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Architecture For Air Pollution Aware Vehicle Rerouting in Smart Cities Using Machine Learning & Ant Colony Algorithm

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Abstract— In this paper, the layered design to investigations and interesting route arranging dependent on the basic parameter Air Pollution is proposed. Different ways have been proposed for limiting the criticality of Air Pollution and its effect on wellbeing. Normally while choosing a route starting with one spot then onto the next spot, one pick the most shortest way or the way which is having lesser traffic density, however for the individual who experiences ailments like exasperated cardiovascular, respiratory sickness, quickened maturing of the lungs, asthma, bronchitis, it is increasingly imperative to know the degree of contamination all through the path which one needs to utilize while voyaging particularly for the riders on bike. Additionally, this mindfulness about the ongoing degree of contamination will assist them in taking prudent activities. The proposed design depends on the Ant colony optimization Technique and Machine learning. The novel part of the proposed architecture is to use the trained model through machine learning methods which compute the importance of the effect of different parameters like Air Pollution, Traffic Density, and Distance on calculating probability which leads towards the selection of an optimal path among all available routes towards the destination. The proposed model calculates decision making dynamically at each junction and this dynamic decision procedure will consider dynamic changes in the parameter like traffic and air pollution would reduce the impact of air pollution on health with increasing the cost of a distance.

1 Introduction

Air contamination is characterized as a marvel hurtful to the environmental framework and the typical states of human presence and improvement when a few substances in the climate surpass a specific fixation.Air contamination kills an expected 7,000,000 individuals worldwide consistently. WHO information shows that 9 out of 10 individuals inhale air containing elevated levels of poisons.[1]

In Proposed model we accept that the finding of ideal way in the urban region where the traffic is relatively higher than the highways or rural area.

In the computational knowledge, essentially two improvement techniques are well known. [2] (1) Particle Swarm Optimization (2) Ant Colony Optimization. Particle swarm improvement strategies are basic and require less calculation when contrasted with ACO. Be that as it may, it faces issue in taking care of combinatorial or discrete improvement issues like discovering shortest way relying upon different parameter like Distance, Traffic and Minimal contamination. Thus we use ant colony optimization technique to solve the problem of shortest path problem considering dynamicity of traffic and in gradually changes in Air pollution in the urban area.

In characterizing our concern we consider þ as set of way which fulfills set of constraints Ω So our solution is to discover S = (þ, Ω). Where Ω(t) is the constraints at time t between þ(i,j). Where i and j show segment of way among intersection$_i$ and intersection$_j$. Vehicle V start its path from Source S towards Destination D. We will start from the S=ø an unfilled set. Where S should comprise of Route R which fulfills requirements Ω During first emphasis V will decide r1,r2..rn ∈ R which is set of routes accessible to Destination D. Out of this routes our proposed design chooses ideal route and present it to the client.

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2 Related Work

A. R. Al-Ali et al. [3]has proposed awireless distributed mobile air pollution monitoring system. The system utilizes city buses to collect pollutant gases such as CO, NO2, and SO2. The pollution data from various mobile sensor arrays are transmitted to a central server that makes this data available on the Internet through a Google Maps interface. The data shows the pollutant levels and their conformance to local air quality standards. While Dang Hai Hoang et al. [4] have worked on Processing and visualizing traffic pollution data in Hanoi city from a Wireless Sensor Network. This paper has suggested using sensors to collect Environment information are low cost. Before presenting to users, data gathered from these sensors are required to pass through two Steps: calibration and data clustering. This group has successfully applied a pilot project for the monitoring pollution data of an urban area of Hanoi City.But the issue with the wireless sensor network is described by R. Shyam Mohan et al. [5] that if we need to increase the coverage of the city then we need to deploy proportionally more sensors. So,in place of static deployment of the sensors, this paper has proposed to use public vehicles as a measuring unit for the pollutant gases.

Deng et al. [6]Old style Dijkstra calculation is a procedure to discover the way with the most minimal cost for example the most shortest way from one node to different node on the city map. Its computation complexity is O(n^2) where n is the

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quantity of nodes in the system. The arrangement works with the appointment of local optima in the would like to acquire a global optimum solution.

Dong et al. [7] have referenced that for a static domain with the ideal data, a conventional way of discovering calculation like A-Star can give the optimal solution. While the environment where variables change like contamination changes, Traffic changes and changes in topology is a lot of dynamic, ordinary way path finding algorithm doesn't work. Social living beings, for example, microscopic organisms, ants, and caterpillars display a collective problem-solving capability, which shows solid versatility and strength to progressively evolving conditions. This property is inspired to use swarm intelligence to resolve our problem to handle dynamic traffic congestion and pollution effect on human bodies during traveling.

A-Star algorithm may not work for the network where topology changes due to heavy traffic blockage or break of the path. Santoso et al [8] have introduced a classification of the different route planning algorithms.This paper has thought about and investigate their presentation when applied to real road networks. On accepting any traffic condition refreshes which may influence the current route of the vehicle, this work reapplies the calculation and change the course of the car. In this case, the best route recalculated and vehicles pursue the new way. In line with this work, Yigit and Unsal [9]have displayed a paper in which they have utilized Ant Colony Optimization to route school transports. Authors have created software that utilized for prescribing the most reasonable and the shortest route represented on a guide by taking instantaneous student wait location online.

Jyothi & Jackson [10] have proposed a time-sensitive methodology for tackling the dynamic way issue in the vehicular ad-hoc network. In this paper, authors have proposed The Ant Queue Optimization Scheme consolidates both proactive and receptive mechanism. In contrast to the ACO, the AQO powerfully settles on choice in picking the most limited best route in highly congested areas. Route determination is dynamic at every junction independent of the size of the traffic. The experimental outcomes show that the AQO has set aside less effort to process every one of the vehicles within a given network when contrasted with ACO.
SUMO Based Simulation Framework for Intelligent Traffic Management System has proposed by Akhter et al [11]. In this paper, the Deep-Neuro-Fuzzy model was proposed and implemented. Dijkstra algorithm is used to select an optimum path from source to destination based on calculated road segment weights from the Deep-Neuro-Fuzzy framework.
Correia et al.[12] works on the basic Dynamic MANET On-demand (DYMO) routing protocol to make use of the ant colony optimization technique and proposed Mobility-aware Ant Colony Optimization Routing (MAR – DYMO). The result of these papers suggests that making use of environmental information can make ACO algorithms more suitable for routing in vehicular ad hoc networks. Using vehicle position and speed, it predicts their movements to find the path of the vehicle.

Most of the shortest path problems like Travelling sales man problem and vehicle routing problem are static in nature. The density of traffic is dynamic in nature and finding an optimal solution for regulating the flow of traffic is a challenging task. [4]

Bedi et al. [13] proposed a novel way to deal with traffic congestion utilizing the Ant colony optimization Technique. This paper depicts another methodology DSATJ (Dynamic System for Avoiding Traffic Jam) expected to locate the best alternative way to keep away from the congestion in terms of traffic and afterward continuing that equivalent path again when the traffic blockage is settled. The congestion on the road is distinguished by detecting the pheromone values on the edge of the graph. Our solution would find support from this methodology by taking advantage of air pollution as a pheromone to discover the best suitable way towards the goal as far as less contamination.

3 PROPOSED SYSTEM ARCHITECTURE

Fundamental shortest path algorithms like Bellman-Ford, Dijkstra [14]can locate the most shortest way proficiently yet the issue with them is that it makes congestion as they don't consider a little longer way which is less in traffic[15]. The proposed architecture relies on ACO. As appeared in fig.1 the proposed architecture is divided into layered design. Here we consider the vehicle as a ant to get the parameters x1, x2… . Xn.

Where
X1 = Air Quality Index [Calculation of AQI is different for different country. In our research we consider AQI for urban areas of India] [3]

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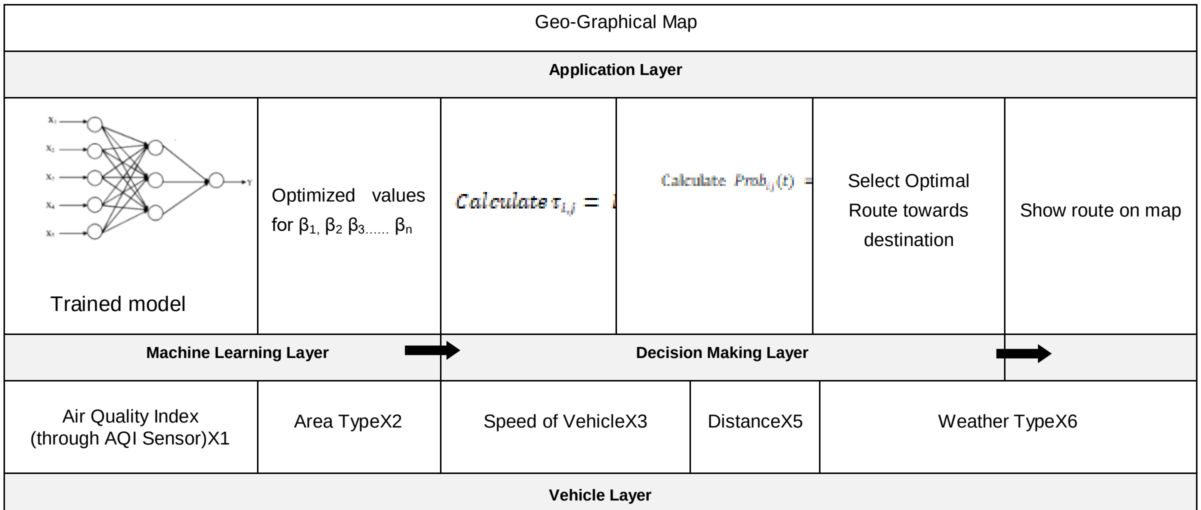

Fig1 : Proposed layered architecture to identify the optimal route considering parameters like Air pollution, Traffic Density, Distance etc.

X2 = Area type which is set of {Industrial, Residential, Forest}

X3 = Distance between {Junctioni,Junctionj}.

X4 = Weather type {rainfall, winter, temperature}

Area type can be obtained using the pre-tagged map of the specific city/urban area. Air quality index can be obtained using a pre-installed low-cost sensor on board of the vehicle. Distance is the weighting parameter associated with edge Eij. The weather type is the predefined parameter.

In the proposed architecture based on the available historical information,we will train the machine learning algorithm. When we have response shown in vehicle layer, we can apply trained machine-learning algorithm to find Optimized values for β1, β2 β3…… βn [In our case ∝,β], which controls the relative impact of parameter mentioned in Feature map X = { X1, X2…. Xn} on finding the optimal path. In the proposed model, Data of the experiment is not known, in such a case we suggest either of the following methods, which gives optimal traveling time and Air Quality Index for the particular route:

1. Multivariable Regression [16] : Multivariable regression is an augmentation of simple linear regression. It is utilized to foresee the estimation of a variable dependent on the estimation of at least two different variables. The variable which we required to predict is the dependent variable. In the following equation, Yi is the predicted value of the dependent variable. Values of the n dependent variable denoted as { X1, X2…. Xn}. βi is the weighted value, which can be obtained by a training model using the below-mentioned optimization algorithm/optimizers. the predicted value of the dependent variable is :

$$Yi = \beta 1X1i + \beta 2X2i + \beta 3X3i + \ldots\ldots + \beta Xnin + \varepsilon i$$

Which is equal to, $\sum_{k=1}^{n} \beta 1X1i +$

Where εi is the unobservable error component

2. Polynomial Regression [16]: In case data are not linear but scattered, linear regression might not the best way to describe the data. A curved or non-linear line might be a better fit for such data. the quadratic equation of polynomial of degree n is:

$$Yi = \beta 0 + \beta 1X + \beta 2X^2 + \beta 3X^3 + \ldots\ldots + \beta nX^n$$

Using optimizers during the training process, we adjust and change the weights of our model to try and minimize the loss function and make our prediction as correct as possible. We propose to use two optimizers to train the model:

a. RMSProp [17]

b. Adam, which is the combination of RMSProp and Stochastic Gradient Descent. [18]

Using the above block of action we get optimized values for β1, β2, β3…… βn which controls the relative impact of parameter mentioned in Feature map X = { X1, X2…. Xn} on finding the optimal path. Feature standardization techniques like feature scaling and/or mean normalization used to standardize the range of Feature map X. It is performed during data pre-processing. Proposed model use these values for calculating the probability, helps to decide between selecting available alternate path towards destination.

Ant colony optimization algorithm lays down pheromone at the time of the backtrack as a part of loop correction. As well as artificial ants contained limited memory to record trip to the destination [19].

At the beginning Dijkstra algorithm executed to find the optimal path from source to destination using graph G., This

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helps to initialize pheromone value for the initial journey of an ant.

Initialize Pheromone $\tau_{i,j}(t=0) = Distance($ Where distance of edge between junction i and j calculated by the Dijkstra algorithm [20].

Pheromone Update:

Ant k Deposits data about its goodness on the pheromone trails of the connections it utilized i.e. Δ Is the pheromone an Ant$_k$ deposited on edge (i,j) given by

Equation 1:

$if\ ant\ k\ visited\ edge(i,j)\ then$

$\Delta\tau_{i,j}^{k} \propto Length\ of\ edge\ (i,j)^{\alpha} + Average\ Air\ Quality\ Level\ in\ terms\ of\ Air\ Qual$

$else\ 0$

Here consider the pollution rate in terms of Air Quality Index. Where AQI = (Current Pollution Level / Pollution Slandered Level) *100.The pollution standard level is maintained by the Central Pollution board In India.

∝&βare the weights obtained from the block of machine learning, which controls the relative importance Distance and pollution level parameters respectively.

So total pheromone on edge (i,j) calculated using equation 1 is $\tau_{i,j} = \sum_{K=1}^{m} \Delta$

The load of the edge gradually increases, by depositing the pheromone, as the level of pheromone increases, as a part of the repulsion effect, the vehicle does not follow the higher pheromone deposited path. This will helps to promote the distribution of traffic, results in decreasing overall traffic and level of pollution to the respective area. Global pheromone trail is updated by evaporating the existing pheromone according to

$$\tau_{i,j} = (1-\rho)\,\tau_{i,j} + \sum \Delta\tau_{i,j}^{k}$$

Where ρ is the rate of pheromone update.

Now from source, at each junction i, vehicle Vi takes the decision to move available alternative junction j in iteration t so that it reaches to destination D based on the following probability:

$$Prob_{i,j}(t) = \frac{\tau_{i,j}}{\sum}$$

The route which is selected based on this algorithm considers as optimal route and it will be displayed in Geo-Graphical map exists in Application Layer.

4 Proposed Algorithm

Step 1: Initialize pheromone trail using Dijkstra algorithm executed on Graph G

$\tau_{i,j}(t=0) = Distance(i,j)$

Step 2: Iteration

Repeat for each ant

1.1 Send Value {X1, X2,X3..Xn} to Train Machine learning model and evaluate weights ∝&βwhich controls relative importance of Distance and pollution level parameters etc.

1.2 Calculate pheromone says , an antk deposited on edge (i,j) based on the Length of edge & Average Air Quality Index.

1.3 Solution construction usingPheromone Trail, calculating $Prob_{ij}(t) = \frac{\tau_{i,j}}{\sum}$

1.4 Select optimal route and present to the application layer.

Update Pheromone Trail

Until Stopping Criteria

5 Result Analysis

5.1 Implementation

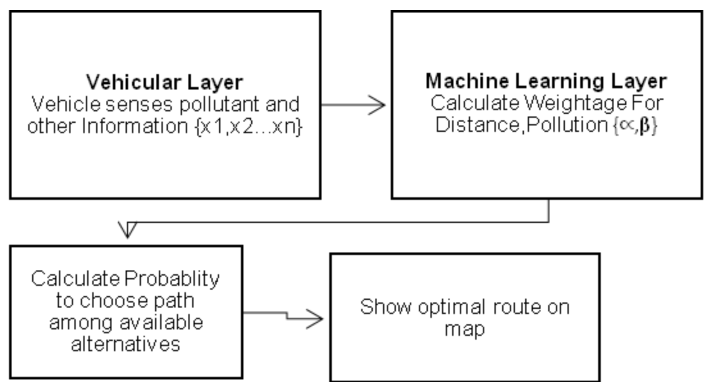

Fig2:Flow of the proposed model

In this section, we discuss the implementation of the proposed model. We have used a multi-model simulator SUMO as a server and Traci as a client. Where Traci have implemented the code of Ant Colony technique to route vehicle from source to destination based on the calculated probability mentioned in the above section.

Onboard, sensors provide real-time values for the Area Type, Weather type, Air Quality Index, Distance covered. In turn this parameter input to the trained model discussed in section 3, and find the weight parameter {∝,β}, Where ∝ is a weight for the distance and β is the weight of the Pollution parameter. i.e. if ∝ is higher and β is lower means distance have higher importance over pollution.

Table 1: ∝ and β values sample for some data[21]

Area Type	Air Quality Index	Weather Type	∝	β
Industrial	144	Rainfall	0.7	0.3
		Winter	0.4	0.6
		Temperature	0.4	0.6
Forest	36	Rainfall	0.9	0.1
		Winter	0.8	0.2

		Temperature	0.7	0.3
Residential	80	Rainfall	0.8	0.2
		Winter	0.7	0.3
		Temperature	0.4	0.6

As described in Table 2, the Impact of pollutants varies with the weather. If it is an Industrial area but there is a rainfall, the Impact of pollutants is lower [23], so β is lower that ∝ i.e. machine learning algorithm gives higher importance to the distance over pollution. And so on.

5.2 Experiment & Discussion

Since, our data are scattered, linear regression may not provide the best result. We have used a polynomial quadratic equation of degree n here. We have used the Stochastic Gradient Descent (SGD) optimizer to train the model. Here, the model is trained to get the optimized value of the parameter ∝and βfor a given path. The different values of the ∝and βhave experimented for different weather types such as rainfall, winter and temperature. Moreover, the parameter of ∝and βalso depends on the area type. Hence, for each area type, we have experimented and derived the optimized value of the ∝and βweather-wise. The optimized weight parameter values of the ∝and βin the inference model derived by experimenting with different values of ∝and β, which varies from 0.1 to 0.9 using SGD optimizer.

The Proposed algorithm is applied on the city map converted to the graph as shown in fig.3. Here we have presented samplefor the start node = 1 and End Node = 4.

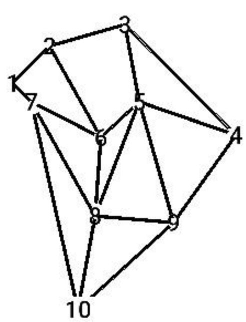

Fig.3 : Graph created for the purpose of experiment

The parameter used in proposed algorithms is Evaporation rate ρ = 0.8.

Case 1:

Here we consider the Industrial area where the Air Quality Index is quite bad, But the Weather-Type we consider is Rainfall. So our trained model gives Relative weight for distance is∝ = 0.7 and Relative weight for Pollution isβ = 0.3.

As shown in Table 2, our proposed approachtakes slightly higher Arrival Time and Route Length, while lower the speed as compared tothe Dijkstra algorithm.. For the derived value of ∝ and β, importance is given to the distance, but the proposed design takes route for which pollutant effectis comparatively lower than Dijkstra.

TABLE 2 : COMPARISON *TRIPINFO* PARAMETER FOR THE PROPOSED ALGORITHM AND DIJKSTRA ALGORITHM

	Proposed approach Case 1	**Proposed approach** Case 2	**Dijkstra**
Arrival Time	108.00	113.34	94.20
Arrival Speed	12.73	12.32	12.81
Route Length	1250.09	1349.43	1164.74
Pollutantamount (Co2 Only)	2.130224762050	1.987637016003	2. 130224762050

#Arrival Time in Secondsunit #Arrival Speed in meter per seconds unit #Route Length in meter #Pollutant in mg/s

Case 2:

Here we consider the Residential area where the Air Quality Index is comparatively good, But the Weather-Type we consider is Temperature/Summer. So our trained model gives Relative weight for distance is∝ = 0.4 and Relative weight for Pollution isβ = 0.6.I.e. Importance is given to the effect of pollution over Distance. So results shownin Table 2,that Route length increased but the effect of pollution is very less as compared to the Dijkstra approach and case 1.

Note that the value of pollutant (Co2) is normalized value against the maximum value.

6 CONCLUSION

The proposed novel layered design presents a machine learning assisted framework to diminish the effect of air pollution on the human body using ant colony optimization technique. Our proposed design consider the surrounding environment parameter like Weather-Type, current air quality index, type of area through which vehicle passes. While choosing optimal path using ant colony technique, the probability equation considers Length of edge i.e. Distance & Average Air Quality Level, in which importance (∝ and β) of respective parameter tuned by machine learning approach. The different values of the ∝ and β have experimented for different weather types such as rainfall, winter, and temperature as well as area Type like Industrial, residential and forest. Experiment results show that for the considered route,route length and amount of pollutant deposited on this route, varies based on the Weather-Type, current air quality index, type of area so that the effect of air pollution can be minimize.In the future, the proposed design will be

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experimented for the repulsion effect i.e. follow the path for which traffic is comparatively lower. In spite of Increasing route length, this will, in turn, reduce the Arrival Time Arrival Speed.

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