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Impacts of Non-Recurrent Events on Pheromone-Based Green Transportation System

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ABSTRACT Green transportation has become a key research focus in recent years. As the evaluation of non-recurrent event is still in the infancy stage, the practicality of using existing pheromone-based system for green transportation is still an open question. To fill this gap, the impacts of non-recurrent events are assessed, when using the proposed Pheromone-based Green Transportation System (PGTS) under some practical scenarios such as accidental situation, heavy rain and their combination. First, accidental situation is evaluated by halting a vehicle on a target road with maximum allowable speed of 10 km/h. Second, heavy rain is modelled by reducing the maximum speed of the affected area by 20 km/h. Third, the performance of PGTS is also gauged based on the impacts from accidental situation and heavy rain. Based on Singapore traffic data, experimental results show that the proposed PGTS achieves competitive performance against all non-recurrent events.

INDEX TERMS Green transportation, multi-agent, non-recurrent events, pheromone.

I. ACRONYMS

The acronyms adopted in this manuscript are given in TABLE 1 as shown in the next page.

II. INTRODUCTION

The application of swarm intelligence in transportation has been increasingly gaining attention in recent years. The notion of pheromone has been adopted to perform short-term traffic forecasting [1], [2] to predict the occurrence of congestion. These forecasting models serve as the integral part to enhance the efficiency of vehicle rerouting and traffic light control strategies [2].

MAS has been applied in various areas including cooperative control of unmanned aerial vehicles, control of robots, and sensor network communication [3]. The problem of consensus of MAS which consists of a set of identical MIMO LTI systems under a time-varying network has been studied in [3]. A further leap is taken to address the admissible output consensus design problems for high-order LTI singular MAS with constant time delays in [4]. Meanwhile, there are several studies that adopt MAS in vehicle rerouting strategies [5]–[11]. Specifically, Multi-Agent-based ant-systems have also been developed to reduce traffic congestion [7], and transport emission [8]. While considering the impact of an accident, the effect of congestion due to rainy conditions is not well explored. In [10], a pheromone-based green vehicle routing strategy that adopts MAS has been proposed to probabilistically distribute vehicles to routes with multiple green signalized intersections to promote green transportation. To promote practicality, the impacts of non-recurrent events should be investigated in future.

As another MAS, Next Road Rerouting [11] is proposed to mitigate congestion under en-route events. Despite a substantial reduction in travel time, the impacts of green transportation due to congestion is still an open question. Travel-time pheromone is developed in [6] to reduce congestion, after improving the existing pheromone-based vehicle routing system in [5]. Similarly, the enhanced system only considers traffic behaviors under normal traffic conditions.

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TABLE 1. Definitions of acronyms.

Acronyms	Definitions
$\#Rd_{Con}$	number of congested roads
$\#Rd_{ConThereshold}$	product of $\%Rd_{Con}$ and $\#TotalRd$
$\#TotalRd$	total number of roads in the vehicular system
$\%Rd_{Con}$	percentage of congested roads in a vehicular system
P_q^j	probability of vehicle j on path q
b	bias of dual formulation
BCa	Bias Corrected accelerated bootstrap confidence interval
CGVR	Cooperative Green Vehicle Routing
CI	Confidence Interval
CTLC	Coordinated Traffic Light Control
d	number of dynamic shortest path
dkSP	dynamic k-shortest path
f_i	fuel consumption model of HBEFA3 in SUMO
H	road network
HDV	average Heavy Duty Vehicle
IA	Intersection Agent
j	the current number of intentional vehicle
K	Radial Basis Function (RBF) Kernel
k	maximum number of paths
LTI	Linear Time Invariant
m	number of downstream road segments
MAS	Multi-Agent System
MIMO	Multi Input Multi Output
NLOS	Non-Line of Sight
od	current Origin-Destination pair of V_{int} on p'
OD_{nei}	total Origin-Destination pair of V_{int} on P_{nei}
p	road unit p
p'	current number of neighbouring road
PC_D_EU4	Diesel driven Passenger Car EURO4
PC_G_EU4	Gasoline driven Passenger Car EURO4
PCP	Pheromone-based Congestion Prediction
$P_{downstream}$	total number of m-hop downstream roads
$p_{downstream}$	current m-hop downstream road
PGTS	Pheromone-based Green Transportation System
$Phase.TL_p$	current phase of traffic lights on road p
$Phase.TLp_{down}$	current phase of traffic light on m-hop downstream road p_{down}
$Phase.TLp_{up}$	current phase of traffic light on r-hop upstream road p_{up}
P_{nei}	total number of neighbouring roads connected to road unit p
p_{up}	current r-hop upstream road
$P_{upstream}$	total number of r-hop upstream roads
q	current path q out of d paths
r	number of upstream road segments
RBF	Radial Basis Function
$Rd_{Con(t)}$	current number of congested road at time step t
Rerouting-τ	pheromone-based rerouting approach
SCATS	Sydney Coordinated Adaptive Traffic System
$State_{coordinate}$	state to check the need of coordination of upstream and downstream traffic lights of the congested road. '0' indicates a positive result while '1' implies a negative result.
SUMO	Simulation of Urban Mobility
t	current time step
$T(p, t+1)$	transport pheromone on road p at time step $t+1$
T_{Con}	transport pheromone intensity of a congested road
$t_{coordinate}$	duration for traffic light coordination
$T_f(p, t+1)$	future pheromone on road p at time step $t+1$
$T_g.TL_p$	green phase duration of traffic light on road p
$T_g.TLp_{down}$	green phase duration of traffic light on m-hop downstream road p_{down}
TLC-CDT	Traffic Light Control Considering Downstream Traffic
TL_p	traffic light on road p
TOC	Traffic Operation Center
Traci	Traffic Control Interface
$T_t(p,t)$	traffic pheromone on road p at time step t
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VA	Vehicle Agent
V_{int}	total number of intention vehicle
α, α^*	dual variables of epsilon-Support Vector Regression
γ	relative importance of T_{Con}
δ_d	dynamic threshold
δ_{heavy}	heavy congestion threshold
δ_{light}	light congestion threshold
εSVR	epsilon-Support Vector Regression

Besides vehicle routing strategy, it is also interesting to adopt evolutionary computing to optimize the signal settings of traffic lights. Ant Colony Optimization has been applied to optimize the traffic signal setting by employing two types of ant behaviors [12]. Meanwhile, Particle Swarm Optimization has also been adopted to provide optimal scheduling of traffic signal program [13]. While achieving significant reduction in transport emissions, the foci are centered on modelling typical traffic scenarios. Recently an attempt has been made to fuse vehicle routing scheme and traffic light control strategy. An integration of dynamic traffic routing schemes and adaptive traffic signal control has been proposed by considering the delay caused by real-time traffic signal operations [14].

In [5], a pheromone-based framework has been introduced by fusing a short-term traffic forecasting model, a vehicle routing scheme, and a traffic light control strategy. While reducing the congestion considerably, the impacts of non-recurrent events are not well explored. A significant improvement has been achieved in [9], which integrates a coordinated traffic light control strategy into a green vehicle routing scheme to further generate green wave scenarios. The improved pheromone-based scheme reduces the upstream congestion through a routing scheme and disseminates downstream traffic through a coordinated traffic light control strategy. Since the impacts of non-recurrent events are not well considered, the robustness of the system under unexpected congestion requires further investigations. Motivated by this issue, a PGTS is proposed which takes into account the impacts of non-recurrent events and green transportation with three significant contributions. First, the impact of an accident is assessed by halting a vehicle on a target road with the maximum allowable speed of 10 km/h. Second, the effect of heavy rain is modelled by reducing the maximum allowable speed by 20 km/h. Third, the impact of the worse-case scenario is evaluated by considering both accidental situation and heavy rain scenario. The performance of PGTS is gauged based on the comparison of absolute values (TABLES 4-8) and percentage change of transport emissions and average time spent with other existing approaches with reference to the normal traffic condition (FIGURES 3-7) and baseline (TABLES 9-12).

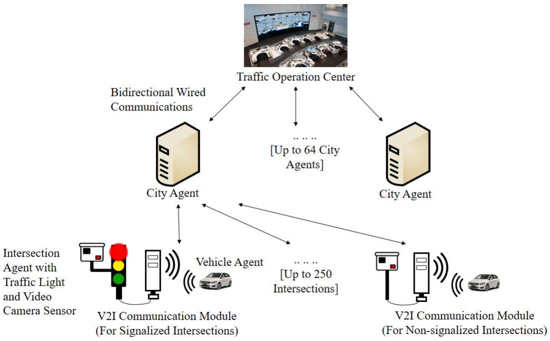
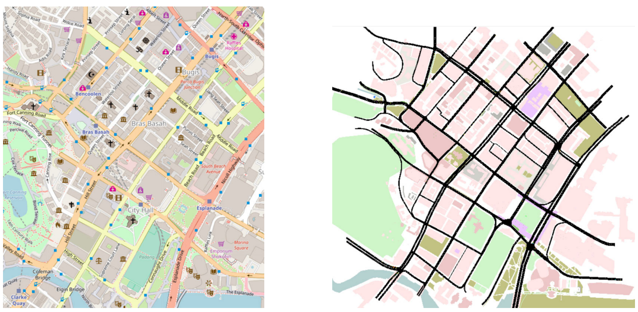
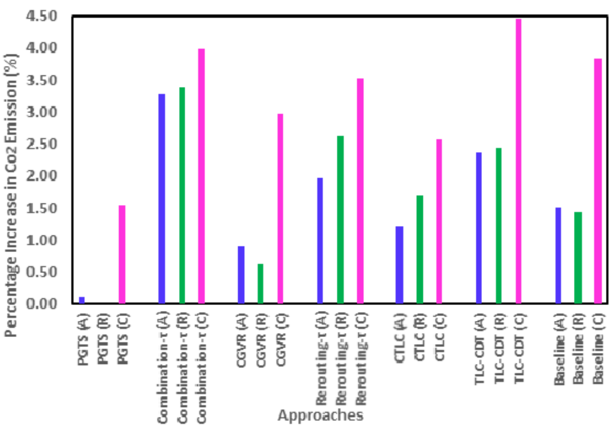


FIGURE 1. Architecture of Pheromone-based green transportation system (PGTS).



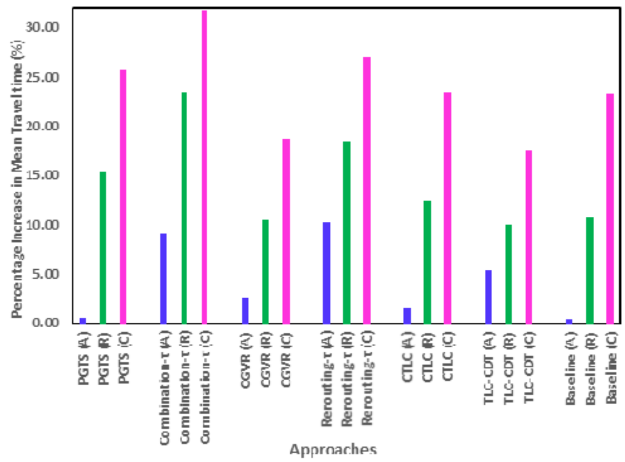
(a) OpenStreetMap (b) SUMO

FIGURE 2. Singapore cityhall map.



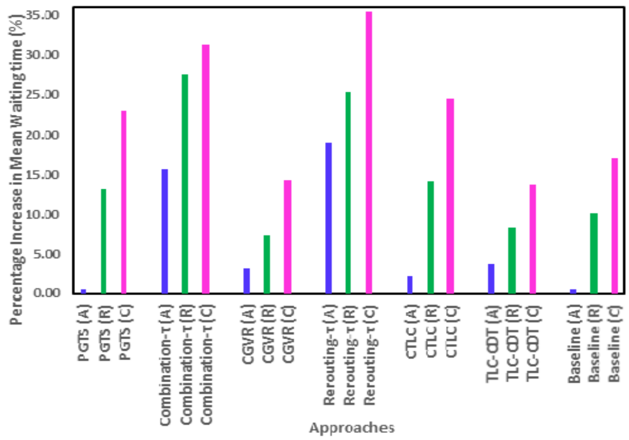
* (A): * technique under accidental situation.
* (R): * technique under heavy rain.
* (C): * technique under the combination of accidental and heavy rain scenario.

FIGURE 3. Percentage increase in carbon dioxide emission in all approaches with reference to the normal traffic condition.



* (A): * technique under accidental situation.
* (R): * technique under heavy rain.
* (C): * technique under the combination of accidental and heavy rain scenario.

FIGURE 4. Percentage increase in mean trip time in all approaches with reference to the normal traffic condition.



* (A): * technique under accidental situation.
* (R): * technique under heavy rain.
* (C): * technique under the combination of accidental and heavy rain scenario.

FIGURE 5. Percentage increase in mean waiting time in all approaches with reference to the normal traffic condition.

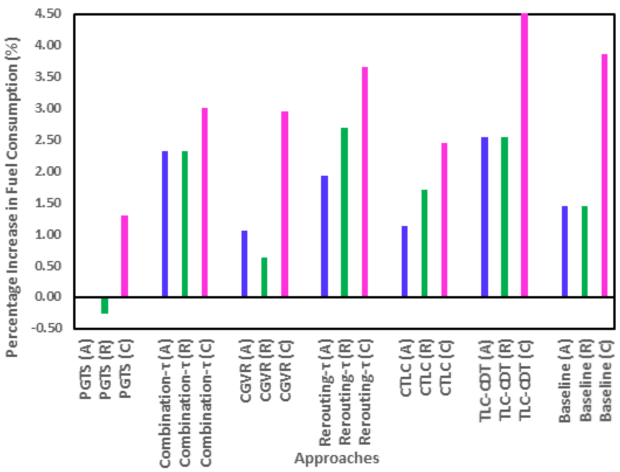
This paper is organized as follows. Section III describes the system architecture of PGTS, and the corresponding impacts of non-recurrent events. Section IV discusses the experimental setup and results whereas Section V provides the conclusion of this research.

III. INVESTIGATION ON THE IMPACT OF NON-RECURRENT EVENTS

A. SYSTEM ARCHITECTURE

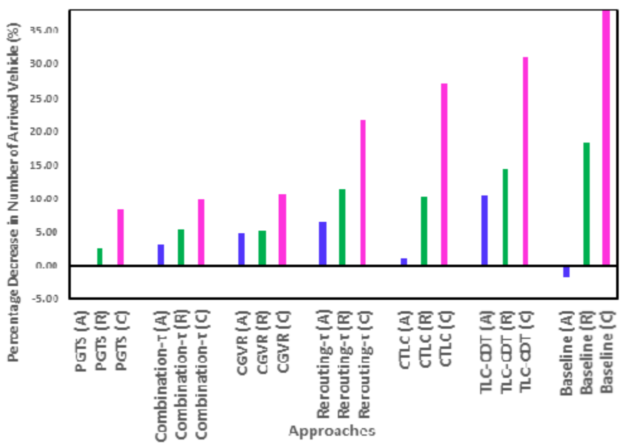
The system architecture of the proposed PGTS is an extension to the existing SCATS [15] through the application of hierarchical multiple agents. The system architecture of PGTS comprises TOC, regional computers, traffic light controllers, IAs, digital cameras, and VAs as shown in Fig. 1. At the top tier, TOC manages up to 64 regional computers while each regional computer interacts with IA to control regional traffic conditions in the middle tier. At the bottom tier, IA predicts traffic conditions through PCP, reroutes vehicles via CGVR and controls traffic signals via CTLC after obtaining the traffic information from VAs via V2I communication.

PGTS is practical and can solve traffic problems owing to the application of MAS which relies on local communication. Bidirectional wired communication is employed among TOC, CAs and IAs for information exchange. The local communication between VAs and IAs relies on V2I rather than V2V which is more susceptible to broadcast storm [16]. Additionally, V2I is less likely to suffer from NLOS



* (A): * technique under accidental situation.
* (R): * technique under heavy rain.
* (C): * technique under the combination of accidental and heavy rain scenario.

FIGURE 6. Percentage increase in fuel consumption in all approaches with reference to the normal traffic condition.



* (A): * technique under accidental situation.
* (R): * technique under heavy rain.
* (C): * technique under the combination of accidental and heavy rain scenario.

FIGURE 7. Percentage increase in number of arrived vehicle in all approaches with reference to the normal traffic condition.

communication issues, signifying almost full coverage is attained at each intersection (which is handled by IA) to avoid signal blockage due to buildings [11]. Furthermore, MAS in PGTS enables effective scaling of system to extremely large vehicular system as it operates in a hierarchical manner through communication among CAs. By considering a bidirectional four-way intersection, each IA is responsible for managing transport pheromone of four road links, which justifies the efficiency of PGTS. Interestingly, PGTS is robust in the event of system failure, especially during power outage within a city, as other agents outside the affected cities can still operate normally through local communication [17]. As MAS has been adopted in several studies [2], [9], [11], the practicality of PGTS to solve traffic problems can therefore be justified. The description of PCP, CTLC and CGVR in PGTS is given below:

1) PHEROMONE-BASED CONGESTION PREDICTION (PCP)

Traffic pheromone $T_t(p,t)$ which indicates the current traffic density on road p at time t, and future pheromone $T_f(p,t+1)$ which represents future traffic density on road p at time t + 1 are employed in PCP [2], [9], [10]. PCP combines these two pheromones to forecast short-term traffic density (transport pheromone) through an online-Support Vector Regression as shown in (1) and (2):

$$T(p, t+1) = \sum_{i=1}^{l} \left(-\boldsymbol{\alpha} + \boldsymbol{\alpha}^*\right) K\left(\boldsymbol{x_i}, \boldsymbol{x_j}\right) + b \tag{1}$$

$$\boldsymbol{x_t} = \left(T_t\left(p, t-1\right), T_f\left(p, t\right)\right) \tag{2}$$

The training set includes $t = 100$ instances.

2) COORDINATED TRAFFIC LIGHT CONTROL (CTLC)

To disseminate downstream traffic, CTLC coordinates m-hop downstream traffic lights through Algorithm 1 below. δ_d is applied to coordinate downstream traffic lights based on the level of congestion. Equations 3(i) and 3(ii) are used for light congestion and heavy congestion respectively. $\#Rd_{ConThreshold}$ is the product of $\%Rd_{Con}$ and $\#TotalRd$. $\#Rd_{Coninitial}$ represents the initial number of congested roads.

$$\delta_d(t) = \begin{cases} \dfrac{\delta_{heavy} - \delta_{light}}{\sqrt{\#Rd_{ConThreshold}}}\sqrt{\#Rd_{ConInitial}(t)} & \\ \quad + \delta_{light}, \quad \delta_{light} < \delta_d(t) < \delta_{heavy} & 3(i) \\ \delta_{heavy}, \quad \delta_d(t) \geq \delta_{heavy} & 3(ii) \end{cases}$$

Algorithm 1 displays the coordination of r-hop upstream and m-hop downstream traffic lights of all congested roads. Line 1 determines if there is any $\#Rd_{Con}(t)$ in the vehicular system. If $\#rd_{Con}(t)$ is present, line 2 initializes the $state_{stopcoordinate}$ to 1. Meanwhile line 3 priorities the congested road with the maximum transport pheromone intensity $t(p, t+1)$. Lines 4-9 check if the congested road leads to a non-signalized intersection. specifically, line 5 removes the checked p from $Rd_{Con}(t)$ if it leads to a non-signalized intersection. If p leads to a signalized-intersection, line 7 sets the traffic light to green with the duration of $t_{coordinate}$. After coordinating the traffic lights, line 8 removes the checked p from $Rd_{Con}(t)$ and line 9 sets $state_{stopcoordinate}$ to 0, showing that there is a need to coordinate its r-hop upstream and m-hop downstream road segments. Line 10 coordinates the traffic lights on the upstream and downstream of p, only if the traffic light of road p has been coordinated in lines 7-9. Lines 11-17 perform similar function as in lines 3-9, by just replacing p with p_{up} and searching for r-hop $p_{upstream}$. Lines 18-24 perform the same function as in lines 3-9, with the replacement of p with p_{down} and finding the m-hop $p_{downstream}$.

3) COOPERATIVE GREEN VEHICLE ROUTING (CGVR)

CGVR aims to direct vehicles away from entering the congested road to reduce upstream congestion, as given by

Algorithm 1 Coordinated Traffic Light Control

Input:
$\#Rd_{Con}(t)$; TL_p; $phase.TL_p$; $t_g.TL_p$; $t_{coordinate}$;
Output:
$phase.TL_p$; $t_g.TL_p$;
while $\#Rd_{Con}(t) > 0$ **do**
  Set $state_{stopcoordinate} = 1$
  Find road $p\epsilon\ Rd_{Con}(t)$ with maximum $T(p, t+1)$
  if $p\epsilon\ Rd_{Con}(t)$ leads to a non-signalized intersection **do**
    Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p$
  else
    $SetGreenPhase(p,\ Rd_{Con}(t),\ phase.TL_p,\ t_g.TL_p)$
    Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p$
    Set $state_{stopcoordinate} = 0$
  if $state_{stopcoordinate} == 0$
    Get r-hop upstream road $P_{upstream}$ of $p\epsilon\ Rd_{Con}(t)$
    for $p_{up}\epsilon P_{upstream}$ **do**
     if $p_{up}\epsilon P_{upstream}$ leads to a non-signalized intersection **do**
      Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p_{up}$
    else
     $SetGreenPhase(p_{up},\ Rd_{Con}(t),\ phase.TL_{pup},\ t_g.TL_{pup})$
      Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p_{up}$
  Get m-hop downstream road $P_{downstream}$ of $p\epsilon\ Rd_{Con}(t)$
  for $p_{down}\epsilon P_{downstream}$ **do**
   if $p_{down}\epsilon P_{downstream}$ leads to a non-signalized intersection **do**
      Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p_{down}$
   else
      $SetGreenPhase(p_{down},\ Rd_{Con}(t),\ phase.TL_{pdown},\ t_g.TL_{pdown})$
      Remove the checked $Rd_{Con}(t) = Rd_{Con}(t) - p_{down}$

Algorithm 2 below. The dkSp equation is proposed to distribute vehicles to d paths as depicted in (4):

$$d = k\exp\left(T_{con}^{\gamma} - 1\right), \quad \delta_d \leq T_{con} \leq 1 \tag{3}$$

Line 1 iteratively loops $\#Rd_{Con}$ while lines 2-15 recursively assign a greener path for each vehicle in each OD_{nei} pair based on global distance, number of intersections, transport pheromone intensity and mean trip speed of m-hop downstream road segments. Specifically, line 2 finds the road $p\epsilon Rd_{Con}$ with maximum $T(p, t+1)$ whereas line 4 searches neighboring roads $p'\epsilon P_{nei}$ for each congested road $p\epsilon Rd_{Con}$. For each neighboring road $p'\epsilon P_{nei}$, line 5 finds vehicle $j\epsilon V_{int}$ having intention to traverse $p\epsilon Rd_{Con}$ while line 6 groups these vehicles V_{int} into OD_{nei} pairs. Line 8 computes dynamic k-shortest paths based on global distance and number of intersections for each OD_{nei} pair. Line 10 ranks the vehicles based on f_i. As different vehicle types have different fuel consumption models [18], vehicles with higher ranking are prioritized and rerouted first. Line 11 computes the probability of vehicles on route selection while line 12 distributes

Algorithm 2 Cooperative Green Vehicle Routing

Input:
H; Rd_{Con}; T; D; M;
Output:
H;
1 **while** $\#Rd_{Con} > 0$ **do**
2 Find road $p\epsilon Rd_{Con}$ with maximum $T(p, t+1)$
3 Get neighboring roads $p'\epsilon P_{nei}$ connected to road p
4   **for** $p'\epsilon P_{nei}$ **do**
5   Obtain vehicles $j\epsilon V_{int}$ having intention to traverse p based on r-hop upstream roads
6   Group $j\epsilon V_{int}$ with the same OD_{nei} Pair
7   **for** $od\epsilon OD_{nei}$ **do**
8   Select d-shortest paths based on global distance and #intersection
9   **for** $j\epsilon V_{int}$ **do**
10   Prioritize vehicle j based on fuel consumption model, f_i
11   Compute probability P_q^j for each vehicle $j\epsilon V_{int}$ *on* each $q\epsilon d$ path based on transport pheromone intensity and mean road speed m-hop downstream links
12   Distribute vehicles to one of the d-paths according to P_q^j
13   Update pheromone $T_f\ (p', t+1)$
14 Remove the congested road p from P_{con}
15 Update and output road network with new transport pheromone on H

the vehicles accordingly. Line 13 updates future pheromone $T_f(p, t+1)$ while line 14 removes the checked road P_{con}. In line 15, the latest transport pheromone intensities are updated in H.

B. SCENARIOS UNDER NON-RECURRENT EVENTS

To promote practicality, the proposed PGTS is evaluated under several non-recurrent events namely accidental situations, heavy rain and their combination, which are described in subsections below:

1) ACCIDENT

An accident refers to the incident that causes slower traffic speed. the impact of an accident can be simulated in three different ways [19]:

- Stopping a vehicle on a road for a specific duration.
- Increasing the red phase duration of the traffic light on the affected road.
- Setting lower speed limit of the target road to inhibit the traffic movement.

As the first option is the simplest to implement, the impact of an accident is modelled by halting a vehicle on the main road for a specific duration of time [20]. To simulate worse-case scenario, the maximum allowable speed of the affected road is limited to 10km/h.

TABLE 2. Comparison of PGTS and other pheromone-based techniques.

#	Approaches	Vehicle Routing Methodology			Traffic Light Control Methodology
		Path Assignment Method	Static Information	Dynamic Information	
1	Baseline, without vehicle routing and traffic light control	-	-	-	-
2	TLC-CDT [5]	-	-	-	Competing Relationship between neighboring roads
3	CTLC	-	-	-	Coordination of traffic lights based on transport pheromone
4	Rerouting-τ [5]	kSP	Global distance	Pheromone intensity	-
5	CGVR	dkSP	Global distance + #intersections	Transport pheromone + mean road speed	-
6	Combination-τ, the combination of TLC-CDT and Rerouting-τ [5]	kSP	Global distance	Pheromone intensity	Competing Relationship between neighboring roads
7	PGTS, the combination of CTLC and CGVR	dkSP	Global distance + #intersections	Transport pheromone + mean road speed	Coordination of traffic lights based on transport pheromone

2) HEAVY RAIN

The unpredictable weather condition leads to serious traffic congestion. Raining is the most common weather condition that reduces the traffic speed in a region. The rainfall has been reported to reduce travel speed by 4.8-16.1km/h in heavy rain, and 1.9-12.9km/h in light rain [21]. To model the impact of heavy rain, the maximum speed of each road segment in a vehicular system is reduced by 20km/h for worst case scenario.

3) COMBINATION

To promote practicality, the impacts of an accident and heavy rain are investigated to further gauge the performance of the PGTS.

IV. EXPERIMENTATION

A. EXPERIMENTAL SETUP

The experiment is conducted through SUMO [22] which aims to assess the performance of the proposed PGTS and other existing approaches as depicted in Table.1. Fig.2 shows the Singapore Cityhall map which is downloaded from OpenStreetMap. Poisson distribution is applied in Singapore traffic data consisting of four vehicle types from March 2018 Singapore DataMall [23] to represent realistic fluctuation of rush hour traffic behavior in an arrival pattern [24]. Additionally, Table. 2 displays the vehicle attributes in the Singapore traffic data. Traci library [25] is employed to provide the commands to control traffic lights and routing in MATLAB. The configuration of PGTS is given as follows:

- 4000 vehicles are employed in an hour simulation with randomly generated trips.
- The parameters of ε-SVR in LIBSVM [26]: $C = 10$, RBF kernel with $\gamma = 0.15$, and $\varepsilon = 0.0001$.
- Dynamic threshold parameters: $\delta_{heavy} = 0.4$, $\delta_{light} = 0.25$, and $\%Rd_{Con} = 0.04$
- Upstream and downstream road segment parameters: $m = r = 3$
- Vehicles arriving destination will park and do not occupy the road.
- The parameters of $d$ksp: $k = 6.5$ and $\gamma = 1$
- Accidental situation: 30 minute duration
- Rainy scenario: 30 minute duration
- Combinatorial case: accident lasts for 35 minutes while heavy rain scenario lasts for 50 minutes.

It is worth noticing that the selection of the parameters is dependent on the location of a city. Each CA handles the map parameters in the target city. As the map can be preloaded into the probe-car system, all the parameters from different cities are optimized before use in real-life. The similar hierarchical MAS has been employed in several studies [2], [9], [11], which further affirms the practicality of the system architecture.

TABLE 3. Vehicle attributes in PGTS.

Vehicle Type	#Vehicle for every 100 vehicles	Maximum velocity (kmh)	Vehicle Length (m)	Emission Class
Petrol-based	75	150	4.7	PC_G_EU4
Diesel-based	4	150	4.7	PC_D_EU4
Truck	19	120	7.1	HDV
Bus	2	100	12.0	Bus

TABLE 4. Summary of carbon dioxide emission in all approaches (e + 09 mg).

Approaches	Normal		Accident		Rain		Combination	
	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)
Baseline	14.60	[14.52,14.68]	14.82	[14.77,14.90]	14.81	[14.77,14.87]	15.16	[15.09,15.24]
TLC-CDT	13.91	[13.77,14.09]	14.24	[14.08,14.42]	14.25	[14.13,14.30]	14.53	[14.47,14.60]
CTLC	12.44	[12.36,12.54]	12.59	[12.47,12.71]	12.65	[12.57,12.67]	12.76	[12.70,12.86]
Rerouting-τ	12.19	[12.07,12.31]	12.43	[12.42,12.47]	12.51	[12.51,12.55]	12.62	[12.62,12.68]
CGVR	11.11	[10.97,11.24]	11.21	[11.15,11.29]	11.18	[11.09,11.27]	11.44	[11.41,11.47]
Combination-τ	10.04	[10.05,10.24]	10.37	[10.29,10.45]	10.38	[10.24,10.52]	10.44	[10.32,10.59]
PGTS	**9.10**	**[9.05,9.16]**	**9.11**	**[9.07,9.13]**	**9.10**	**[9.04,9.15]**	**9.24**	**[9.15,9.44]**

TABLE 5. Summary of mean trip time in all approaches (s).

Approaches	Normal		Accident		Rain		Combination	
	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)
Baseline	1421.20	[1405.00,1433.00]	1427.50	[1418.00,1441.00]	1572.80	[1565.00,1577.00]	1753.10	[1717.00,1790.00]
TLC-CDT	1462.90	[1440.00,1490.00]	1541.00	[1512.00,1573.00]	1608.30	[1596.00,1618.00]	1721.20	[1710.00,1734.00]
CTLC	1221.80	[1209.00,1236.00]	1240.40	[1222.00,1258.00]	1373.50	[1369.00,1381.00]	1508.00	[1479.00,1552.00]
Rerouting-τ	1008.80	[997.00,1021.00]	1111.50	[1109.00,1117.00]	1195.40	[1192.00,1202.00]	1281.70	[1274.00,1291.00]
CGVR	976.89	[958.10,993.20]	1002.40	[993.00,1013.00]	1079.10	[1069.00,1091.00]	1159.90	[1157.00,1165.00]
Combination-τ	775.45	[765.60,785.50]	846.81	[836.70,855.90]	957.35	[942.60,972.90]	1021.80	[1007.00,1037.00]
PGTS	**745.83**	**[738.90,752.60]**	**750.10**	**[745.60,753.40]**	**860.95**	**[853.90,867.90]**	**937.86**	**[926.60,962.00]**

TABLE 6. Summary of mean waiting time in all approaches (e + 06 s).

Approaches	Normal		Accident		Rain		Combination	
	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)
Baseline	4.26	[4.20,4.31]	4.28	[4.24,4.33]	4.69	[4.65,4.71	4.99	[4.93,5.04]
TLC-CDT	4.23	[4.16,4.32]	4.39	[4.30,4.49]	4.58	[4.55,4.61]	4.81	[4.79,4.84]
CTLC	3.18	[3.13,3.23]	3.25	[3.18,3.31]	3.63	[3.61,3.65]	3.96	[3.89,4.05]
Rerouting-τ	2.73	[2.69,2.77]	3.25	[3.23,3.27]	3.42	[3.41,3.45]	3.70	[3.67,3.74]
CGVR	2.85	[2.77,2.92]	2.94	[2.90,2.98]	3.06	[3.02,3.11]	3.26	[3.25,3.28]
Combination-τ	1.85	[1.82,1.88]	2.14	[2.09,2.18]	2.36	[2.31,2.43]	2.43	[2.38,2.48]
PGTS	**1.82**	**[1.79,1.84]**	**1.83**	**[1.81,1.84]**	**2.06**	**[2.03,2.08]**	**2.24**	**[2.20,2.34]**

TABLE 7. Summary of fuel consumption in all approaches (e + 06 ml).

Approaches	Normal		Accident		Rain		Combination	
	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)
Baseline	6.22	[6.19,6.25]	6.31	[6.29,6.35]	6.31	[6.28,6.32]	6.46	[6.43,6.48]
TLC-CDT	5.92	[5.86,6.00]	6.07	[5.99,6.14]	6.07	[6.04,6.10]	6.19	[6.17,6.23]
CTLC	5.30	[5.26,5.34]	5.36	[5.31,5.41]	5.39	[5.36,5.40]	5.43	[5.41,5.47]
Rerouting-τ	5.19	[5.14,5.24]	5.29	[5.29,5.31]	5.33	[5.32,5.34]	5.38	[5.37,5.40]
CGVR	4.73	[4.67,4.79]	4.78	[4.75,4.81]	4.76	[4.73,4.80]	4.87	[4.86,4.88]
Combination-τ	4.32	[4.28,4.36]	4.42	[4.38,4.45]	4.42	[4.36,4.48]	4.45	[4.40,4.51]
PGTS	**3.88**	**[3.85,3.90]**	**3.88**	**[3.86,3.89]**	**3.87**	**[3.85,3.90]**	**3.93**	**[3.90,4.02]**

B. RESULTS AND DISCUSSIONS

To ease explanation, the term 'transport emission' is used to represent carbon dioxide emission and fuel consumption while the term 'average time spent' is employed to represent both mean travel time and mean waiting time. In all approaches, it can be generally discerned that transport emission and average time spent are relatively higher under all non-recurrent scenario as compared to the normal traffic condition, being the combination of an accident and heavy rain the highest value, as shown in TABLES 4-8. The BCa [27] is employed to represent the non-normal distribution nature of the samples. It provides 95% CI through the consideration of both bias and skew. The proposed PGTS achieves the best result in accidental situation, heavy rain and the combinatorial scenario, showing that PGTS promotes green transportation even under non-recurrent events. To provide deeper insights, the percentage change of evaluation metrics is analysed in two perspectives as follows:

1) WITH REFERENCE TO THE NORMAL TRAFFIC CONDITIONS

Figs. 3-7 depict the percentage increase in transport emissions and average time spent, as well as the percentage decrease in the number of arrived vehicles with reference to the normal

TABLE 8. Summary of number of arrived vehicle in all approaches.

Approaches	Normal		Accident		Rain		All	
	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)	Mean	BCa (95%CI)
Baseline	2448	[2404,2500]	2490	[2439,2525]	2000	[1985,2022]	1496	[1406,1585]
TLC-CDT	1987	[1933,2033]	1777	[1698,1859]	1702	[1680,1724]	1373	[1340,1410]
CTLC	2813	[2778,2850]	2782	[2739,2828]	2520	[2501,2534]	2051	[1934,2132]
Rerouting-τ	3648	[3626,3665]	3405	[3375,3425]	3231	[3220,3238]	2855	[2797,2900]
CGVR	3554	[3514,3592]	3380	[3342,3412]	3368	[3330,3398]	3177	[3155,3195]
Combination-τ	3866	[3840,3889]	3744	[3713,3776]	3660	[3597,3706]	3488	[3451,3528]
PGTS	**3981**	**[3977,3985]**	**3971**	**[3969,3975]**	**3881**	**[3865,3898]**	**3651**	**[3602,3688]**

traffic condition. The main objective of referencing to the normal condition is to access the robustness of PGTS with all other approaches against non-recurrent events.

In the event of baseline under accidental scenario, the increase in frequency of acceleration owing to the halting vehicle leads to the percentage rise in transport emission as shown in Figs. 3 and 6. Similarly, there is a percentage rise in transport emission under heavy rain as vehicles are traversing at lower speed. Nevertheless, the percentage rise in average time spent in heavy rain is higher than that in an accident as depicted in Figs. 4 and 5. This is mainly due to longer time spent in the city under heavy rain, whereas the impact of accident causes traffic jam in the affected region only. In Figs. 3-6, the percentage rise in both transport emission and average time spent is the highest under the combinatorial scenario, exhibiting that the congestion is the most serious under this worse-case condition. Therefore, the slump in the number of arrived vehicles in Fig. 7 is more significant in the combinatorial case, as compared to either accidental case or heavy rain scenario.

In Figs. 3 and 6, it is fascinating to discern that the percentage rise in transport emissions in TLC-CDT is the highest among all approaches, displaying its inefficiency in reducing the environmental impacts of congestion under non-recurrent events. Despite the substantial rise in these percentages, the corresponding absolute value of average fuel consumption and carbon dioxide emission (TABLES 4 and 7) in TLC-CDT is still lower than that of the baseline. Considering the accidental situation, CTLC performs better than TLC-CDT owing to the coordination of downstream traffic lights. In fact, CTLC exhibits a lower percentage increase in transport emission (Figs. 3 and 6) and a lower percentage reduction in the number of arrived vehicles (Fig. 7) than TLC-CDT. While achieving a competitive percentage increase in average time spent (Figs. 4 and 5) as compared to TLC-CDT, CTLC exhibits a lower absolute value of 234.80s in mean travel time and $0.95e+06$s in average waiting time under heavy rain scenario. The prime reason is that TLC-CDT independently sets the traffic lights to green, leaving the coordination of downstream traffic lights an open question. The efficiency of CTLC is more pronounced under the combinatorial case as CTLC takes a further leap to generate green wave scenarios.

There is a much lower percentage increase in transport emission and average time spent in CGVR as compared to Rerouting-τ under both accidental situation and heavy rain condition as shown in Figs. 3 and 6. In an accident, CGVR probabilistically directs vehicles to greener paths to reduce upstream congestion. CGVR is different from Rerouting-τ as it includes mean road speed in the routing cost to select paths with fewer frequency of acceleration (deceleration). The beauty of the improved routing cost reduces the percentage increase of transport emission (Figs. 3 and 6) and average time spent (Figs. 4 and 5), as well as the percentage decrease in the number of arrived vehicles (Fig. 7) under rainy condition. The contribution of CGVR is more significant when it achieves better performance than Rerouting-τ even under the combinatorial case, attesting a higher efficiency to alleviate traffic congestion.

As compared to Combination-τ, PGTS takes the advantage of the integration of CTLC and CGVR to promote green transportation, with insignificant percentage increase in transport emission under accidental situation and heavy rain scenario as depicted in Figs. 3 and 6. While a relatively higher percentage increase in average time spent (Figs. 4 and 5) is depicted in PGTS as compared to baseline, the lowest absolute value than all other techniques ensures vehicles arriving at destination with the lowest delay. PGTS distributes upstream traffic through CGVR and disseminates downstream traffic through CTLC, enjoying a better performance than Combination-τ even in the combinatorial case. Hence, the percentage decrease in the number of arrived vehicles is significantly lower than that in Combination-τ, as shown in Fig. 7. Therefore, PGTS is robust against all non-recurrent events as compared to other techniques.

2) WITH REFERENCE TO THE BASELINE

TABLES 9-12 display the percentage change of all performance metrics by taking baseline as the reference. The main objective is to evaluate the better performance of PGTS when comparing with other existing techniques under both typical and atypical traffic conditions. Interestingly, PGTS shows an insignificant difference in percentage change of transport emission and average time spent when comparing the normal condition with other non-recurrent events in TABLES 9-12. The better performance of PGTS is further affirmed when the highest percentage decrease in transport emission and average time spent is achieved under all traffic conditions as compared to other approaches. In PGTS, the downstream traffic can be effectively disseminated through the coordination of traffic lights in CTLC, followed by rerouting upstream vehicles to enter these cleared paths through CGVR. The

TABLE 9. Percentage change of evaluation metrics under normal condition with reference to the baseline.

Approaches	Carbon Dioxide Emission	Mean Trip Time	Mean Waiting Time	Fuel Consumption	Number of Arrived Vehicle
TLC-CDT	-4.7	+2.9	-0.7	-4.8	-18.8
CTLC	-14.8	-14.0	-25.4	-14.8	+14.9
Recouting- τ	-16.5	-29.0	-35.9	-16.6	+49.0
CGVR	-23.9	-31.3	-33.1	-24.0	+45.2
Combination- τ	-31.2	-45.4	-56.6	-30.5	+57.9
PGTS	-37.7	-47.5	-57.3	-37.6	+62.6

TABLE 10. Percentage change of evaluation metrics under accident scenario with reference to the baseline.

Approaches	Carbon Dioxide Emission	Mean Trip Time	Mean Waiting Time	Fuel Consumption	Number of Arrived Vehicle
TLC-CDT	-3.9	+8.0	+2.6	-3.8	-28.6
CTLC	-15.0	-13.1	-24.1	-15.1	+11.7
Recouting- τ	-16.1	-22.1	-24.1	-16.2	+36.7
CGVR	-24.4	-29.8	-31.3	-24.3	+35.7
Combination- τ	-30.0	-40.7	-50.0	-30.0	+50.4
PGTS	-38.5	-47.5	-57.2	-38.5	+59.5

TABLE 11. Percentage change of evaluation metrics under heavy rain scenario with reference to the baseline.

Approaches	Carbon Dioxide Emission	Mean Trip Time	Mean Waiting Time	Fuel Consumption	Number of Arrived Vehicle
TLC-CDT	-3.8	+2.3	+2.3	-3.8	-14.9
CTLC	-14.6	-12.7	-22.6	-14.6	+26.0
Recouting- τ	-15.5	-24.0	-27.1	-15.5	+61.6
CGVR	-24.5	-31.4	-34.8	-24.6	+68.4
Combination- τ	-29.9	-39.1	-49.7	-30.0	+83.0
PGTS	-38.6	-45.3	-56.1	-38.7	+94.1

TABLE 12. Percentage change of evaluation metrics under combinatorial case with reference to the baseline.

Approaches	Carbon Dioxide Emission	Mean Trip Time	Mean Waiting Time	Fuel Consumption	Number of Arrived Vehicle
TLC-CDT	-4.2	-1.8	-3.6	-4.2	-8.2
CTLC	-15.8	-14.0	-20.6	-15.9	+37.1
Recouting- τ	-16.8	-26.9	-25.9	-16.7	+90.8
CGVR	-24.5	-33.8	-34.7	-24.6	+112.4
Combination- τ	-31.1	-41.7	-51.3	-31.1	+133.2
PGTS	-39.1	-46.5	-55.1	-39.2	+144.1

beauty of this integration adds values to the better performance of PGTS.

Among all approaches, the difference of percentage change in the number of arrived vehicles at designated destinations is the highest in PGTS when comparing the normal condition (TABLE 9) and the combinatorial case (TABLE 12). The prime factor is the significant reduction of arrived vehicle number to 1496 in baseline and a relatively slight decrease in this number to 3651 in PGTS as shown in TABLE 8. This further attests that PGTS is effective to mitigate traffic congestion even under the combinatorial case with the highest number of arrived vehicles at designated destinations. To summarize, PGTS achieves the best performance with the highest percentage change in all evaluation metrics under all traffic conditions when comparing to the baseline.

V. CONCLUSION

To fill the gap of existing pheromone-based systems which focus on typical traffic conditions, this paper aims to assess the impacts of non-recurrent events specifically accidents, rainy weather, and their combination through the proposed PGTS. In essence, the accident case is modelled by halting a vehicle on a target road with the maximum speed limit of 10km/h. Meanwhile, the maximum speed of the affected area is reduced by 20km/h to represent heavy rain scenario. To promote practicality, the worse-case situation is modelled by including the impacts of both accidents and heavy rain.

At the first glance, experiments show that PGTS achieves the best performance with the lowest transport emission and average time spent, as well as the highest number of arrived vehicles at designated destinations. Different from existing works, this paper takes a further leap to analyze the percentage change of evaluation metrics in two perspectives: (1) with reference to normal condition, and (2) with reference to baseline. By referencing the percentage change to typical conditions, experiments display that PGTS is robust against all non-recurrent events due to the integration of CTLC and CGVR. Referencing the percentage change to the baseline further shows that PGTS achieves the best performance with the highest percentage decrease in transport emission and average time spent, along with the highest percentage increase in arrived vehicle numbers. In future, PGTS can be extended to include the impacts of driver behaviors such as the familiarity of drivers using the suggested route in non-recurrent events.

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REFERENCES

[1] S. Kurihara, H. Tamaki, M. Numao, J. Yano, K. Kagawa, and T. Morita, "Traffic congestion forecasting based on pheromone communication model for intelligent transport systems," in *Proc. IEEE Congr. Evol. Comput.*, May 2009, pp. 2879–2884.

[2] K. L. Soon, J. M.-Y. Lim, and R. Parthiban, "Extended pheromone-based short-term traffic forecasting models for vehicular systems," *Eng. Appl. Artif. Intell.*, vol. 82, pp. 60–75, Jun. 2019.

[3] H. Kim, H. Shim, J. Back, and J. H. Seo, "Consensus of output-coupled linear multi-agent systems under fast switching network: Averaging approach," *Automatica*, vol. 49, no. 1, pp. 267–272, Jan. 2013.

[4] J. Xi, M. He, H. Liu, and J. Zheng, "Admissible output consensualization control for singular multi-agent systems with time delays," *J. Franklin Inst.*, vol. 353, no. 16, pp. 4074–4090, Nov. 2016.

[5] Z. Cao, S. Jiang, J. Zhang, and H. Guo, "A unified framework for vehicle rerouting and traffic light control to reduce traffic congestion," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 7, pp. 1958–1973, Jul. 2017.

[6] M. C. Ho, J. M.-Y. Lim, K. L. Soon, and C. Y. Chong, "An improved pheromone-based vehicle rerouting system to reduce traffic congestion," *Appl. Soft Comput.*, vol. 84, Nov. 2019, Art. no. 105702.

[7] M. R. Jabbarpour, A. Jalooli, E. Shaghaghi, R. M. Noor, L. Rothkrantz, R. H. Khokhar, and N. B. Anuar, "Ant-based vehicle congestion avoidance system using vehicular networks," *Eng. Appl. Artif. Intell.*, vol. 36, pp. 303–319, Nov. 2014.

[8] M. R. Jabbarpour, R. M. Noor, and R. H. Khokhar, "Green vehicle traffic routing system using ant-based algorithm," *J. Netw. Comput. Appl.*, vol. 58, pp. 294–308, Dec. 2015.

[9] K. L. Soon, J. M.-Y. Lim, and R. Parthiban, "Coordinated traffic light control in cooperative green vehicle routing for pheromone-based multi–agent systems," *Appl. Soft Comput.*, vol. 81, Aug. 2019, Art. no. 105486.

[10] K. L. Soon, J. M.-Y. Lim, R. Parthiban, and M. C. Ho, "Proactive eco-friendly pheromone-based green vehicle routing for multi-agent systems," *Expert Syst. Appl.*, vol. 121, pp. 324–337, May 2019.

[11] S. Wang, S. Djahel, Z. Zhang, and J. Mcmanis, "Next road rerouting: A multiagent system for mitigating unexpected urban traffic congestion," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 10, pp. 2888–2899, Oct. 2016.

[12] L. D'Acierno, M. Gallo, and B. Montella, "An ant colony optimisation algorithm for solving the asymmetric traffic assignment problem," *Eur. J. Oper. Res.*, vol. 217, no. 2, pp. 459–469, Mar. 2012.

[13] A. C. Olivera, J. M. García-Nieto, and E. Alba, "Reducing vehicle emissions and fuel consumption in the city by using particle swarm optimization," *Appl. Intell.*, vol. 42, no. 3, pp. 389–405, Apr. 2015.

[14] H. Chai, H. Zhang, D. Ghosal, and C.-N. Chuah, "Dynamic traffic routing in a network with adaptive signal control," *Transp. Res. C, Emerg. Technol.*, vol. 85, pp. 64–85, Dec. 2017.

[15] A. Sims and K. Dobinson, "The Sydney coordinated adaptive traffic (SCAT) system philosophy and benefits," *IEEE Trans. Veh. Technol.*, vol. VT-29, no. 2, pp. 130–137, May 1980.

[16] T. Sukuvaara, "Development, implementation and evaluation of an architecture for vehicle-to-vehicle and vehicle-to-infrastructure networking," Ph.D. dissertation, Ilmatieteen Laitos, Helsinki, Finland, 2015.

[17] D. Mckenney and T. White, "Distributed and adaptive traffic signal control within a realistic traffic simulation," *Eng. Appl. Artif. Intell.*, vol. 26, no. 1, pp. 574–583, Jan. 2013.

[18] D. Krajzewicz, M. Behrisch, P. Wagner, R. Luz, and M. Krumnow, "Second generation of pollutant emission models for SUMO," in *Modeling Mobility With Open Data*. Springer, 2015, pp. 203–221. [Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-15024-6_12

[19] D. Smith, S. Djahel, and J. Murphy, "A SUMO based evaluation of road incidents' impact on traffic congestion level in smart cities," in *Proc. 39th Annu. IEEE Conf. Local Comput. Netw. Workshops*, Sep. 2014, pp. 702–710.

[20] F. Hrizi and F. Filali, "An integrated and realistic simulation platform for vehicular networks," in *Proc. 3rd Int. ICST Conf. Simulation Tools Techn.*, 2010, p. 37.

[21] J. C. Tanner, "Effect of weather on traffic flow," *Nature*, vol. 169, no. 4290, p. 107, Jan. 1952.

[22] M. Behrisch, L. Bieker, J. Erdmann, and D. Krajzewicz, "SUMO-simulation of urban mobility: An overview," in *Proc. 3rd Int. Conf. Adv. Syst. Simulation (SIMUL)*, 2011.

[23] Land Transport Authority Singapore. (2018). *DataMall*. [Online]. Available: https://www.mytransport.sg/content/mytransport/home/dataMall.html

[24] R. Blokpoel and W. Niebel, "Advantage of cooperative traffic light control algorithms," *IET Intell. Transp. Syst.*, vol. 11, no. 7, pp. 379–386, Sep. 2017.

[25] A. Wegener, M. Piórkowski, M. Raya, H. Hellbrück, S. Fischer, and J.-P. Hubaux, "TraCI: An interface for coupling road traffic and network simulators," in *Proc. 11th Commun. Netw. Simulation Symp. (CNS)*, 2008, pp. 155–163.

[26] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, pp. 1–27, Apr. 2011.

[27] B. Efron, "Better bootstrap confidence intervals," *J. Amer. Stat. Assoc.*, vol. 82, no. 397, pp. 171–185, 1987.

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