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Real Time Traffic Condition Based Smart Signal System

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Abstract: ***Intheeraofcrowddeliveryvehiclerouting and traffic management in smart cities, a complex challenge appears indistinctly, affecting both developed and developing nationsworldwide.Thischallengingprobleminvolvesoptimizing multi-depot routes while addressing various hurdles: minimizing travel time, distance, fuel consumption, and carbon emissions,all while navigating dynamic traffic congestion across diverse pathways.Existingapproachesoftenfocusonisolatedaspectslike shortestpaths,carbonemissions,ortrafficprediction,leavingthe comprehensive multi-depot traffic management problem unad-dressed. In response, this research work proposes an Intelligent Multi-DepotVehicleRoutingandManagement(IM-VRM)model which provides a comprehensive and holistic solution. It employs aGraphNeuralNetwork(GNN)learning-basedroutingwith agreedyoptimizationtoestablishinitialoptimalpathways for multi-depot journeys. Subsequently, the IM-VRM model integrates traffic congestion prediction with green parameter computation,engagingtheDijkstraalgorithmtoselectthe mostadmissibleroutes. This consecutive steps-based travel route guidance process optimizes routing for heterogeneous vehicles, including both heavy-duty and light-duty types. It accounts for load-dependentfuelconsumption,velocity,andcarbonemissions. By doing so, it simplifies the complexities of multi-depot traffic routing and management. The proposed model has been rigor-ously evaluated using a real-world multi-depot traffic dataset, demonstrating its practical viability. Notably, IM-VRM model achieves a remarkable improvement in fuel savings, reduced carbonemissions,andshortertraveltimeoutperformingprevious state-of-the-art methods in both efficiency and precision.***

Index Terms— Crowd delivery, carbon emission, congestion, multi-depot rides, traffic management.

I. INTRODUCTION

IN MODERN urban landscapes, the efficient coordination ofdeliveryroutesacrossmultipledepotsandvehicle trafficmanagementinthesmartcitiespresentsignificant challenges[1],[2].Theincreasingnumberofdeliveryvehicles intensifies urban congestion, leading to higher fuel consump-tion[3],airpollution,andcarbondioxide($CO2$)emissions [4],[5].Whilestrategiessuchascar-poolingandcrowd deliveryhavebeenproposed,theyoftensufferfrominade-quateimplementationandmanagement.Post-COVIDtrends havefurtherexacerbatedthesituation,withemissionsfrom individual activities, such as taxi rides and delivery services, haverisen up noticeably.Delivery vehicles,particularly those used forfood delivery, aremajor contributors to airpollution, withthetransportationsectorresponsibleforapproximately 28%ofglobalgreenhousegasemissions[6],[7].Thegrowing prevalence of online food delivery services has led to a 20% increaseinVehicleMilesTraveled(VMT)intheUnitedStates from 2010 to 2020 [8], further straining urban infrastructure. This surge in delivery vehicles exacerbates traffic congestion andresultsinexcessiveemissionsofpollutantssuchas$CO2$, nitrogenoxides,andparticulatematter[9],[10],[11].

To address these challenges, there is a critical need for scalable, sustainable, and computationally efficient solutions that can meet the growing demands of urban logistics while mitigating the environmental impact of delivery systems in smart city environments. The critical question is how to developaneffectiveframeworkforoptimizingmulti-depot delivery operations in real-time that minimizes travel times, distances,fuelconsumption, andemissionswhiledynamically adapting to fluctuating traffic conditions.

A. Related Work

Several innovative vehicle routing strategies have been proposed for efficient delivery management in smart cities. Jolfaei and Alinaghian [12]addressed the multi-depot vehicle routing problem with roaming delivery locations and hardtime windows, presenting a mathematical model and two heuristic algorithms, including a hybrid evolutionary logical search-basedapproachforlarge-scalesolutions.CrowDNet, a spatial crowdsourcing-based system was proposed in [13], leveraging existing taxis for food delivery, using evolutionary algorithms, improved insertion approaches, and a ranking modulebasedonmodernportfolio theorytooptimizedelivery cost and timeliness. Chen [14]and Kouziokas et al.

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[15]proposedNN-basedDeepReinforcementLearningbasedrout-ing and search algorithms to predict traffic congestion. Joeand Lau [16]proposed the Deep Reinforcement Learning Approach for Dynamic Vehicle Routing Problems, combin-ing neural network-based learning with stochastic routing heuristics. Wang and Su [17]proposed a two-stage control strategyfor CAV platoons, focusing on fast platoon for-mation and fuel-efficient, safe junction crossings, optimized for urban traffic management. Liu et al. [18]suggested a Green Vehicle Routing Optimization algorithm for emission reduction. Abbatecola et al. [19]proposed a Decision Support Approach for postal delivery and waste collection, optimizing vehicleassignmentandrouting.Perbolietal.[20]presented a multi-stage heuristic based on simulation optimization for dynamic and stochastic vehicle routing problems. Chen et al.

[21]proposedCROWDDELIVER,utilizingoccupiedcabsfor city-wide package delivery while Du et al. [13]presented CrowDNet,asystemleveragingspatialcrowdsourcingforfood delivery. Kafle et al. [22]designed a crowd-source-enabled system for last-leg deliveries, reducing overall transportation costs. Hong et al. [23]presented a framework for improved crowd-sourcing multi-hop package delivery, utilizing spare capacity in urban vehicles.

B. ResearchGapandPaperContributions

Despitenumerousproposedstrategiesformanagingdelivery time,$CO2$emission, and travel distance constrained with mitigation of dynamic traffic congestion. types,etc.[12],[13],[14],[15],[16],[17],[18],[19],[20], [21],[24].Thereremainsaneedforacomprehensiveand ride.practical solution that is highly effective and less complex ensuringseamlessintegrationintotheever-evolvingsmartcity landscape. In this context, this paper proposed an **I**ntelligent **M**ulti-Depot **V**ehicle **R**outing and **M**anagement (**IM-VRM**) model which provides a comprehensive and holistic solution. The key contributions are fourfold:

- A novelmulti-depotcrowd delivery vehicle routingman-agement model is proposed which addresses multiple challenges including optimized fuel consumption, trave time,CO2emission, and travel distance constrained with mitigation of dynamic traffic congestion.
- AninnovativeconceptofemployingGreedyoptimization within a GNN is introduced to determine optimal route selection for multi-depot rides.
- IM-VRM model illustrates seamless integration of traffic congestion prediction with the computation of green parameters to determine the most optimal routes. The progressive, step-based travel route guidance process not only streamlines the intricate challenges of multi-depot traffic routing and management but also surpasses the complexity of existing state-of-the-art methods.
- Experimental simulations and evaluations using real-world benchmark data demonstrate that the IM-VRM model outperforms conventional and state-of-the-art (SOTA) approaches across key performance metrics for dynamic transport management.

C. Paper Organization

The considered problem is formulated in Section II“Prob-lem Formulation” which describes the challenges, assump-tions,andconstraintsundertakenassociatedwiththeaddressed multi-depotcrowddeliveryroutingmanagementproblem.The proposedmethodisdiscussedinSectionIII“IM-VRMModel” which includes travel route network optimization using distance-orientedgreedyoptimizationoftravelrouteGNN (inSub-sectionIII-A)followedbytrafficcongestionhan-dling with green parameters optimization (Sub-section III-B); andconcisediscussionofoperationaldesignandcomplex-ity computation (Sub-section IV). Section V“Performance Evaluation” discusses experimental setup, implementation, dataset description, and results of initial route selection, han-dling traffic congestion, green parameters constrained optimal deliveryrouteselection,andcomprehensiveperformanceanal-ysis of the proposed model versus without proposed model. Section VI“Conclusion” entails conclusive remarks and the future scope of the proposed work. The symbols alongwith their meaning used throughout the paper are described inTable I.

II. PROBLEM FORMULATION

Considernsingle-depotormulti-depotdeliveryrides requests$\{R1,R2,...,Rn\}_{R1}$forrecommendingmostadmissible

travelroutessuchas$\{S:D,D,...,D_a\}$,$\{S:D$,

systemsinsmartcities,theyoftenfacechallengesinreal-

R R ^1R ^2R R 1

worldscalability,adaptabilitywithdynamicallyvaryingtraffic

$D_2{}^2,...,D_b{}^2\}$,and$\{S^{R_n}:D_1{}^n,D_2{}^n,...,D_c{}^n\}$,wherein,

conditions,congestion,andintegrationofdiversevehicle
$a_{th} \geq 1, b \geq 1$, and $_{Ri}c \geq 1$; S^{Ri}_{th} represents source site o_{th} f
i ride(R_i) and D specifies j
destination site of i
An *IntelligentTrafficOrganizerandManagementEngine* (ITOME) receives route selection requests and generates n responses respective to each request. ITOME operates the city trafficbyusingthreeknowledgedatabasesincluding*LiveCity Traffic* (kd-LCT) which are maintained and updated with the help of Global Positioning System (GPS), capturing the live trafficmovement;*VehicleRoutesConnectingCity*(kd-VRCC) containing all travel routes connecting every site within the city;and*HistoricalTrafficDataRepository*(kd-HTDR)which keeps track records of previous temporal vehicle traffic about

TABLEI
LISTOFSYMBOLSANDNOTATIONS

Symbol	Meaning	Symbol	Meaning
R	Ride request	$\aleph$	Maximum load of vehicle
S	Source cite	C	Fuel cost
D	Destination site	E_k	Ending time
t	Time instance	B_k	Beginning time
OR	Optimal route	V	Set of nodes
Vh	Heterogeneous vehicle	VH	Set of vehicles
τ	Traffic condition	A	Set of routes
TW	Time Window	U	Set of vehicle types
AP	Air pollution	M	Set of all time periods
TD	Travel distance	E	Set of edges
TC	Travel cost	F_u	Fuel tank capacity
Vh^{HD}	Heavy duty vehicle	Θ^{status}	Traffic congestion status
Vh^{LD}	Light duty vehicle	φ	Latitute
S	Speed	Ω	Longitute
L	Travel load	v	Node in GNN
G	GNN	ϑ	Central angle
ds	Historical traffic data	D^{Ac}	Actual data
BL	Base learner	D^{Pr}	Predicted data
F	Feature vector	O	Predicted output by BL
X_{ij}	Route $(i; j)$ traveled status	u	vehicle type

eachrouteofthecity.The coreobjectiveofITOMEisto map every online (i.e., currently moving vehicle) or offline (i.e., standby vehicle) requested ride with the most admissible routes considering the situation of live city traffic for t^{th} time instance. The essential challenges with intended constraints and design goals with assumptions are outlined in the subse-quent sub-sections.

A. Challenges and Assumptions

ITOME possesses the request data $\{R1, R2, \ldots, Rn\}$ that need to be addressed with the most admissible route selection proactively while addressingthe following critical challenges:

- *Heterogeneousvehicles*$\{Vh1, Vh2, ..., Vhn\} \in$ VH withdifferentcapacities,constraints,andcapabilities impose vehicle specific constraints to be considered dur-ingoptimalroute$\{OR1, OR2, ..., O\,Rn\}$selection.
- Theever-changingtrafficconditions$\{\tau 1, \tau 2, ..., \tau cr\}$on *cr*cityroutespresenta*dynamicadaptabilitychallenge* forgeneratingreal-timeornear-real-timesolutions.
- Asthenumberofdepotsandvehiclesincreases,thecomputationalcomplexityofgeneratingoptimaldeliveryroutesgrowsexponentially. Thisposesacriticalchallenge tothecapabilityoffindingoptimalsolutions$\{OR1, OR2, ..., ORn\}$withinareasonabletimeframe.
- Incorporating*timewindows*(*TW*),*airpollution*(*AP*), *traveldistance*(*TD*),and*travelcost*(*TC*),intothe routing problem adds complexity and requires adherence to customer service time constraints.

Aligningwiththeabovechallenges,thefollowingassumptions are considered:

- The heterogeneity of vehicle is restricted to heavy-duty vehicletype(Vh^{HD})and light-duty vehicle type (Vh^{LD}) suchthat$\{H\,D, L\,D\} \in U$.
- The*n*deliveryrides$\{R1, R2, ..., Rn\}$applyspecific timewindows:$\{TW1, TW2, ..., TWn\}$whichisstrictly incorporated into the routing problem.
- IM-VRM model decides the priority of $T\,W$, AP, $T\,D$, and $T\,C$while requesting for the optimal route.

- ITOMEislinkedwithkd-LCT,kd-VRCC,andkd-HTDR of each travel route connecting the city site.

B. DesignGoals

Based on the problem description, intended challenges, and assumptions, the design goals for ITOME are as follows:

1) Vehicle Fuel Consumption: A vehicle fuel consumption modelisdevelopedusing[25]whichisderivedfromtheCom-prehensive Module Emissions Model (CMEM) by [26]for estimationofvehicles'fuelconsumptionrates($FCVhu(S,L)$) as a function of vehicle speed S and load L. Considering a heavy-dutyvehicle(Vh^{HD}) traveling on aroad with no slope, the VFCR function is stated in Eq. (1);

$$FCVhu(S,L)=\alpha 1Vhu S^{-1}+\alpha 2Vhu S^{2}+\alpha 3Vhu+\alpha 4Vhu L \quad (1)$$

where$u\in\{HD,LD\}$,$\alpha 1Vhu$,$\alpha 2Vhu$,$\alpha 3Vhu$,and$\alpha 4Vhu$;are the coefficients associated with the vehicle type u. The cost value of VFCR ($Cijku$) for a vehicle type u traveling from i^{th}site toj^{th}site in the city in k^{th}time-period is computed by adding first three terms in Eq. (1). Additionally, VFCR due to the vehicle's travel load(L) is calculatedusingthe last termin Eq. (1)such as $\alpha 4V\ hu\ Li\ jVh$, where $Li\ jVh$is the travel load vehicleVhwhenitistravelingfromsite$i$tosite$j$.

2) Carbon Emission: The carbon emission depends on the rate of the vehicle fuel consumption (Eq. 1). Accordingly, the objectivefunctionofcarbonemissionisformulatedasdepicted in Eq. (2)by substituting Eq. (3)and Eq. (4)[18],[27]. The terms,VH:setofallvehicles;A:setofroutesformedby allpairsofcitysites(i,j)suchthat(i≠ j);U:setof all vehicle types; M : set of all time-periods;ℵu: maximum payloadofvehicletypeu;Cijku:costoffuelconsumption;

÷Vhu: {0, 1} value indicating whether vehicle Vh belongs to type u; $Di\ j$: total distance traveled between source site i and destination site j ; $di\ jkVh$: continuous variable indicating the traveleddistanceofroute(i;j)inperiod$k$byvehicleVh.

$$CO_2=\sum_{Vh\in VH}\sum_{(i,j)\in A}\sum_{u\in\{U\}} CEC_1+CEC_2 \quad (2)$$

$$CEC_1=\sum_{k\in M}\aleph_u C_{ijku}\ominus_u \div Vh^u d_{ijkV\ h} \quad (3)$$

$$CEC_2=\aleph_u \div V\ h^u L_{i\ jV\ h^u} D_{i\ j} \quad (4)$$

In Eq. (2), the first term accounts for the carbon emissions producedbythevehiclesthemselves,whilethesecondterm representsemissionsattributedtotheloadscarriedbythevehi-cles. To facilitate flexible scheduling and enable fuel-savingor CO_2emission reduction during traffic congestion, the continuous variable $di\ jkV\ h$serves as the primary decision variable. It allows the route (i ; j) to be partitioned into multiple segments that can be traveled at different periods. This approach permits the possibility of discontinuous travel, where the vehicle can be temporarily off the road to mitigate emissions while navigating through congested traffic.

*3) Effective Incorporation of Time Window:*Travel time($TijkVh$)respectivetoavehicle(Vh)fromi^{th}sitetojthsite for k time-period, is computed in minutes using Eq. (5)whichislinearbecausetravelspeed(Sijk)isaparameter considered in km/h. Additionally, the total travel time of vehicle (V h) in period k is restricted by applying time-bound via Eq. (6), wherein Ekand Bkare the ending and beginning time, respectively, of a trip (i;j).$dijkVh$

$$T_{ijkVh}=60\times\frac{d_{ijkVh}}{s_{ijk}} \quad A(i,j)\in A, k\in M, Vh\in VH \quad (5)$$

$$\sum_{(i,j)\in A} T_{ijkVh}\le E_k-B_k \quad Ak\in M, Vh\in VH \quad (6)$$

Thetimewindowincorporationisconstrainedwiththefollowing Eqs.(7)–(11),wherein, Γ_i and Γ_j arethedeparturesfrom i^{th} siteandarrivaltimeat j^{th} site,respectively; x_{ijkVh} is abinaryvariableindicatingwhetherroute(i;j)istraveledin period k by vehicle Vh (1)ornot(0); Xij isabinaryvariable indicatingwhetherroute(i;j)istraveled(1)ornot(0);and $[\Delta^B,\Delta^E]$ representsstartandendtimeconstitutingatime window to serve i^{th} ride service.

$$\Gamma_i^l \leq E_k - T_{ijkVh} + E_m \times (1 - x_{ijkVh}) \quad (7)$$

$$\Gamma_j^a \leq B_k + T_{ijkVh} - E_m \times (1 - x_{ijkVh}) \quad (8)$$

$$\Gamma_j^a \leq \Gamma_i^l + \sum_{k=1}^{m} \sum_{h=1}^{q} T_{ijkVh} - E_m \times (1 - X_{ij}) \; A(i,j) \in A \quad (9)$$

$$\Gamma_i^a + \Gamma^s \leq \Gamma_i^l \; A i \in \{1, \ldots, n\} \quad (10)$$

$$\Delta^B \leq \Gamma_i^a \leq \Delta_i^E \; A i \in \{1, \ldots, n\} \quad (11)$$

Constraint(Eq.7)guaranteesthatifroute(i,j)istraveledin period $k$by vehicle V h(indicatedby $x_{ijkVh} = 1$), site $i$must bedepartedfrombeforetheperiod'sendtimeminusthetravel time of the route, where, $A(i,j) \in A, k \in M, V$ $h \in V$ H . Constraint(Eq.8)ensuresthatthearrivaltimeatnode j mustbegreaterthanorequaltotheperiod'sstarttimeplusthetravel time of the route (i ,j). Constraint (Eq. 9) calculates earliest arrival times, active only for selected arcs (x_{ij}). Constraint (Eq. 10) guarantees the vehicle departs after serving a node, considering service time. Finally, the constraint (Eq. 11) sets the bounds on arrival time at customer node i . Together,these constraints manage time-related aspects of the vehicle routingproblem,ensuringtimelyserviceandadherencetotime windows.

4) *Travel Distance:* The objective function for travel dis-tance(TD)isdesignedtoenforcethemaximumtravel distance limits of vehicles based on their fuel tank capacity (Fu),isformulated inEq.(12)and Eq. (13),where, $Vh \in$ VH. Itensuresthatthetotalamountoffuelconsumedbyvehicle V h (second term) does not exceed its fuel tank capacity (first term).Thisiscrucialtopreventvehiclesfromtravelingbeyond their fuel constraints and helps in maintaining efficient and feasible routes for the vehicle routing problem. By optimizing the objective function T D, the solution aims to minimize traveldistancewhilesatisfyingthesefuelconstraintsforall vehiclesinthefleet

5) *Traffic Congestion:* The traffic congestion model associ-ated with a specific vehicle ($①Vhu$) is formulated using Eqs. (14-19).Ataninstance t,fuelconsumptionrate($FCVhu$), carbon emission ($CO2$), travel time ($TijkVhu$), travel distance($TDVhu$),andtrafficconditiononroute($dijkVh \times \tau ijkVh$) respectivetovehicle(Vh^u)decidesitstrafficcongestion status ($①^{status}_{Vh^u}$)basedonthecorrespondingthresholdparameters'

$$TD = \sum_{(i,j) \in A} D_{ij} \times X_{ij} \quad \text{subjectto} \quad (12)$$

$$\sum_{u \in U} F_u \geq \sum_{(i,j) \in A} \sum_{k \in K} \sum_{u \in U} C_{ijku} d_{ijkVh} + \sum_{u \in U} L_{ijVh} d_{ij} \quad (13)$$

values $\{\omega^{FC}_{Vh_u}, \omega^{}_{Vh_u}, \omega^{}_{Vh^u}, \omega^{TD}_{Vh^u}, \omega^{\tau}_{u}\}$.

$$①_{Vh^u} = ①_{Vh^u} + ①_{Vh^u} + ①_{Vh^u} + ①_{Vh^u} + ①_{Vh^u} \quad (14)$$

$$①^{FC}_{u} = FC_{Vh^u} \times \omega^{FC}_{u} \quad (15)$$

$$①^{CO_2}_{Vh^u} = CO_{2\,Vh}{}_{u} \times \omega^{Vh^{CO_2}}_{u} \quad (16)$$

$$①_{Vh^u} = T_{ijkVh^u} \times \omega_{Vh^u} \quad (17)$$

$$①^{TD}_{Vh^u} = TD_{Vhu} \times \omega Vh^u \quad (18)$$

$$①^{status}_{Vh^u} = Vh^u \times d_{ijkVh^u} \times \tau_{ijkVh^u} \times \omega^{\tau}_{u} \quad (19)$$

C. Problem Statement

Specifically,theconsideredproblemdiscussedabove,isa Multipleobjectivesconstrainedcrowddeliveryvehicletraffic trade-offsamongthem.Firstandforemost,wemustadhere tostricttraveltimewindows[Δ^B,Δ^E]toensuretimely deliveries or services at customer locations. Concurrently, minimizing the travel distance ($T\,D$) is of utmost importance, as it not only reduces operational costs but also curtails fuel consumption(FC)andcarbonemissions($CO2$),aligningwith sustainability goals. Nevertheless, optimizing travel distance must account for potential traffic congestion, as congested routes can lead to delays and inefficiencies. Accordingly, the problem can be mathematically stated as Eq. (20)subject to constraints specified in Eq. (21).

$$\max_{i=i} OR_i = MIN(FC_{Vh^u}(S,L); CO_{2\,Vh^u}; T_{ijkVh^u}; TD_{Vh^u}; ①_{Vh^u})$$

$$s.t.\{C_1 - C_7\} \quad (20)$$

$$C_1: \quad X_{ij} + X_{ji} \le 1 \mathrm{A}(i,j) \in A$$

$$C_2: \quad X_{ij} \ge y_{ijVh} \quad \mathrm{A}(i,j) \in A, Vh \in VH$$

$$C_3: \quad X_{ij} \ge x_{ijkVh} \mathrm{A}(i,j) \in A, Vh \in VH, k \in M$$

$$C_4: \quad \max_{i=0} yi0Vh \le 1 \mathrm{A}Vh \in VH$$

$$C_5: \quad \div_{Vh^u} C_u \ge \div_{Vh^u} \max_{i=0} \max_{j=1} r_j \times y_{ijVh}$$

$$\mathrm{A}Vh \in VH, u \in U$$

$$C_6: \quad 1 \le \max_{i=1} X_{i0} \le q$$

$$C_7: \quad 1 \le \max_{j=1} X_{0j} \le q\} \quad (21)$$

C_1:Onerouteshouldbetraveledatmostonce;C_2:Ifa

route(i,j)isnotselected,ally_{ijVh}shouldbezero;C_3:If

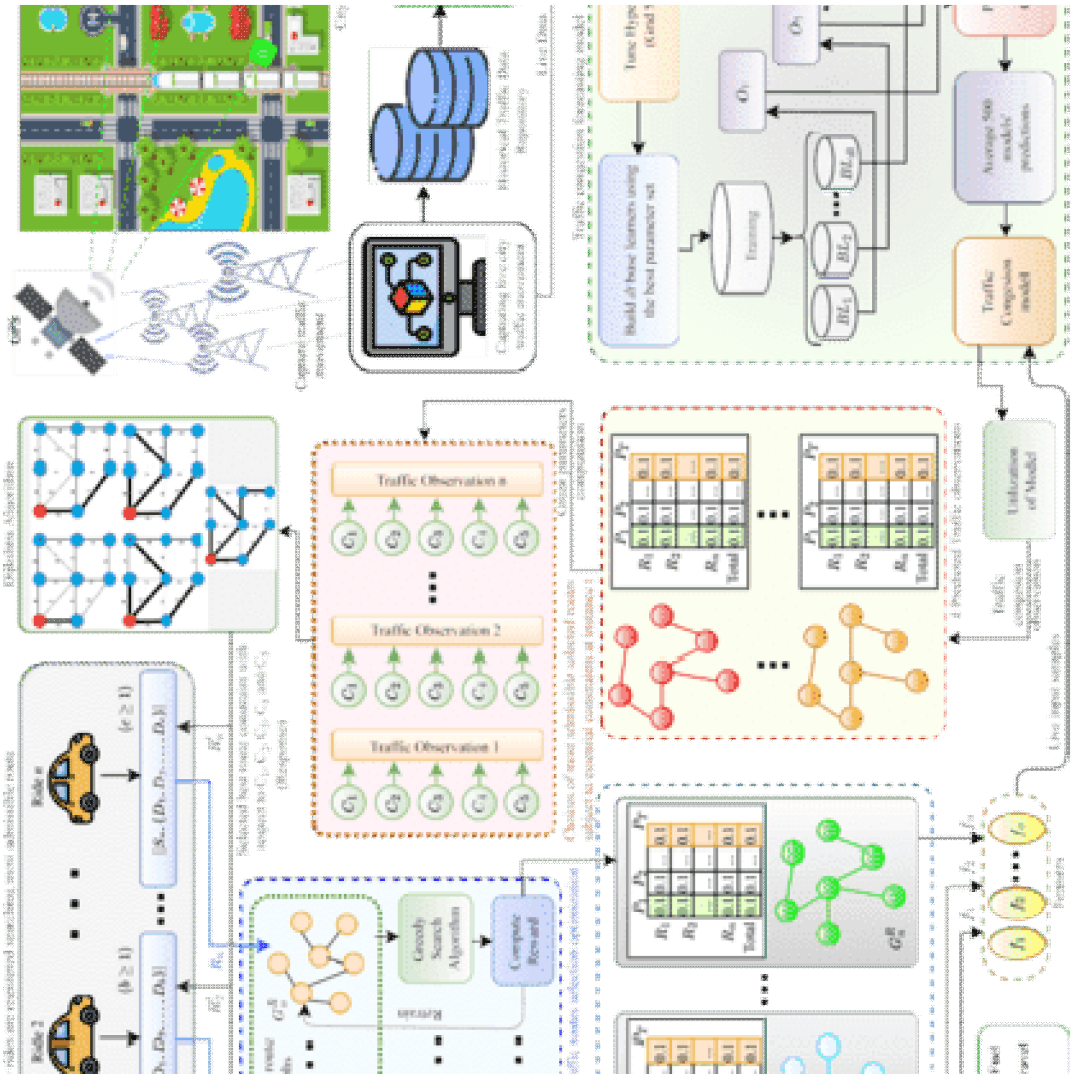


Fig.1. Real Time Traffic Condition Based Smart Signal System.

a route (i ,j) is not selected,allx_{ijkVh}should be zero; $C4$: Each vehicle returns to depot only once;$C5$: load capacity ofa vehicle should not be violated;$C6$: total number of returnsto the depot is in [1, q]; $C7$: total number of departures from thedepotisin[1, q], q:totalnumberofvehicles.

III. IM-VRMMODEL

Leteachofthesingle-depotormulti-depotdeliveryride node $v \in V$ is associated with features $x_v$that describe its specific attributes. requests{$R1$,$R2$,...,Rn}isrepresentedasaGNNto$v$ capturespatialrelationshipsbetweenlocationsasillustrated in Fig. 1. For each ride, the number of possible travel routes coveringmultipledepotssitesstartingfromthesourcesite,are generated using the information about locations viz.,

latitude (ϕ) and longitude (▲) of the source site and depot sites which allowscomputationofthedistancebetweentwolocations ($v_i$and v_j) using *haversine function* ($hav(\vartheta)$) via following mathematical derivation:

Let the *central angle* (ϑ) between any two points on a sphere be computed using Eq. (22), where d is the distance between the two points on the sphere, and$r$is the radius of the sphere.

Here,$l$representsthecurrentlayeroftheGNN, $N(v)$denotes thesetofneighboring nodes of v,and $h^{(l)}$ refers tothefeature representationofnodevatlayer$l$.Thefunction AGGREGATE collects and consolidates information from the neighboring nodes, while COMBINE merges the aggregated information with the node's existing features. These equations are applied iterativelyacrossmultiplelayers,allowingtheGNNtocapture complex dependencies and relationships within the graph structure.

A. TravelRouteNetworkOptimization

$$\underline{D}\,\vartheta = r \quad (22)$$

Then GNNs$\{G_1,G_2,...,G_n\}$areoptimizedwitha specific objective, i.e., minimizing distance. This objective is

The haversine of $\vartheta(hav(\vartheta))$ is computed directly from the latitude(ϕ) and longitude (▲)of the source site and depotsites using *haversine formula* as stated in Eq. (23), where, $\phi 1$, $\phi 2$arelatitudeofpoint1andpoint2,respectively,and▲1, ▲2arelongitudeofpoint1andpoint2,respectively.

$$hav(\vartheta)=hav(\phi 2-\phi 1)+cos(\phi 1)cos(\phi 2)hav(▲2-▲1) \quad (23)$$

Applying *haversine function* ($hav(\vartheta)$) to both the *central angle*(ϑ)anddifferencesinlatitudeandlongitudeisgiven by Eq. (24):

$$hav(\vartheta)=sin^2\frac{\vartheta}{2}=\frac{1-cos(\vartheta)}{} \quad (24)$$

haversine)to$h=hav(\vartheta)$asstatedindetailusingEq.(25):

This model incorporates GNNs, which are specifically designed to effectively model graph-structured data. These networksareparticularlywell-suitedfortasksthatinvolverela-tional and spatial information. GNNs leverage a mechanism known as message passing, where, nodes iteratively exchange and aggregate information from their neighbors. This enables the network to learn rich and expressive representations of graph elements while preserving the underlying structural dependencies. In this model, the travel routes are represented asan input graph $G(V,E)$, where Vdenotes the set ofnodes representing locations. These locations include the source site

node $v \in V$ is associated with features $x_v$that describe its specific attributes.

To update these node features, the GNN employs a layered message-passing mechanism. At each layer, the node features are updated iteratively using the following Eqs. (26and 27):

$$h^{(l+1)} = \text{AGGREGATE}\{h^{(l)} | u \in N(v)\} \quad (26)$$

$$h^{(l+1)} = \text{COMBINE}h^{(l)}, h^{(l+1)} \quad (27)$$

incorporated by adding a loss function (Lf) that measures the error between the predicted values (e.g., distances) and the truevalues(groundtruthdistances).Let'sdenotethepredicted distance between nodes $v1$and $v2$as $\hat{d}(v1,v2)$and the true distanceas$d(v1,v2)$.

ThelossfunctionLfortheGNNcan be defined as a sum of squared errors over all edges in the graph as stated in Eq. (28):

$$Lf = \sum_{(u,v)\in E} \hat{d}(v1,v2) - d(v1,v2)^2 \quad (28)$$

TheGNN'sparametersareadjustedtominimizethislossusing the Gradient Descent algorithm. Thereafter, GNN is utilizedtocomputenodeembeddingsthatencodeinformationabout 22 thelocationsandtheirrelationships.Theseembeddingscan

Thehaversinefunctioncomputesthehalfa*versine*oftheangle

ϑ.Thedistance$d$iscomputedusingthearchaversine (*inverse* be extracted from the final GNN layer's node representations by applying

Eq. (29), where $\theta$is the final layer of the GNN.

$$Embedding(v)=h^{(\theta)} \quad (29)$$

$$d=r\cdot archav(h)=2r\cdot arcsin(\sqrt{h}) \quad (25)$$

TheGreedySearch(GS)algorithmoperateswiththeini- andmultipledepotsites,givenbyS^{Ri},$\{D^{Ri},_1D^{Ri},_2...,D_a^{Ri}\}$, where$1\leq i\leq n$.Theset$E$representstheedges,which tialization of a starting node (e.g., the starting point of your route),andthenodeembeddingsobtainedfromtheGNN. GSalgorithmiterativelyselectsthenextnodebasedonthesmallestdistanceintheembeddingspace,denotedas Eq.(30),where,N/R representsthesetofunvisitednodes,and $Embedding(v)$representsthe embedding of node $v$obtained from the GNN.

$$v=\arg Min_{v\in N/R}\text{Embedding}(v) \quad (30)$$

TheGSoptimizationiscontinueduntilallnodeshave been visited or a termination condition is achieved. The integration of GNNs and the GS algorithm enables leveraging ofthespatialrelationshipscapturedbytheGNNtoguidethe correspondtopotentialroutesbetweentheselocations.Each selectionofnodesduringrouteoptimization.

A. HandlingTrafficCongestionWithGreenParameters Optimization

Efficientvehicletrafficmanagementisachievedthroughthe theregularizationterm, denoted by Win Eq. (35), preventsthe model from overfitting by applying penalties to the model's complexity:

TrafficCongestionForecastingModelunit(TCFMu),whichis designedtohandledynamictrafficconditionsthroughperiodic

$$L_t= \quad i \quad)$$

X^s.

$$L(O,O$$

$$+BL(F))+W(BL\cdot$$

(34)

trainingandretraining.Thetrainingprocessisinitiatedusing

$i=1$

t $1-$ t t

historicaltrafficdata,representedastheset$\{ds1,ds2,...,ds_m\}$,sourcedfromthe*HistoricalTrafficDataRepository*(kd-HTDR).Toensurehighdataquality,preprocessingtechniques

Theregularizationtermisdefinedas:

$$W(BL)=\gamma K+\frac{1}{2}\|w\|^2 \quad (35)$$

t $-\lambda$

areapplied,includinghandlingmissingvalues(e.g.,through

mean imputation), and preparing the dataset for both training and testing purposes.

Following preprocessing, *Feature Selection* identifies the mostrelevantfeaturesforpredictingtrafficcongestion.The *Pearson correlation coefficient* (P^{Corr}), which measures thelinearrelationshipbetweencontinuousvariables,isused.

Itranges from–1 (perfect negative) to+1 (perfect positive), withvaluesnear0indicatingnorelationship.Theformulafor $P^{Corr}$is given by Eq. (31), where, $x_i$and$y_i$are the values of thecharacteristic and target variables at the data point i, with $\bar{x}$ and $\bar{y}$ as their respective means.

P_z

where$\gamma$and$\lambda$are regularization parameters, $K$is the number ofleavesinthedecisiontree,and$w$representstheweights of the tree splits.

This iterative model enhancement helps to optimize both predictive performance and model complexity by gradually correcting errors, incorporating more data, and carefully balancing model bias and variance.

After the model is trained, it is applied to live data, such as traffic data fromthe *Live City Traffic* (kd-LCT) database, to predict traffic congestion for upcoming time intervals.

Once the model generates congestion predictions, high-congestion routes are discarded, and *Dijkstra's algorithm* is usedforrouteoptimization.Thisalgorithmidentifiesthe

$$P^{Corr} = \frac{\sum_{i=1}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{P_z \cdot P_z}} \quad (31)$$

shortestpathinagraph,accountingforpredictedconges-tionlevelsandvarious*GreenParameters*suchasvehicle fuelconsumption,carbonemissions,timewindows,and

After feature selection, *Feature Encoding* transforms cate-gorical variables into numerical values using *Label Encoding*, assigning each unique category a distinct integer. The dataset is then split into training and testing subsets. For modeling, *Extreme Gradient Boosting* (XGBoost), an efficient gradient boosting method, trains the Traffic Congestion Forecasting Model(TCFMu).XGBoostconstructsanensembleofdecision traveldistance.The*Greenparameters*arecomputedusing Eqs. (36- 39):

$$\text{FuelConsumption(FC)} = \sum_{i=1}^{n} FC_i Vh(S,L) \quad (36)$$

$$\text{CarbonEmission(CE)} = \sum_{i=1}^{n} CO2_i \quad (37)$$

trees, iteratively adding new trees to correct previous errors, minimizing an objective function that combines prediction accuracy and regularization at each step. To evaluate the performance of TCFMu, we use the *Mean Squared Error* (MSE)score,calculatedusingEq.(32),where*m*isthetotal

$$\text{TravelTime} = \sum_{i=1}^{n} \sum_{i=1}^{n} Tijk_{Vh} \quad (38)$$

numberofdatapoints,andD^{Ac}andD^{Pr}representtheactual

$$\text{TravelDistance} = \sum_{i} TD_i \quad (39)$$

i $ii=1$

andpredicteddatafordatapoint*i*,respectively:

$$MSE = \frac{1}{2} \sum_{m} D^{Ac} - D^{Pr} \quad (32)$$

By carefully optimizing these green parameters, we aim to balance traffic efficiency with environmental sustainability.

m i i

i=1

XGBoost enhances predictive power by building the model incrementally with decision trees, minimizing the loss function.Themodelconsistsofasetofbaselearners(decision trees)denoted asBL=$\{BL$,BL,...,$BL$$\}$,which output predictions as stated in Eq. (33), where, dt is the number of decision trees:

$$O = \sum_{z=1}^{dt} BL_z(Fi) Ai \in \{1,2,...,s\} \quad (33)$$

During each iteration, the algorithm attempts to minimize theobjectivefunction,whichiscomposedoftwoterms: a loss term, which measures the prediction error, and a regularization term, which penalizes the complexity of the model.Thelossterm,denotedby$L$ inEq.(34),quantifies the difference between the actual and predicted values, while

IV. OPERATIONAL DESIGN AND COMPLEXITY

TheIM-VRMmodel,asoutlinedinAlgorithm1,uti-lizes three primary knowledge databases: Live City Traffic (*kd-LCT*), Vehicle Routes Connecting City (*kd-VRCC*), and HistoricalTrafficDataRepository(*kd-HTDR*).Customersgen-eratemulti-depotdeliveryriderequestsineachtimeinterval t,t+Δt (Step 1), which triggers the system to create travel routegraphs(TRGs)foreachrequest(Step2).EachTRG undergoes optimization via a Greedy Search algorithm that generatesarewardscorebasedontraveltimeandcost (Step 3). The system then predicts congestion on the travel routeusingtheXGBoost-basedTrafficCongestionForecasting Model (Step 4). If no congestion is detected (Step 5), green parameters such as vehicle fuel consumption (FC_{Vhu}), carbon emissions($C\ O_2V\ h^u$),traveltime($T\ i\ jk^{Vhu}$),anddistance (TD^{Vhu})arecalculated,andDijkstra'salgorithmisapplied to select the most admissible route based on these green constraints (Step 6). If congestion is predicted for a route(Step 7), the system re-schedules the route and generates an alternative path to continue the process. Thus, the IM-VRM modelensuresoptimizedandenvironmentallyefficientvehicle routing in dynamic traffic conditions.

Algorithm1IM-VRM:OperationalSummary

Input: Three knowledge databases: *Live City Traffic* (kd-LCT),*VehicleRoutesConnectingCity*(kd-VRCC), and *Historical Traffic Data Repository* (kd-HTDR);
for*eachtime-interval*$\{t, t+\Delta t\}$**do**
  Step1:Customersgeneratemulti-depotdelivery riderequests$\{R_1, R_2, \ldots, R_n\}$;
  for*eachride*$\{R_1, R_2, \ldots, R_n\}$**do**
    Step2:Generatetravelroutegraphs(TRGs) $\{G_1^{Ri}, G_2^{Ri}, \ldots G_z^{Ri} | i \in [1, \ldots,]n\}$,wherenodes representmintended,depot,sites;
    for*each*$TRG\{G_1, G_2, \ldots, G_z\}$**do**
      Step3:UsetheGreedySearchalgorithmto optimize and generate the 'reward score' iteratively,consideringtraveltimeandcost for each route;
      Step 4: CALL XGBoost algorithm-based Traffic Congestion (④) Forecasting Model (TCFMu)toforecasttravelroutecongestion status④$^{status}_{tt_{i-j}^{Ri}}$fortherespectivenode;
      if④$^{status}_{tt_{i-j}^{Ri}}$ ==*FALSE***then**
        Step5:Computethecostofg*reen parameters*:FC_{Vhu}, CO_{2Vhu}, T_{ijkVhu}, andTD_{Vhu}usingEqs.(36-38)and Eq.(39),respectively;
        Step6:ApplyDijkstra'salgorithmto selectthemostadmissibletravelroute constrainedbygreenparameters;
      else
        Step7:Re-scheduletheTRGwithan alternativerouteandcontinue;

Time complexity: The time complexity of the IM-VRM modeliscomposedofseveralkeycomponents.First,in Line 2, the model iterates over Δt time intervals, contribut-ing a complexity of $O(\Delta t)$. In *Step 1*, generating multi-depot ride requests has a constant time complexity of $O(1)$. Then,in Step 2, processing n rides results in a complexity of $O(n)$. For processing TRGs, Step 3 involves Greedy optimization, whichhasaconstantcomplexityof$O(1)$.Step4applies theXGBoost-basedTrafficCongestionForecastingModel (TCFMu),contributingacomplexityof$O(t^{\dagger} . d^{\dagger})$,where$t^{\dagger}$ and$d^{\dagger}$arethenumberoftreesandtheirdepth,respectively.

The complexity for processing the travel route graphs (TRGs) usingGNNis$O(Z . (N+E))$,where$Z$isthenumberof layers,Nisthenumberofnodes,and$E$isthenumberof edges.Step5,whichcalculatesgreenparameters,andStep7 re-schedulingtheTRGs,bothhaveconstantcomplexityof $O(1)$.Step6,whereDijkstra'salgorithmisappliedforroute selection, contributes a complexity of$O((N+E) . \log N)$. Combiningallthesefactors,theoveralltimecomplexityofthe IM-VRMmodelisexpressedas:$O(\Delta t . n . t^{\dagger} . d^{\dagger} + Z . (N+E) + (N+E) \log N)$. This demonstrates the scalability and efficiency of the model for real-time, large-scale operations

V. PERFORMANCE EVALUATION

A. ExperimentalSetup

The experimental work is carried out on a server machine comprising two Intel® Xeon® Silver 4114 CPU with a 40 core processor and having 2.20 GHz clock speed. The simulation machinerunonUbuntu16.04,an64-bitLTSoperatingsystem comprising 128 GB of main memory. Enactment of the pro-posed work is carried out using Python 3.9 over an extended version of the T-Drive trajectory dataset [28].

B. Implementation

Thedesignandoperationalflowoftheproposedmodel is implemented and evaluated in three consecutive steps as depicted inFig.2.Inessence,theIM-VRMmodelistheresult of collaborative work among different modules as follows:

- *ride initialization()*: The users generate requests formulti-depot rides i.e. crowd deliveries. These rides canbe initialized for different vehicles categorized into three types heavy, middle, and lightweight.
- *constraints*:Constraintsplayacrucialroleinshaping the effectiveness of the IM-VRM model. Each ride is subject to specific constraints, such as ensuring depots aren't repeated, the origin and destination are distinct,and rerouting in case of congestion, among others.
- *initial route selection()*: GNN employing a greedy opti-mizationapproachisdeployed togenerateaninitialroute for a ride. These routes are further processed for coun-tering traffic congestion and green parameters. Table IIshowcases the parameter value utilized for the model in this step.
- *trafficcongestionprediction()*:Thesystempredictspoten-tial traffic congestion on the initially chosen route by using a combination of live and historical data stored in itsknowledge base.Table IIdepicts the parameter details utilizedforthemodeltrainingatthisstep.
- *Time complexity*: The time complexity of the IM-VRM modeliscomposedofseveralkeycomponents.First,in Line 2, the model iterates over Δt time intervals, contribut-ing a complexity of $O(\Delta t)$. In *Step 1*, generating multi-depot ride requests has a constant time complexity of $O(1)$. Then,in Step 2, processing n rides results in a complexity of $O(n)$. For processing TRGs, Step 3 involves Greedy optimization, whichhasaconstantcomplexityof$O(1)$.Step4applies theXGBoost-basedTrafficCongestionForecastingModel (TCFMu),contributingacomplexityof$O(t^{\dagger} . d^{\dagger})$,where$t^{\dagger}$ and$d^{\dagger}$arethenumberoftreesandtheirdepth,respectively.

The complexity for processing the travel route graphs (TRGs) usingGNNis$O(Z.(N+E))$,where$Z$isthenumberof layers,Nisthenumberofnodes,and$E$isthenumberof edges.Step5,whichcalculatesgreenparameters,andStep7,

- *knowledge database*: A data repository comprising live traffic details captured from Global Positioning System (GPS) and historical details from different data reposi-tories. Data accumulation is an ongoing and continuous process to capture data for further analysis.
- kd-LCT:aknowledgedatabaseforLiveCityTraffic
- kd-VRCC:aknowledge databaseforVehicleRoutes Connecting City
- kd-HTDR:aknowledgedatabaseforHistoricalTraf-fic
- *greenparameters()*:Majorgreenparametersforthe IM-VRM model include minimizing carbon emissions, reducing fuel consumption, lowering fuel costs, optimiz-ing route distances, and minimizing travel time.

TABLEIIIDATASET DESCRIPTION

Van-passenger	1000
Mini-compact	1253
Truck-small	2235

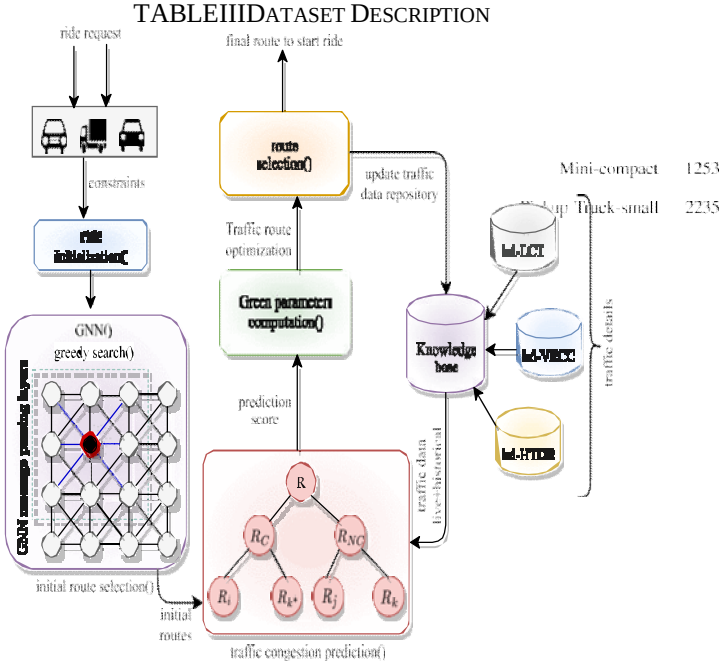


Fig.2.ImplementationworkflowforIM-VRMmodel.

TABLEIIEXPERIMENTALPARAMETERS

GNN parameters setup for initial route selection			
Parameter	**Value**	**Parameter**	**Value**
Learning rate	3e-4	Entropy value	0.01
Hidden node dimension	128	Eps clip	0.2
Hidden edge dimension	16	Time step	1
Epoch	100	ppo epoch	3
Batch size	512	Data size	512000
Convolution layers	4	Validation size	10000
XGBoost parameters setup for traffic congestion prediction			
Parameter	**Value**	**Parameter**	**Value**
Base score	0.05	Learning rate	0.5
Booster	gbtree	Max delta step	0
Colsample_bylevel	1	Max depth	5
Colsample_bynode	1	Min child weight	1
Colsample_bytree	1	n_estimators	1200
Gamma	0	objective	multi:softprob
Seed	5	Verbosity	1

- *optimalrouteselection()*:UtilizingtheDijkstraalgorithm, an optimal ride is planned by considering relevant green parameters and congestion prediction value.

C. Dataset

The performance of the proposed model is evaluated using an extended T-Drive trajectory dataset of Beijing city which contains a one-week trajectories of 10,357 taxis. The dataset consistsofapproximately15milliondatapointsandcov-ers trajectories spanning a total distance of about 9 million kilometers[28].Fortheextendeddataset,thereareover40,000 training samples. Each sample includes ten features for each vehicle, such as longitude, latitude, timestamp, vehicle type, manufacturer, model, vehicle class, engine size, fuel type, cylinders, and transmission. Some features, such as distance, speed and time to travel, are derived from the above attributes to assess traffic congestion for route optimization based on green parameters. The traffic conditions are categorized as: 'no-traffic,''mild-traffic,'and'heavy-traffic.'Thedetailsofthe range of parameters for the extended dataset and information on vehicle categories and their respective fuel types are given in Table III.

TABLEIIIDATASET DESCRIPTION

Features description			
Feature	**Range**	**Feature**	**Range**
Speed	0 to 89.104 km/h	Date	02-02-2008 to 08-08-2008
Distance	0 to 29.14 km	Time	13:33:02 to 17:39:15
Time	0 to 1.54 hour	Longitude	115.0736 to 117.43605
CO_2 Emission	0 to 8.090 kg	Lattitude	38.81899 to 42.35342
Fuel Consumption	0 to 4.268 litre		

Vehicle types description			
Vehicle	**Name**	**# Instances**	**# VFT**
Heavy (16224)	Pickup Truck-standard	15224	E = 0 D = 3003 X = 13324 C = 0
	Van-cargo	1000	
	Van-passenger	1000	
Middle (4488)	Mini-compact	1253	E = 1005 D = 0 X = 2230 C = 1253
	Pickup Truck-small	2235	
Light (22550)	SUV-small	15802	E = 1005 D = 3451 X = 17107 C = 1992
	SUV-standard	6748	

E: Electric, D: Diesel, X: Petrol, C: CNG, # VFT: Number of vehicles of specific fuel types

D. PerformanceParameterAnalysis

*1) InitialTravelRouteSelection:*TableIVpresentstheout-comes generated by employing a Greedy approach optimized GNN for the initial route selection in crowd delivery rides.The primary goal of this approach is to choose a route withthe minimum travel distance while ensuring the successful delivery of parcels to their intended destination depots.

Notably, as the learning process unfolds across multiple epochs, the average travel distance progressively diminishes. This trend signifies the efficacy of the appliedGNN optimiza-tion technique. Our experiments spanned a range of epochs, from 10 to 100, with the most favorable results emergingafter thirty epochs, as depicted in Table IV. These results encompass comprehensive insights into the rewards and loss pointsobservedduringsuccessivebatchesoverthecourse ofthethirty-epochlearningperiod.Therewardsfallwithin the [2.9-3.9] range, while the loss points range from [—0.01-3.6].AnintriguingobservationisthedecliningP-valueover batcheswithinconsecutiveepochs.Thistrendsuggeststhatthe outcomes obtained are not mere chance occurrences; rather, they indicate a statistically significant relationship or effect within the experimental data.

The experiments encompassed a diverse set of multi-depot delivery rides. However, due to space constraints, in Fig. 3,we present the initially selected routes resulting from GNN optimization for a subset of nine multi-depot delivery rides.To clarify the graph's content, the X-axis and Y-axis rep-resent the scaled latitudinal and longitudinal coordinates ofthe respective depots in each ride. In these graphical rep-resentations,theredbolddotservesasthestartingpoint for the multi-depot ride, while the green dots symbolize multiple delivery depots or drop-off points. In this particular visualization, we focus on rides with precisely eight delivery depots. These routes represent the outcomes of a greedy optimization approach aimed at minimizing travel distance using GNN. Notably, these optimizations do not take into account additional constraints such as traffic congestion, car-bonemissions,fuelconsumption,andotherenvironmentally

TABLEIV
INITIALTRAVELROUTEOPTIMIZATIONFORARANDOMMULTI-DEPOTRIDE

Epoch	Batch	Reward	Loss	Execution Time	P-value	Avg. Distance
Epoch 0	1/100	4.7740	-8.6047	1.4016	0.0	-
	51/100	3.2444	-5.3351	1.2512		
	99/100	3.2360	-1.3253	1.2285		
Epoch 1	1/100	3.1970	-0.5888	1.2480	4.0017	-
	51/100	3.0930	-0.1101	1.2581		
	99/100	3.1210	-0.1692	1.2369		
Epoch 2	1/100	3.1060	-0.3881	1.2463	7.6766	3.0409
	51/100	3.0650	-0.3148	1.2355		
	99/100	3.0700	-0.1318	1.2459		
Epoch 3	1/100	3.0500	-0.1648	1.2699	5.8369	3.0214
	51/100	3.0340	-0.2091	1.2367		
	99/100	3.0410	-0.0789	1.2539		
Epoch 4	1/100	3.0390	-0.1130	1.2652	3.8271	3.0046
	51/100	3.0070	-0.1192	1.2389		
	99/100	3.0430	-0.1230	1.2312		
Epoch 5	1/100	3.0370	-0.3522	1.2358	0.0001	2.9951
	51/100	2.9970	-0.1253	1.2319		
	99/100	3.0270	-0.06590	1.2438		
Epoch 6	1/100	3.0170	-0.1943	1.2345	7.0902	2.9951
	51/100	2.9760	-0.1055	1.2336		
	99/100	3.0170	-0.1231	1.2362		
Epoch 7	1/100	3.0070	-0.1557	1.4053	0.1070	2.9798
	51/100	2.9710	-0.1306	1.2923		
	99/100	3.0100	-0.1445	1.2626		
Epoch 8	1/100	2.9980	-0.19777	1.2943	1.3652	2.9660
	51/100	2.9610	-0.08730	1.2593		
	99/100	3.0030	-0.11240	1.2899		
Epoch 9	1/100	2.9810	-0.1854	1.2920	0.0221	2.9599
	51/100	2.9580	-0.1392	1.2896		
	99/100	2.9830	-0.0717	1.2995		
Epoch 10	1/100	2.9590	-0.1264	1.3008	4.7907	2.9469
	51/100	2.9520	-0.1687	1.2701		
	99/100	2.9830	-0.1914	1.2723		
Epoch 11	1/100	2.9570	-0.0898	1.3094	0.1379	2.9442
	51/100	2.9480	-0.1569	1.3344		
	99/100	2.969	-0.0862	1.3290		
Epoch 12	1/100	2.9510	-0.0910	1.3215	3.9143	2.9369
	51/100	2.9360	-0.0899	1.2779		
	99/100	2.9650	-0.1096	1.2837		
Epoch 13	1/100	2.9520	-0.1596	1.4045	0.0006	2.9310
	51/100	2.9240	-0.0840	1.3307		
	99/100	2.9560	-0.0803	1.4764		
Epoch 14	1/100	2.933	-0.0974	1.3844		2.9332
	51/100	2.9250	-0.0888	1.3686		
	99/100	2.9640	-0.1192	1.2796		
Epoch 15	1/100	2.941	-0.1226	1.3428	-	2.9335
	51/100	2.932	-0.2217	1.3089		
	99/100	2.9720	-0.1685	1.2777		
Epoch 16	1/100	2.943	-0.1094	1.3221	0.0724	2.9283
	51/100	2.932	-0.1764	1.3693		
	99/100	2.9410	-0.0934	1.4555		
Epoch 17	1/100	2.9370	-0.0788	1.3852	0.0069	2.9269
	51/100	2.9320	-0.1764	1.3693		
	99/100	2.9520	-0.0882	1.3502		
Epoch 18	1/100	2.941	-0.2044	1.2928	0.0722	2.9249
	51/100	2.9170	-0.0648	1.2916		
	99/100	2.9470	-0.0872	1.3683		
Epoch 19	1/100	2.9310	-0.1024	1.4664	0.0115	2.9233
	51/100	2.9190	-0.0848	1.2947		
	99/100	2.9440	-0.0773	1.3575		
Epoch 20	1/100	2.9380	-0.1572	1.4329	-	2.9236
	51/100	2.9090	-0.0498	1.3352		
	99/100	2.9490	-0.1532	1.3035		
Epoch 21	1/100	2.9270	-0.0825	1.3245	-	2.9236
	51/100	2.9210	-0.0995	1.3177		
	99/100	2.9450	-0.0593	1.3452		
Epoch 22	1/100	2.9240	-0.0733	1.3348	0.0583	2.9209
	51/100	2.9180	-0.0968	1.3109		
	99/100	2.9440	-0.0644	1.2873		
Epoch 23	1/100	2.9230	-0.0800	1.3463	0.1092	2.9217
	51/100	2.9090	-0.0582	1.2970		
	99/100	2.9430	-0.0472	1.3279		
Epoch 24	1/100	2.9210	-0.0719	1.3253	0.0971	2.9213
	51/100	2.9080	-0.0461	1.3422		
	99/100	2.9460	-0.0579	1.3290		
Epoch 25	1/100	2.9240	-0.0776	1.3270	-	2.9204
	51/100	2.9080	-0.0521	1.3967		
	99/100	2.9370	-0.0278	1.2845		
Epoch 26	1/100	2.9150	-0.0547	1.3551	-	2.9205
	51/100	2.910	-0.0731	1.2873		
	99/100	2.940	-0.0606	1.2845		
Epoch 27	1/100	2.9130	-0.0352	1.2582	0.1123	2.9188
	51/100	2.911	-0.1023	1.3313		
	99/100	2.932	-0.0382	1.2416		
Epoch 28	1/100	2.9160	-0.0499	1.2767	0.2900	2.9197
	51/100	2.9100	-0.0773	1.2439		
	99/100	2.9450	-0.1026	1.2824		
Epoch 29	1/100	2.9210	-0.0772	1.3133	0.2099	2.9193
	51/100	2.9100	-0.0664	1.2797		
	99/100	2.9350	-0.0568	1.3013		

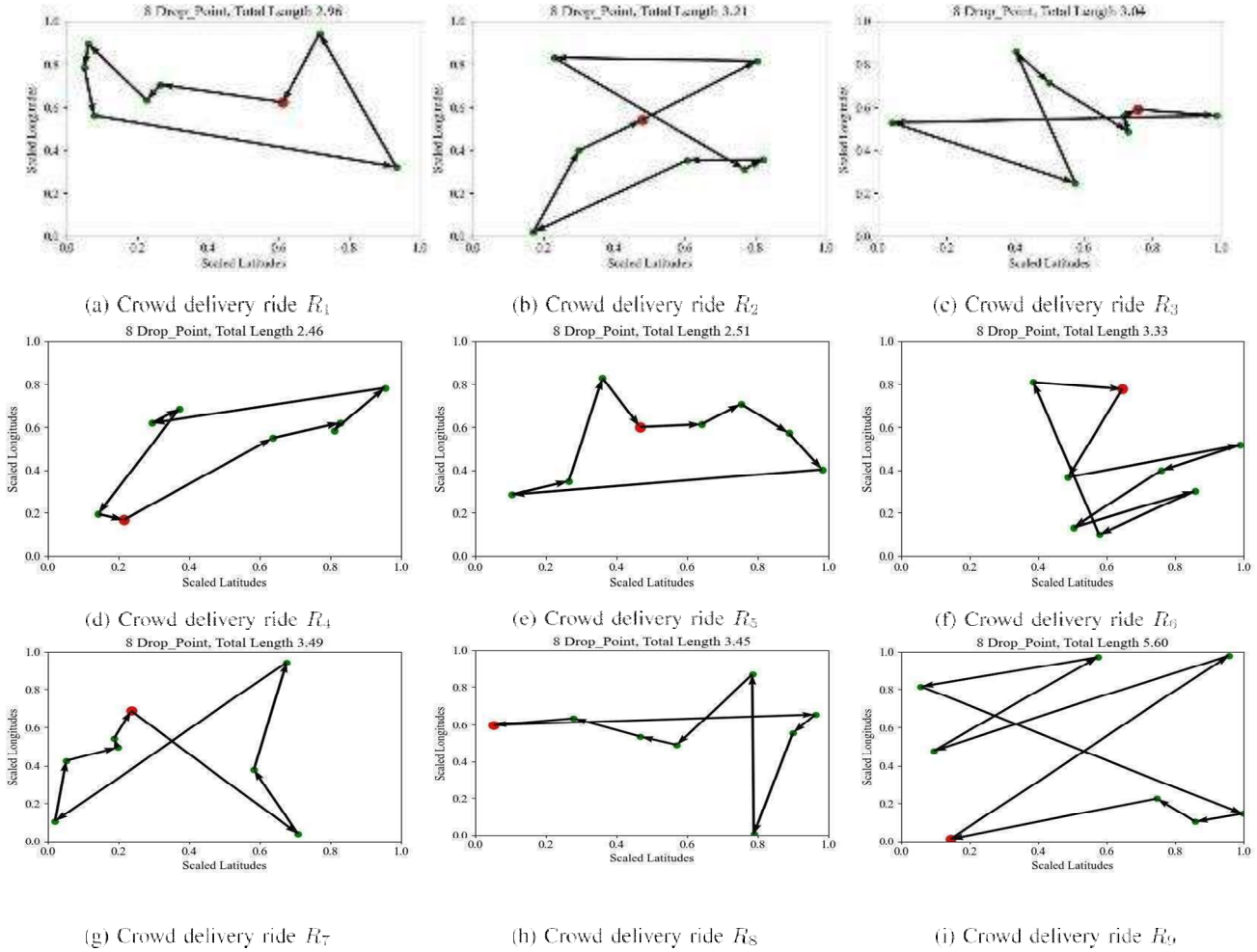
consciousparameters.Thetotaltraveldistanceachievedduring the initial route optimization is prominently displayed at the topofeachgraph,providingaclearreferencefortheefficiency of the selected routes in these multi-depot rides. Further, the outcomeoftravelroutesoptimizationconsideringallthegreen parameters constraints are presented in subsequent sections.

2) Traffic Congestion Prediction: The experimental results pertaining to the accuracy of traffic congestion prediction for a range of multi-depot rides exhibit a gradual variation across different learning rates, falling within the intervals of [0.01-0.28]and[0.10-0.98].Thesevariationsarevisuallyrepresented in Fig. 4(a)and Fig. 4(b), respectively. In Fig. 4(a), it is observedthataccuracyscores fortrafficcongestionpredic-tion as they change with different learning rates within the rangeof[0.01-0.28].Fig.4(b)presentsasimilardepiction but focuses on the range [0.10-0.98]. Notably, the average accuracy score for predicting traffic congestion in various multi-depot rides reaches an impressive level of up to 92.5%acrossthisspectrumoflearningrates.Theexperimentalresults highlight a key observation: the deviation in prediction accu-racy performance during both training and testing sessions is inimized when learning rates are within the range of [0.10-0.98]. In contrast, when learning rates fall within the range [0.01-0.28], the accuracy scores exhibit greater fluctuations.

This finding reflects the enhanced efficiency and robustnessof accurate traffic prediction in scenarios where learning rates are set within the range of [0.10-0.98].

Moreover, Fig. 5illustrates the accuracy scores obtainedfor a systematic range of minimum child weight values, ranging from 0.0 to 4.0, with increments of 0.5. These evaluations were conducted within the learning rate range of [0.10-0.98]. The purpose of these graphs is to showcase the consistent performance exhibited during both the training and testing phases of our proposed traffic congestion prediction approach, which leverages the XGBoost algorithm. In Fig. 6,a comprehensive summary of the average results is provided.Itincludespredictionaccuracy,precision,recall,andF1score, all achieved within the context of the learning rate falling within the [0.10-0.98] range. Impressively, the accuracy score reaches a peak of 92.5%, while precision, recall, and F1 score valuesreachashighas0.93.Thisdetailedanalysisemphasizes the robust and dependable performance of traffic congestion prediction across varying minimum child weight values and highlights the significant predictive capabilities of XGBoost algorithm within the specified range of learning rate.

3) Optimal Travel Route Constrained With Green Param-eters: In Fig. 7, the attained optimal delivery routes for a variety of multi-depot rides are presented in both zoomed-in and zoomed-out view. These routes are the result of a com-prehensive optimization process that involves the utilizationof GNN optimization, traffic congestion prediction, and the application of theDijkstra algorithm tooptimize greenparam-eters. These green parameters include factors such as optimal fuel consumption, minimal carbon emissions, and the least time required for delivery. The routes depicted in the figure represent the most recommended and viable routes for each multi-depot ride. They take into account real-time traffic con-gestion conditions and are meticulously designed to achievean optimal balance between fuel efficiency, environmental considerations (carbon emissions), and the *efficient* use of time. Fig. 8and Fig. 9provide a detailed illustration of the performanceofthepproposedmodel.Thesefiguresdepict the computation of critical green parameters, including fuel consumption, carbon emissions, and distance traveled, under twodistinctscenarios:oneinthepresenceoftrafficcongestion

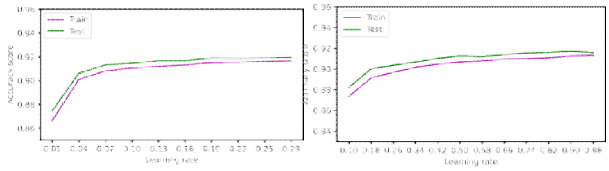


(a) Crowd delivery ride R_1 (b) Crowd delivery ride R_2 (c) Crowd delivery ride R_3

(d) Crowd delivery ride R_4 (e) Crowd delivery ride R_5 (f) Crowd delivery ride R_6

(g) Crowd delivery ride R_7 (h) Crowd delivery ride R_8 (i) Crowd delivery ride R_9

Fig.3.GNN-optimizedinitialtravelrouteselection.



(a) Learning rate [0.01-0.28] (b) Learning rate [0.10-0.98]

Fig.4.Trafficcongestionpredictionaccuracy

(Fig.8) and the other in the absence of traffic congestion(Fig.9).Whenconfrontedwithtrafficcongestion,theanalysis reveals that a total distance of 4.8 kilometers is covered. During this journey, fuel consumption rates exhibit variabil-ity, ranging from [0.5-1] liters per kilometer, while carbon emission rates span the spectrum of [0.4-1.6] kilograms.These figures meticulously capture the intricate interplay of these factors, showcasing their impact on the efficiency and environmental footprint of the transportation process. This reflects the versatility and adaptability of IM-VRM model whendealingwithchallengingtrafficconditions.Incon-trast, under ideal conditions, when traffic congestion isabsent, the distance traveled extends to 12 kilometers. Thefuel consumption rate in this scenario fluctuates between [0.75-2.5] liters per kilometer, while carbon emissions spantherangeof[2-4.5]kilograms.Thesefindingsemphasize the significant adjustments in distance, fuel consumption, and carbon emissions that can be achieved when operating in favorable, congestion-free circumstances, further illustrating the capabilities of our IM-VRM model in optimizing various aspects of transportation efficiency.

Fig. 10presents a comparative analysis of green parameter values using two different methods: one with the proposed approachandtheotherwithoutit.Thisanalysispertainsto a specific journey taken by a middle-type Van passenger, encompassing five depots.

The results of this experimental case study demonstrate the noteworthy advantages of our proposed vehicle traffic man-agementsystem.Byincorporatingthissystem,weobserved a substantial reduction in various key metrics, namely, the distance traveled, travel time, carbon emissions, and fuel consumptionforeachdepotorhopalongtheroute.This, inturn,contributestoanoverallenhancementofgreenparam-eters,assummarizedinTableV.Thepivotalreasonfor such significant improvements in multi-depot vehicle traffic management lies in the system's ability to accurately predict and subsequently mitigate traffic congestion. This is achieved byselectingcongestion-freeroutesafterthetravelroute GNN optimization and employing the Dijkstra algorithm to find multiple optimal routes that adhere to green parameter constraints.

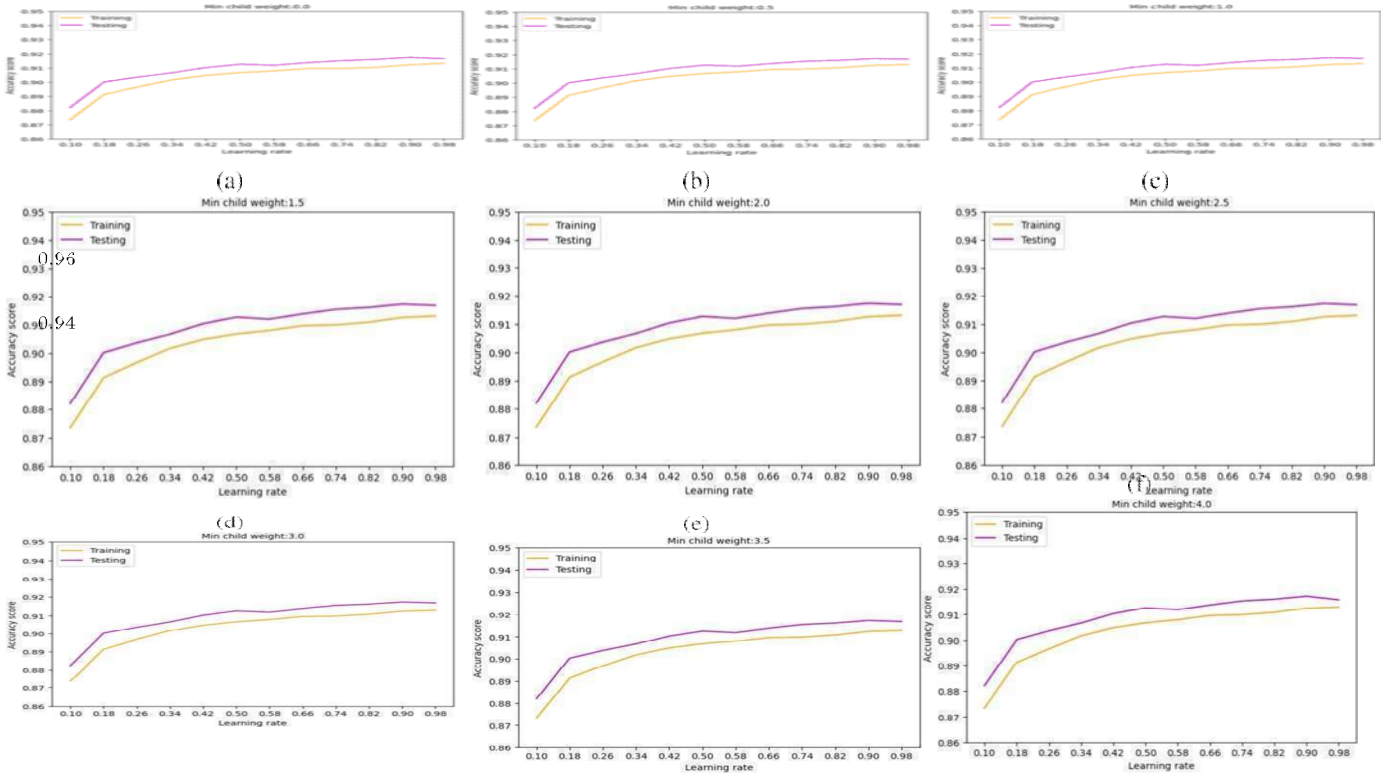


Fig.5.Trafficpredictionaccuracyovervaryingminchildweightintherange[0.0-0.4].

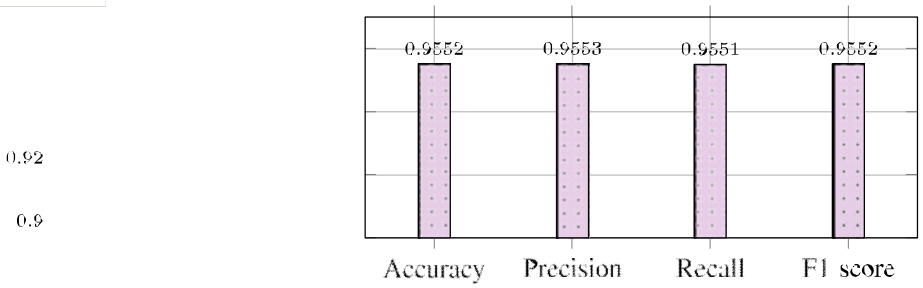


Fig.6.Trafficcongestionpredictionperformanceparameters.

TABLEV
OVERALLPERFORMANCEANALYSISOFGREENPARAMETERS

Parameter	IM-VRM	Without IM-VRM
Distance (km)	31.9	39.3
Time (minutes)	59	90
Fuel Consumption (litre)	5.2635	6.4845
CO_2 Emission (kg)	12.1	14.94

E. Comparison

Table VIpresents a comparative analysis of the proposed IM-VRM model against state-of-the-art (SoTA) approaches, including *Periodic Traffic Data Convolution-based deep Neu-ralNetworkmodeling*(PCNN)[14],*LongShort-TermMemory*

TABLEVICOMPARISONWITHSOTA

Models	Approach Analysis		Loss	
	Method	Dataset		
PCNN [14]	Deep Convolution Network	Vehicle Passage Records	30.71	0.557
LSTM [15]		Traffic data from Cal-trans PeMS in Oak-land	46.73	0.601
GNN [29]		Traffic data form Bei-jing and Hangzhou city	32.71	0.302
IM-VRM	XGBoost, GNN	T-Drive trajectory dataset of Beijing city [28]	12.92	0.187

Metrics
RMSE

Network (LSTM) [15], and GNN [29]. IM-VRM, leveraging XGBoostandGNNontheT-Drivedataset,achievesthe best results with the lowest Loss (12.92) and RMSE (0.187), demonstrating its superior accuracy and predictive capability. This improvement stems from the effective integration of graph-based learning and optimized gradient boosting, which efficientlycapturespatial-temporaltrafficdynamics.IM-VRM achievesarobustbalancebetweenefficiencyandprecision

(a) Scaled route R1 (zoomed out) (b) Travel route R1 (zoomed in) (c) Scaled route R2 (zoomed out) (d) Travel route R2 (zoomed in)

Fig.7.Optimalrouteformulti-depotrides:R1andR2.

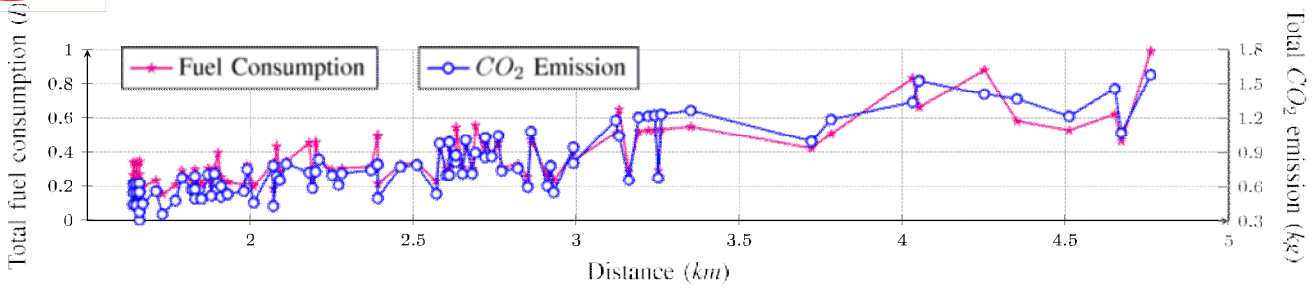


Fig.8.Evaluatedgreenparametersinpresenceoftrafficcongestion.

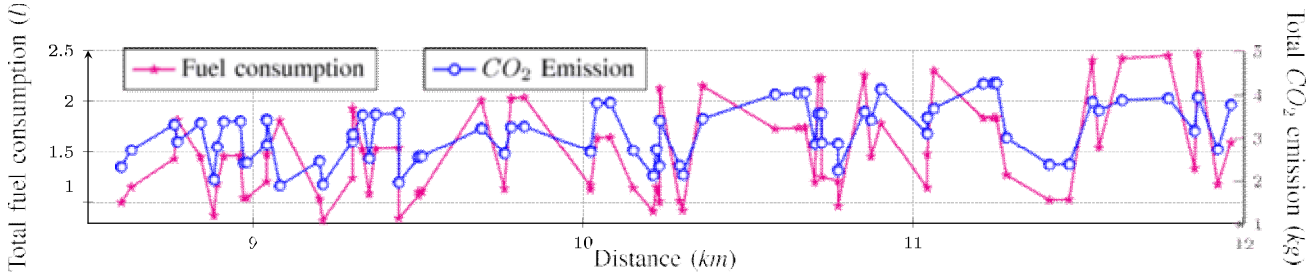


Fig.9.Evaluatedgreenparametersinabsenceoftrafficcongestion.

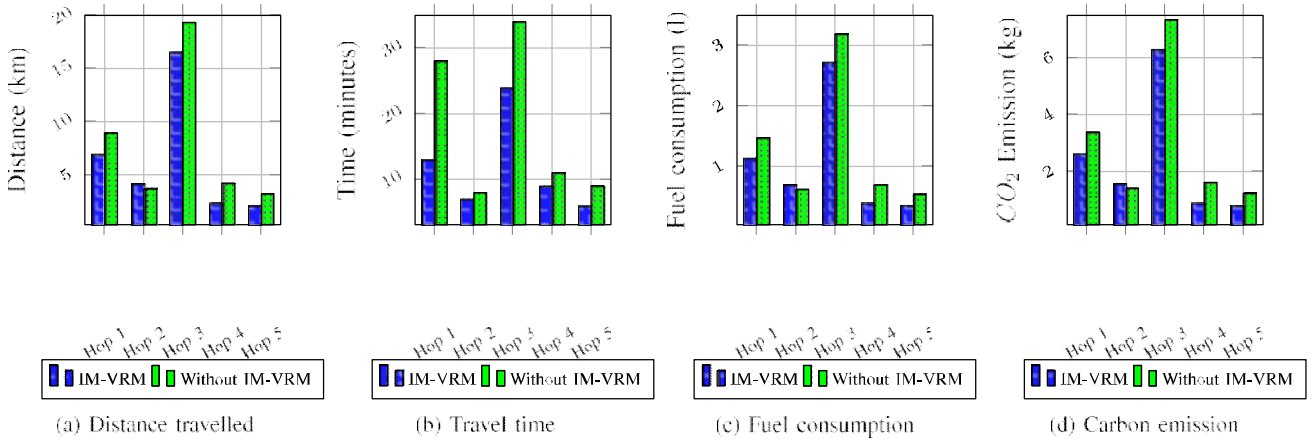


Fig.10.Greenparametersanalysis.

whileoptimizinggreenparameterswithoutcompromisingits enhanced performance.

F. OverallPerformanceAnalysisofIM-VRM

The proposed IM-VRM model exhibits exceptional perfor-manceinoptimizingmulti-depotdeliveryroutesbyeffectively integrating GNN-based route selection, traffic congestion prediction, and green parameter constraints. Through exper-imental evaluation, IM-VRM achieves substantial reductions in travel distance, carbon emissions, and fuel consumption across diverse scenarios, whether in the presence or absenceoftrafficcongestion.Themodelexcelsinpredictingand mitigatingcongestionusing accuratetrafficpredictions ,asevi-dencedbyanimpressive92.5%predictionaccuracyatoptimal learning rates [0.10-0.98]. When benchmarked against state-of-the-art methods, including PCNN, LSTM, and GNN-based approaches, IM-VRM consistently outperforms by delivering superior accuracy, evidenced by the lowest loss (12.92) and RMSE (0.187) on the T-Drive dataset. Moreover, its com-putational efficiency, achieved via graph-based learning and XGBoost, reflects its robustness in capturing spatial-temporal traffic dynamics. These findings affirm IM-VRM's capability to optimize transportation efficiency while promoting sustain-ability.

VI. CONCLUSION

This paper proposes an innovative and comprehensive approach to tackle the challenging problem of crowd delivery vehicle routing and traffic management problem. By combin-ing GNN with greedy optimization for initial route selection and incorporating traffic congestion prediction with green parametercomputationtooptimi zerouteguidanceusing theDijkstraalgorithm, weprovidean efficientand effec-tive solution.

This approach simplifies the multi-depot traffic route guidance and management problem compared to pre-viousstate-of-the-artmethods.Futureresearchwillfocus on real-time weather conditions with real-time traffic data integration and user-focused priorities to enhance practical implementation. Additionally, we will explore the scalability of the proposed approach for larger and more complex traffic networks while providing valuable insights into addressing evolving challenges in crowd delivery vehicle routing and traffic management.

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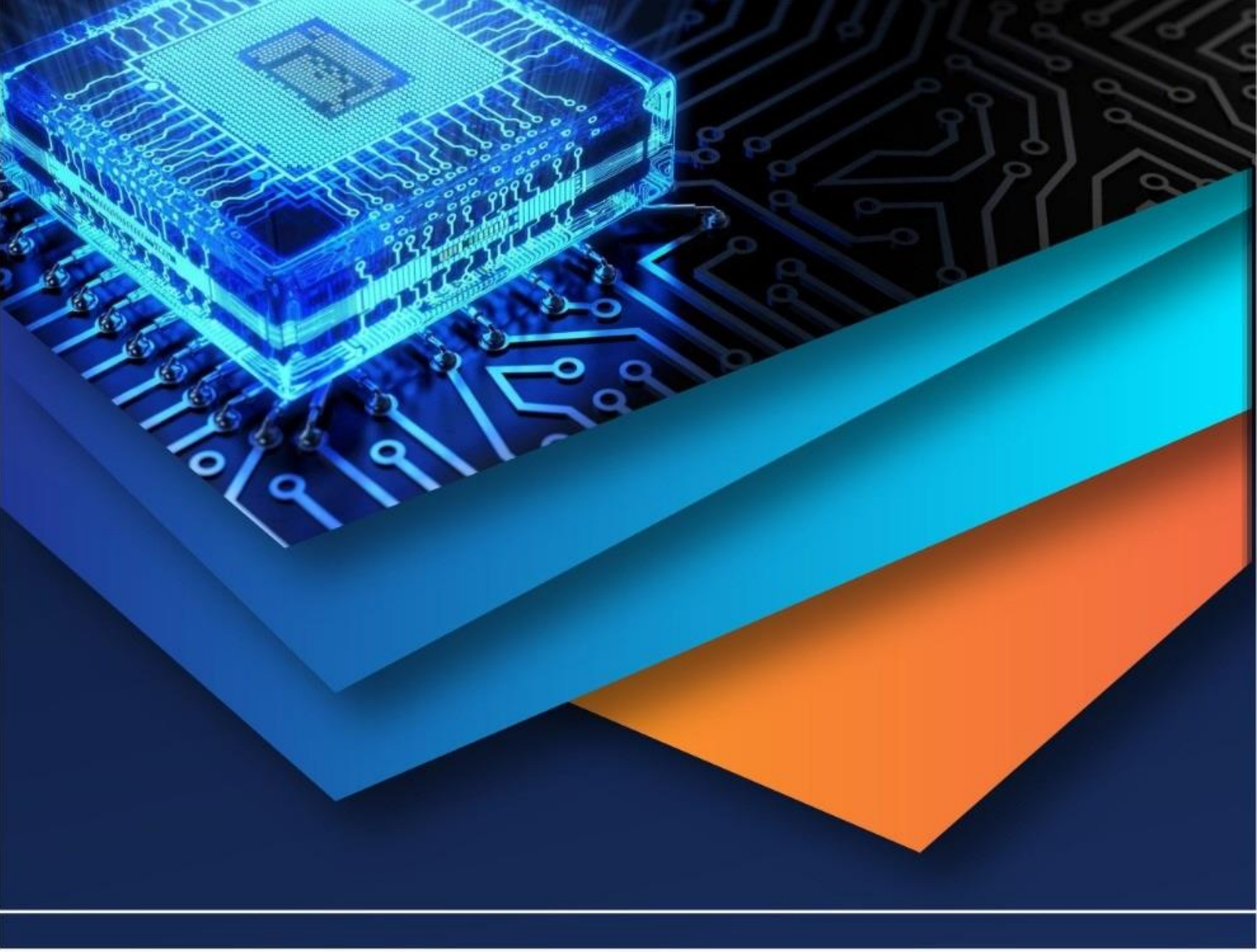

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