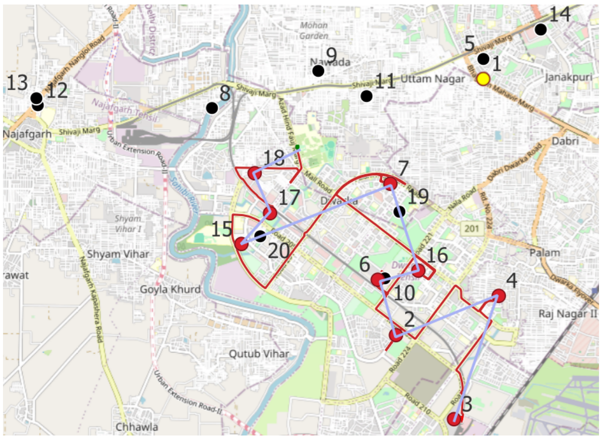

Figure 10: Sample snippet from simulation starting from the node 18 to node 3

5 Declarations

5.1 Acknowledgements

First and foremost, we extend our heartfelt gratitude to Gaurav Singal Sir for their invaluable guidance and mentorship throughout this project. Their expertise, patience, and dedication were pivotal in shaping the project's direction and ensuring its successful completion.
We also wish to express our sincere appreciation to all the individuals and resources that we consulted during this project. Their expertise, insights, and feedback greatly influenced the project's trajectory and contributed to its ultimate success.

5.2 Resources Used:

1. Datasheet of Ultrasonic Sensor, MQ-135 Air-Quality Module and Neo-6M GPS Module.
2. Datasheet of Arduino UNO and ESP-32 microcontroller.
3. ThingSpeak API documentation.
4. Tom-Tom API documentation.

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