JOURNAL OF TRAFFIC AND TRANSPORTATION ENGINEERING (ENGLISH EDITION) 2020; 7 (4): 447–466

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Original Research Paper

Prediction based traffic management in a metropolitan area

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HIGHLIGHTS

- Emergent intelligence technique collects, analyzes, shares and monitors traffic and resources.
- Developed traffic management system architecture and analyzed zones and regions with respect to traffic and resources.
- Described the emergent intelligence technique based traffic management in a metropolitan area.
- Performance analysis is performed in realistic scenario by integrating NS2, SUMO, OSM and MOVE tool.

ARTICLE INFO

Article history:
Received 12 November 2017
Received in revised form
12 May 2018
Accepted 16 May 2018
Available online 4 July 2019

Keywords:
Traffic management
Traffic prediction
Travel time prediction
Agent
Emergent intelligence
Swarm intelligence

ABSTRACT

In recent years, modern metropolitan areas are the main indicators of economic growth of nation. In metropolitan areas, number and frequency of vehicles have increased tremendously, and they create issues, like traffic congestion, accidents, environmental pollution, economical losses and unnecessary waste of fuel. In this paper, we propose traffic management system based on the prediction information to reduce the above mentioned issues in a metropolitan area. The proposed traffic management system makes use of static and mobile agents, where the static agent available at region creates and dispatches mobile agents to zones in a metropolitan area. The migrated mobile agents use emergent intelligence technique to collect and share traffic flow parameters (speed and density), historical data, resource information, spatio-temporal data and so on, and are analyzes the static agent. The emergent intelligence technique at static agent uses analyzed, historical and spatio-temporal data for monitoring and predicting the expected patterns of traffic density (commuters and vehicles) and travel times in each zone and region. The static agent optimizes predicted and analyzed data for choosing optimal routes to divert the traffic, in order to ensure smooth traffic flow and reduce frequency of occurrence of traffic congestion, reduce traffic density and travel time. The performance analysis is performed in realistic scenario by integrating NS2, SUMO, OpenStreatMap (OSM) and MOVE tool. The effectiveness of the proposed approach has been compared with the existing approach.

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Peer review under responsibility of Periodical Offices of Chang'an University.
https://doi.org/10.1016/j.jtte.2018.05.003

1. Introduction

A metropolitan area is densely populated urban core area and is surrounded by less populated territories, sharing industry, housing, and infrastructure. It consists of urban areas, satellite cities, rural areas and towns, and these are socio-economically tied to the urban core, and are typically measured by commuting patterns of commuters. The rapid development, urbanization, national and international trades in a metropolitan area leads to increase in the traffic congestion, demands, freight flows and frequency of vehicles. The increase of these factors results in growing of frequency of traffic jams, accidents and fatalities (Bickel et al., 2007), and they lead to significant recurring delay in a metropolitan area. Most of the time these factors depend on the type of place and periods of time. Therefore, in a metropolitan area traffic congestion is an unbearable event for commuters and wastes their precious time and burns money in the form of fuel (Boarnet et al., 1998; Stathopoulos et al., 2002, 2003). Hence, in near future most of the metropolitan areas will become less attractive to business and new residents.

The growing metropolitan areas are facing challenges, such as real time traffic collection, analysis and sharing, traffic density and travel time predictions on routes, to improve the traffic management (Chavhan and Venkataram, 2017). These challenges heavily impacts on daily routine activities and economic losses of commuters and transit operators. Hence, commuters and transit operators will plan on extra amount of trip time to ensure that should not arrive late to their desired destination and reach their required expectations. Therefore, the commuters, and transit operators, greatest interests are to know with some certainty, traffic flow densities pattern, resource utilization pattern and travel time patterns would occur in the near future on routes and areas. Some of these are achieved by using prediction models (Ghosh et al., 2009; Herring et al., 2010; Vlahogianni et al., 2005, 2006), and they provide more accurate and realistic traffic information than the more recently estimated information.

Short term traffic methods, such as k-nearest neighbor (KNN), artificial neural network (ANN), time series analysis (TSA) and support vector regression (SVR) (Castro-Neto et al., 2009; Clark, 2003; Hou et al., 2013, 2015; Kim and Hong, 2015; Lippi et al., 2013; Lv et al., 2015; Quek et al., 2006), data mining and deep learning (Guo, 2016; He et al., 2013; Panagaiotou et al., 2016; Polson and Sokolov, 2017; Raj et al., 2016; Zamani et al., 2010) techniques are used for traffic analysis, prediction and management. These methods may suffer from several drawbacks, including adaptability during dynamic changes in road conditions and new structures, low computing speed and more processing time. These drawbacks have motivated us to re-examine the analysis, sharing, monitoring, prediction and management of resources, traffic and travel time using emergent intelligence (EI) technique (Chavhan and Venkataram, 2015, 2019a, b; Li et al., 2006; Rzevski and Skobelev, 2007) in a metropolitan area. Because the EI technique adapts to dynamic behavior in distributed environments and is the best choice for dynamic traffic management system, which also improves the traffic efficiency, reduces waiting time and under-utilization of resources (like number of vehicles, amount of fuel, parking space, etc.).

In this paper, we propose an intelligent traffic management system using prediction information in a metropolitan area. The proposed system makes use of static and mobile agents. The static agent deployed at each region, which creates and dispatches mobile agents to their respective zones in a metropolitan area. The migrated mobile agents use EI technique for collecting, analyzing and sharing the traffic flow parameters (speed and density), historical data, resource information, spatio-temporal data and so on. The static agent uses these analyzed and historical information for predicting the expected patterns of traffic density (commuters and vehicles) and travel times in each zone and region of metropolitan area. The predicted information along with the spatio-temporal data (e.g., place and time period) are used for dynamic traffic management in a metropolitan area. The proposed model reduces frequency of occurrence of traffic congestion, growth of traffic density at particular place and travel time in each zone and region.

The organization of the rest of the paper is as follows: in section 2, presents the literature survey; in section 3, discusses agents and EI technique; in section 4, presents the proposed traffic management system architecture; in section 5, discusses resource, traffic and travel time analysis in zones and regions of metropolitan area; in section 6, presents EI based traffic management; simulation and analysis results are given in section 7; the existing and proposed models results discussion are presented in section 8; and conclusions are drawn in section 9.

2. Literature survey

In this section, we describe few existing works on traffic analysis, prediction, scheduling and management using short term traffic prediction methods (parametric, non-parametric and artificial intelligence), data mining, deep learning, swarm intelligence and agent based techniques in different networks and scenarios.

Articles (Castro-Neto et al., 2009; Clark, 2003; Hou et al., 2013; Kim and Hong, 2015; Lippi et al., 2013; Quek et al., 2006) proposed methods for traffic prediction and management using KNN, ANN, TSA and SVR models. In Lippi et al. (2013) accurate prediction and efficiently computation are done by using TSA model, which performs highly competitive for predicting traffic flow during highly congested periods of time. During the typical and atypical conditions traffic flow prediction for short term is done using SVR model (Castro-Neto et al., 2009). In Clark (2003) and Hou et al. (2013) the multivariate non-parametric KNN model is used for traffic congestion prediction based on speed, traffic flow and density measured at loop detector on a per minute basis. In Kim and Hong (2015) and Quek et al. (2006) ANN models are used for predicting traffic flow prediction in urban area. These methods have their own drawbacks, like being difficult to manage immediate changes in the road conditions and new road structure, low computing speed and high processing time requirements as size of the processing information increases.

Van Hinsbergen et al. (2011) used the neural networks for prediction of travel time because they can deal with noisy data. For training the networks, they have used the Bayesian techniques which results in lesser error and predicts accurate confidence bounds. Min and Wynter (2011) developed the method for real time traffic prediction at a fine granularity over different time periods in a day by making use of advanced and smart transportation technologies. The method provides real-time route guidance and short term traffic prediction from the point of view of network operators and commuters. Ayeni (1978) demonstrated the use of entropy maximizing models in analyzing the impacts of government policies and metropolitan area plans. Models are simplified versions of reality, and they constitute mechanisms for understanding city systems and for designing the future city.

Raj et al. (2016), Zamani et al. (2010), Guo (2016) and He et al. (2013) used data mining techniques for traffic analysis, density estimation, prediction and traffic management. They used KNN and ANN as tools for data mining, and these data are collected using the sensors.

Jere et al. (2014) analyzed the change of commuters' pattern in railway networks at different time periods in weekdays and weekends. The objective was achieved using the proposed two data mining techniques, namely common orthogonal basis extraction (COBE), and joint and individual variation explained (JIVE).

Jia et al. (2017), Manoharan (2016), and Polson and Sokolov (2017) used deep learning techniques for traffic flows prediction. Polson and Sokolov (2017) described their methodology on road sensor data and predict traffic flows during two special events, i.e., football game and an extreme snowstorm event. Both the cases have sharp traffic flow regime changes, occurring very suddenly, and showed that how deep learning technique provides precise short term traffic flow prediction. Jia et al. (2017) and Manoharan (2016) predicted the traffic flows under rainfall situation using the deep learning techniques, which uses NN as the tool.

He and Peeta (2015) proposed the model of day to day traffic evolution based on strategic thinking and marginal decision rule. They have analyzed the theoretical properties, which includes invariance, asymptotic stability and relationship with the rational behavioral adjustment process. Nantes et al. (2015) have built real time traffic prediction model for arterial corridors using the collected traffic data through various sensors, such as loop detectors, cell phones, probe vehicles, video cameras, Bluetooth, remote sensing and public transport smart cards.

Viriyasitavat et al. (2009), Abu-Ghazaleh and Alfa (2008), and Xue et al. (2009) carried out the traffic mobility pattern and routes prediction in VANETs and urban areas. Viriyasitavat et al. (2009) analyzed vehicular traffic using cellular automata (CA) approach. During analysis they have identified problems in routing and provided some important insights for designing routing protocol for urban traffic. In Viriyasitavat et al. (2009), transit and non-transit traffic pattern are considered in urban areas. Abu-Ghazaleh and Alfa (2008) have developed prediction model using Markov Renewal process. They have predicted the mobility and activity of network users and estimated the traffic population of users at each location in a network coverage area. Xue et al. (2009) predicted vehicular route based on the mobility patterns of vehicles in urban areas.

Kammoun et al. (2014), Monteiro and Corria (1999), Sachdeva et al. (2007), Desai et al. (2011), Osaba et al. (2016), Zargari et al. (2012), Adler et al. (2005), Harnandez et al. (2002), Adler and Blue (2002), Franziska et al. (2006) and Chen and Cheng (2010) described the traffic congestion and management using multiagent system (MAS) at different conditions, scenarios and parameters. The authors in article (Kammoun et al., 2014) have proposed an adaptive MAS for managing road traffic using swarm intelligence (SI), such as ant colony and hierarchical fuzzy system. SI is used for itinerary evaluations by integrating contextual parameters influencing the route choice. They have collected the travel time taken by drivers and real time traffic information required to reach destinations, for improving the quality of road network (during jams and congestions). In Monteiro and Corria (1999), MAS approach was used to control the traffic in telecommunication networks, such as public switched telephone network (PSTN), integrated services digital network (ISDN) or transmission networks. Sachdeva et al. (2007) proposed a MAS based real time centralized evolutionary optimization technique for management of urban traffic in the area of traffic signal control. They have summarized different evolutionary techniques available for avoiding congestion and managing the traffic in intelligent transportation systems (ITS).

Desai et al. (2011) discussed existing MAS based congestion management in ITS and described their advantages over other techniques. Osaba et al. (2016) discussed decentralized management of traffic congestion in a highway and the prediction of pollution level in a city using distributed artificial intelligence based on classification techniques. Adler et al. (2005) described mathematical framework and simulation model for a cooperative traffic management and route guidance system. They have explored the use of cooperative, distributed MAS to improve the traffic management and dynamic routing strategy. Hernndez et al. (2002) described and compared two scheme: integrated TRYS and autonomous TRYS centralized and decentralized intelligent traffic management systems, respectively in the urban motorway network. Both these schemes uses traffic management agents which uses similar knowledge-based reasoning techniques in order to deal with local traffic issues. Adler and Blue (2002) proposed a cooperative MAS based transportation management and route guidance system by negotiation among agents (network managers), service providers, and drivers equipped with route guidance systems.

Teodorovic (2008), Ilie and Bădică (2013), Ducatelle et al. (2010), Teodorovic (2003), Hu et al. (2016), Garcia-Nieto et al. (2011, 2012), Renfrew and Yu (2009) and Tatomir and Rothkrantz (2006) described the SI technique based road traffic control, traffic signal control, traffic light scheduling, traffic and transportation management at different conditions in urban system. Teodorovic (2008), Ilie and Bădică (2013), Ducatelle et al. (2010) and Teodorovic (2003) discussed the framework, principles and applications of swarm intelligence for modeling complex traffic and

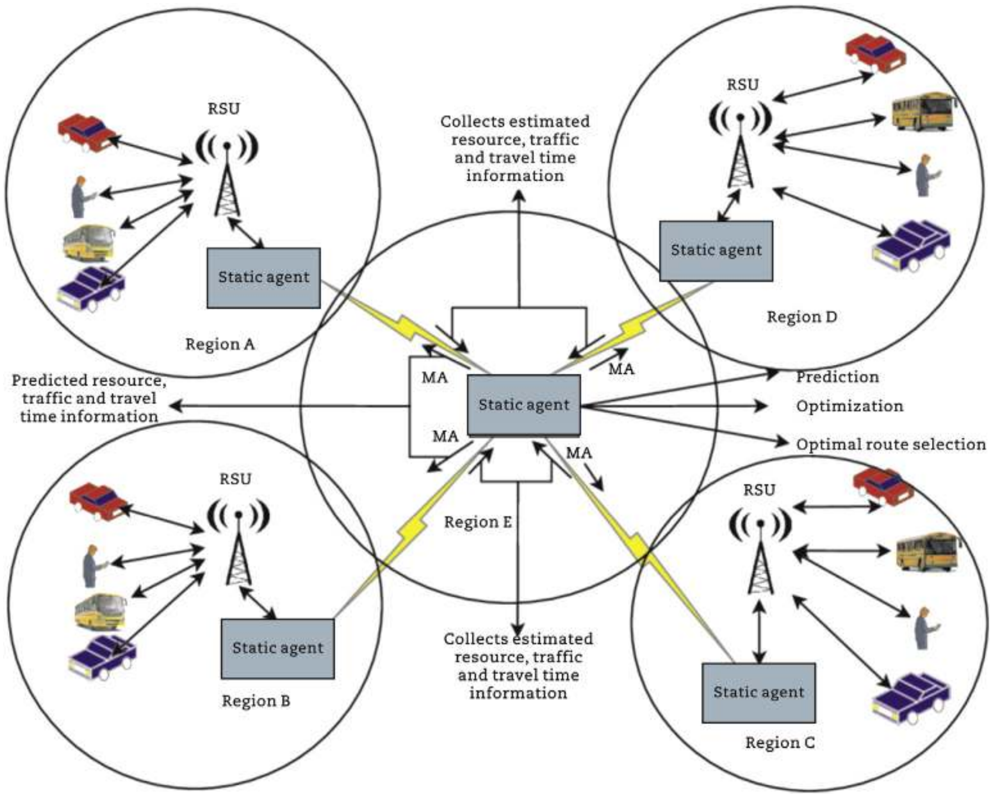

Fig. 1 – Emergent intelligence technique based group formation and interaction among agents, vehicles, commuters and roadside units in a metropolitan area.

transportation system, adaptive routing in telecommunication networks and transport modeling. Hu et al. (2016) and Garcia-Nieto et al. (2011, 2012), described road traffic management and traffic light management application in the real urban traffic networks.

In this paper, we use EI technique which is very much suitable in dynamic situations for resource and traffic density analysis, collection, monitoring, sharing and management in a metropolitan area. The proposed traffic management system using prediction information resolves the problems faced by the existing methods. Because EI technique provides parallel processing; autonomously replenishes environment by interconnecting synchronized groups of agents; adapts to dynamic environments; and takes smart and dynamic decentralized decisions to achieve common goal of system.

3. Overview of agents and emergent intelligence technique

In this section, we describe agent technology and emergent intelligence (EI) technique, which are very much relevant in the proposed traffic management system in a metropolitan area.

3.1. *Agent technology*

Agents are distributed and autonomous codes, executing at depot and performs actions on behalf of humans or others. The interesting properties are autonomy, reactivity, mobility, communication skills and many more. Depending upon these properties they have categorized. In this paper, we have used stationary and mobile agents (depending upon their mobility pattern they have categorized) for collection, analysis and allocation of resources and traffic information at different remote places, and also taking autonomous decisions.

3.2. *Emergent intelligence (EI)*

It is the group intelligence, and group consists of neighborhood roadside units, vehicles, pedestrians and agents, and these are spontaneously and periodically interacts among them (Chavhan and Venkataram, 2015, 2019a, b; Li et al., 2006). It is the integration of MAS and SI, and hence it can be considered as sub-field of computational intelligence (CI). EI appears whenever there will be occurrence of events (predictable or unpredictable) and exists till the problem solving processes completed. Hence, it reacts on events, schedule resources, coordinate plans, monitor plans execution, deliver services and reschedule resources during the mismatch between current plan and current situation. Based on some fundamental concepts of self-organization and evolutionary, the EI technique adapts to any kind of situations and provides dynamic decisions in dynamic environment to achieve common goals of the whole system. The adaptability in EI technique recognizes user needs, changes in plans, behavior and reconfiguration of resources in a real time for predicting the events with cooperation,

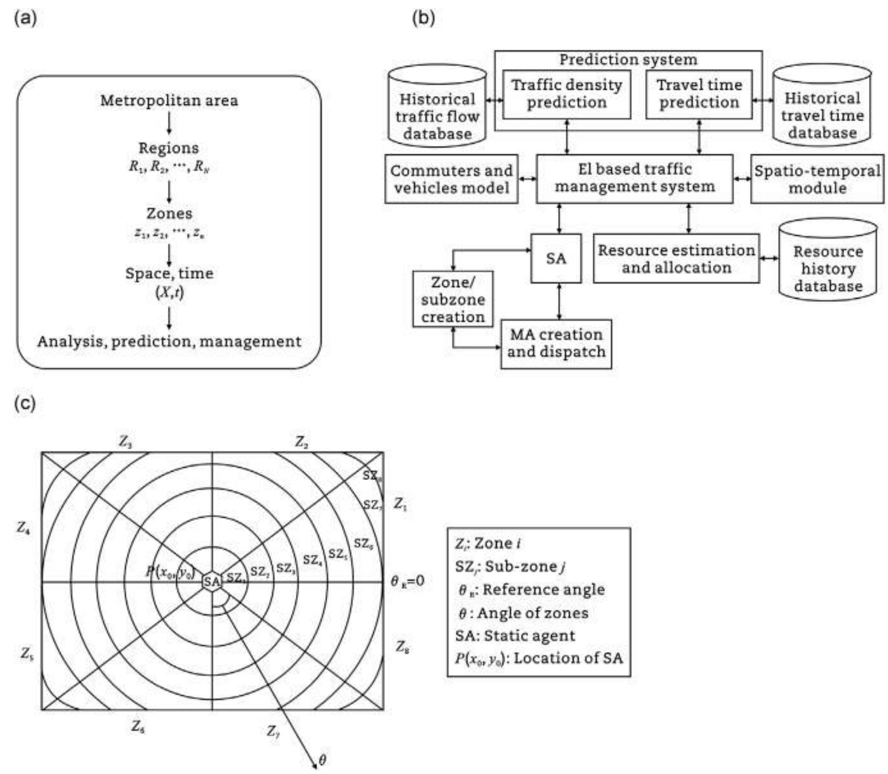

Fig. 2 – Proposed traffic management system architecture. (a) Hierarchical division of metropolitan area. (b) Traffic management system architecture at depot. (c) Zone and sub-zone formation.

competence, negotiation and collaboration of neighbor entities for providing optimal resource or services.

The EI technique's salient features consists of parallel processing, adaptability, autonomously replenishing, dynamic decision making, self-organizing, evolutionary, cooperating, collaborating, negotiating, and competing. These features make EI technique more suitable for geographically distributed dynamic and complex non-linear systems.

EI technique's decision making (Fig. 1) steps are as follows.

(1) Initiator depot's agent forms group, which consists of transport depot staffs, roadside units (RSUs), agents and vehicles, continuously and periodically whenever they have certain common interests among them otherwise abandons them.
(2) It analyzes, refines and estimates resource required, and decides type and amount of information need to be shared periodically.
(3) It anticipates resources, traffic jam, waiting time, etc., using analyzed and historical data.
(4) It uses anticipated information for deciding staffs and agents cooperation, competence and negotiation.
(5) It spontaneously and periodically collects, analyzes, monitors, shares, allocates and accesses certain amount of anticipated information.
(6) It takes smart, independent and decentralized dynamic decisions to solve problems (either partial or full) and informs to the concerned agents for further actions (like transportation, evacuation, etc.).

Fig. 1 shows formation of group, interactions, collection, sharing and prediction of information among static agent (SA), multiagents (MAs), vehicles, pedestrians and RSUs using EI technique.

The benefits of EI with agents in transportation system domain are as follows.

(1) It has the ability to reduce complexity due to the concise and natural modeling of the problem domain.
(2) It enhances robustness and adaptability due to self organization and evolutionary nature of the subsystems.
(3) It replenishes environment by creating autonomous regenerating feedback loop by interactions among group of agents.
(4) It provides more communication flexibility in the geographically distributed complex systems.

Transportation and traffic management operation in the metropolitan area is geographically distributed and its continuous alternating busy and idle operating characteristics are well suited to EI technique's features with agents. The necessities of EI technique in this paper are as follows.

(1) Resource and traffic information collection, analysis and sharing among the groups of agents (both static and mobile agents) in zones and regions.
(2) Prediction of resource required, traffic density, travel time on routes, etc., in zones and regions.

Algorithm 1 Logical zone and sub-zone formation

```
Begin
Define Length L and radius ℜ = L/2 of region.
Define a depot with a point P(x0, y0) at center.
Define variables n (required number of zones), k_i (number of sub zones of zone i, Z_i (i^th zone) and SZ_j (j^th sub-zone)
Define θ (angle of each zone), θ_r (Reference angle) and θ_m (Measured angle).
Initialize i = 1 and θ_r = 0.
for i = 1 to n do
  if θ_i ≤ 360 then
    θ_m = 360/n and θ_r = 0.
    θ_i = θ_m + θ_r
    Z_i = (θ_i, θ_r) and θ_r = θ_i
    Define α_{j-1} = 0
    for j = 1 to k_i do
      α_j = ℜ/k_i
      if α_j ≤ ℜ then
        α_j = α_{j-1} + α_j
        SZ_j = (α_{j-1}, α_j)
      end if
    end for
  end if
end for
End
```

Fig. 3 – Algorithm 1.

(3) Optimal allocation of resources (like vehicles, staffs, etc.) and dynamic traffic management in a metropolitan area.

4. Proposed traffic management system architecture

In this section, we present hierarchical division of metropolitan area and architecture of the proposed system available at depots. The main objective of proposed work is to analyze, predict and management of resource, traffic and travel time in every zones and regions of metropolitan area.

The metropolitan area is divided into N number of regions and each region contains a depot with SA. Again, each region is subdivided into n number of zones. The hierarchical division of metropolitan area is shown in Fig. 2(a).

The proposed traffic management system architecture is shown in Fig. 2 (b), which is available at each depot in a metropolitan area. It consists of region and zone formation module; spatio-temporal module; commuters and vehicles model; resource estimation and allocation module; traffic density prediction module; travel time prediction module; and emergent intelligence based traffic management module. These are explained in subsequent subsections.

4.1. *Formation of zones and sub-zones*

We have modeled the metropolitan area as network of nodes and links, where nodes represent depots and links corresponds to routes between the depots. Given the radius of region ($R = L/2$), the region centered with SA deployed in depot, and it uses coordinate techniques to logically divide the region into required number of zones and sub-zones as shown in Fig. 2(c). The procedure of zones and sub-zones formation is explained in the algorithm 1 (Fig. 3).

4.2. *Static agent (SA)*

SA resided at depot creates and dispatches mobile agents (MAs) to zones. The functions of SA at the depot in a metropolitan area are as follows.

(1) It forms the logical zones and sub-zones.
(2) It creates and dispatches MAs to all zones in a metropolitan area periodically to collect resource information, traffic density, historical information, etc.
(3) It analyzes and predicts the exact situation, requirements, growth or decline of traffic density, resource utilization, and travel time in each zone in a metropolitan area.
(4) It shares analyzed and predicted information to MAs, and these MAs shares with RSUs, vehicles and pedestrians for managing the traffic flow in a metropolitan area.

4.3. *Spatio-temporal module (STM)*

It consists of finite set of points with location information, relationships between pairs of points, time dependent attributes attached to points and relationships. It attempts to capture the dynamic behavior and complex statistical dependencies that can arise from the evolution of phenomena at many spatial and temporal scales. It provides traffic data to the traffic management system in the form of spatial-time series and are collected at specific locations and constant intervals of time for predicting the actual behavior and conditions of regions.

4.4. *Commuters and vehicles model*

At each zone, the roadside units (RSUs) are deployed to provide seamless network connectivity and we further assume that the coverage intersection is insignificant. The commuters' arrivals to the zones are shown in Fig. 4(a) along with their arrival rates. Table 1 shows the notations and their meanings used in the commuters and vehicles model.

Let $N^{i}_{c,x,t}$ represents the total number of commuters at time t occupying in a given length x of zone i is given by

$$N^{i}_{c,x,t} = \frac{\lambda_i(t)R}{\Delta x \overline{\upsilon_i}} \tag{1}$$

where $\lambda_i(t)$, $\overline{\upsilon_i}$, x, and R represent arriving rate of commuters, average speed of commuters, commuters occupying length and coverage area of zone i at time t, respectively.

Similarly, the vehicles' arriving rates to zones is shown in Fig. 4(b) along with their arrival rates. Javed et al. (2015) estimated vehicle densities in a particular range, and they have considered only the distance and bandwidth utilization. But they have not considered the arrival rates and vehicles speed in that range for realistic estimation of vehicles density. In this paper, we have considered all the above mentioned parameters for estimating the vehicles density in a zone. The vehicle density at time t occupying in a given length x of zone i is given by

$$N^{i}_{v,x,t} = \frac{\mu_i(t)R}{\Delta x \overline{s_i}} \tag{2}$$

where $\mu_i(t)$, $\overline{s_i}$, x and R represents the arriving rate of vehicles, the average speed of vehicles, vehicles occupying length and the coverage area of zone i at time t, respectively.

Let $N^{i}_{vb,x,t}$ represents the average number of vehicle breakdowns in zone i at t is given by

$$N^{i}_{vb,x,t} = \sum_{j=1}^{N^{i}_{v,x,t}} V_j P(V_j) \tag{3}$$

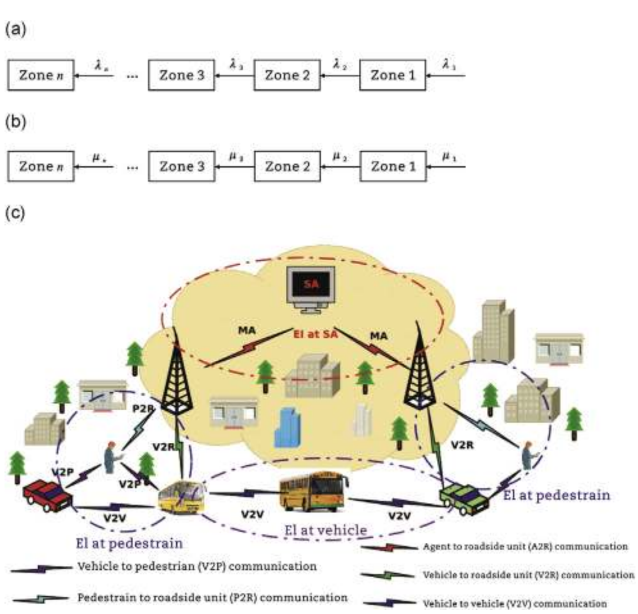

Fig. 4 – Scenario of commuters' arrival to the region with different communication. (a) Commuters' arrival model. (b) Vehicles' arrival model. (c) Different communications involved at regions in a metropolitan area for traffic management.

$$P(V_j) = \begin{cases} 0 & \mathrm{TB_i(total\,breakdowns)\ and\ PB_i(partial\ breakdowns)} \\ 1 & \mathrm{NB_i(no\,breakdowns)} \end{cases}$$

where $P(V_j)$ is the probability of breakdowns of jth vehicle.

4.5. *Resource estimation and allocation module*

In this subsection, we estimate the resource requirements, resource availability, surplus and deficit resource, and resource allocation in each zone. The notations and their meanings used in this subsection are mentioned in the Table 2.

Let $R^{i}_{1,x,t}$, $R^{i}_{2,x,t}$, $\cdots$, $R^{i}_{k,x,t}$ are resources available in zone i at a transport depot, where $R^{i}_{1,x,t}$ is the number of vehicles, $R^{i}_{2,x,t}$ is the number of staff, $R^{i}_{3,x,t}$ is amount of fuel in zone i at x of a transport depot, etc., where k is the total number of resources, and $i = 1, 2, \cdots, n$ and n is the total number of zones in the vicinity of transport depots in a metropolitan area.

Let $R^{i}_{j,x,t}(\mathrm{avail})$ represents average number of resources available in zone i at place x and time t, and is given by

$$R^{i}_{j,x,t}(\mathrm{avail}) = \sum_j r^{i}_{j,x,t}(\mathrm{avail}) P\left[r^{i}_{j,x,t}(\mathrm{avail})\right] \tag{4}$$

where $r^{i}_{j,x,t}(\mathrm{avail})$ is the percentage of jth resource available in the zone i at place x and time t and is given by

$$r^{i}_{j,x,t}(\mathrm{avail}) = \frac{A - B}{A} \tag{5}$$

where A is the maximum capacity of jth resource, and B is the amount of jth resources allocated in zone i at same place x in past.

The estimation of minimum and maximum of jth resource requirements in zone i at time t, $R^{i}_{j,x,t}(\min)$ and $R^{i}_{j,x,t}(\max)$ respectively, by taking weighted average of minimum and maximum resource requirements ($R^{i}_{j,x,t}(\mathrm{avg},\min)$ and $R^{i}_{j,x,t}(\mathrm{avg},\max)$) and the lowest and highest resource requirements in the past ($R^{i}_{j,x,t}(\mathrm{past},\min)$ and $R^{i}_{j,x,t}(\mathrm{past},\max)$) in zone i. The minimum and maximum of jth resource requirements in zone i at time t is given as

$$R^{i}_{j,x,t}(\min) = \frac{R^{i}_{j,x,t}(\mathrm{avg},\min) + R^{i}_{j,x,t}(\mathrm{past},\min)}{1+\sigma} \tag{6}$$

and

$$R^{i}_{j,x,t}(\max) = \frac{R^{i}_{j,x,t}(\mathrm{avg},\max) + R^{i}_{j,x,t}(\mathrm{past},\max)}{1+\sigma} \tag{7}$$

where σ is 0 when resource required in the same zone and is 1 when resource required in neighbors zone.

The weighted average of minimum and maximum of jth resource requirements at place x in zone i at time t is given as

$$R^{i}_{j,x,t}(\mathrm{avg},\ \min) = \frac{1}{M}\sum_{k=1}^{M} R^{i}_{j,k,t}(\min) H^{i}_{j,x,t} \tag{8}$$

and

$$R^{i}_{j,x,t}(\mathrm{avg},\ \max) = \frac{1}{M}\sum_{k=1}^{M} R^{i}_{j,k,t}(\max) H^{i}_{j,x,t} \tag{9}$$

Table 1 – Notations and their meanings in section 4.4.

Notation	Description
$N^i_{c,x,t}(t)$	Total number of commuters at time t in a given length Δx of zone i
$\lambda_i(t)$	Commuters' arrival rate
R	Coverage area of zone i
$\overline{v_i}$	Average speed of commutsers
$N^i_{v,x,t}$	Vehicle density at time t occupying in a given length Δx of zone i
$\mu_i(t)$	Vehicles' arrival rate
$\overline{s_i}$	Average speed of vehicles
$N^i_{vb,x,t}$	Average number of vehicle breakdowns in zone i at time t

where M is the number of neighbors require the same resource, and $H^i_{j,x,t}$ is the historical percentage of jth resource utilized in zone i at time t.

The $H^i_{j,x,t}$ helps agent to know about commuters' resource requirements during emergency conditions, and is given as

$$H^i_{j,x,t} = \frac{1}{m_a}\sum_{k=1}^{m_a}\frac{R^i_{k,x,t}(\max) - R^i_{k,x,t}(\mathrm{alloc})}{R^i_{k,x,t}(\max) - R^i_{k,x,t}(\min)} \tag{10}$$

where m_a is the total number of resources allocated in zone i and $R^i_{j,x,t}(\mathrm{alloc})$ is the amount of jth resource allocated in past history.

The $R^i_{j,x,t}(\mathrm{alloc})$ is a resource allocation function, which determines how much resources (i.e., number of vehicles, number of staff, amount of fuel, etc.) have been allocated in the zone i at time t in a metropolitan area, and is given as

$$R^i_{j,x,t}(\mathrm{alloc}) = \frac{R^i_{j,x,t}(\min) + R^i_{j,x,t}(\max)}{2} \tag{11}$$

Excess availability of resources are termed as surplus resource. The estimation of surplus resource of jth resource in zone i at time t is given as

$$R^i_{j,x,t}(\mathrm{surp}) = r^i_{j,x,t}(\mathrm{avail}) - R^i_{j,x,t}(\mathrm{alloc}) \tag{12}$$

Insufficient amount of resource required are termed as deficit resource. The deficit resource of jth resource in zone i at time t is given as

$$R^i_{j,x,t}(\mathrm{def}) = R^i_{j,x,t}(\mathrm{req}) - R^i_{j,x,t}(\mathrm{alloc}) \tag{13}$$

where $R^i_{j,x,t}(\mathrm{req})$ is the required amount of jth resource for the current available commuters in the zone i.

4.6. *Prediction of traffic and travel time*

In this subsection, we discuss the prediction of traffic growth or decline of commuters, vehicles and travel times prediction in a metropolitan area. Table 3 shows notations and their meanings used in following subsections.

4.6.1. *Prediction of commuters' density*

The predicted growth or decline of commuters' density in zone i at time t is denoted as $\Delta TV^i_{c,x,t}$. The total number of commuters' at zone i and time t is estimated using Eq. (1). The commuters' arrival is a Poisson point process with density β. The probability of finding n_c number of commuters' in the zone i is given by

$$p^i(n_c, R) = \frac{(\beta R)^{n_c} e^{-\beta R}}{n_c!} \tag{14}$$

The predicted commuters' density at place x in zone i is sum of total number of commuters' available at zone i at time t, probability of n_c number of commuters' in the zone i and unexpected number of commuters' arrival density as compare to history database, and is given as

$$\Delta TV^i_{c,x,t} = N^i_{c,x,t} + p^i(n_c, R) + \max\left\{H^i_{c,x,t}, -\left[N^i_{c,x,t} + p^i(n_c, R)\right], 0\right\} \tag{15}$$

where $H^i_{c,x,t}$ is the historical commuters' traffic density occurred in zone i.

Table 2 – Notations and their meanings in section 4.5.

Notation	Description
$R^i_{j,x,t}$ (avail)	Average number of resources available in zone i at place x and time t
$r^i_{j,x,t}$ (avail)	Percentage of jth resource available in the zone i at place x and time t
$R^i_{j,x,t}$ (min) and $R^i_{j,x,t}$ (max)	Minimum and maximum of jth resource requirements in zone i at time t
$R^i_{j,x,t}$ (avg, min) and $R^i_{j,x,t}$ (avg, max)	Weighted average of minimum and maximum resource requirements
$R^i_{j,x,t}$ (past, min) and $R^i_{j,x,t}$ (past, max)	Weighted average of lowest and highest resource requirements in the past in zone i
$H^i_{j,x,t}$	Historical percentage of jth resource utilized in zone i
m_a	Total number of resources allocated in zone i
$R^i_{j,x,t}$ (alloc)	Amount of ith resource allocated in zone i
$R^i_{j,x,t}$ (surp)	Surplus of jth resource in zone i at time t
$R^i_{j,x,t}$ (def)	Deficit of jth resource in zone i at time t
$R^i_{j,x,t}$ (req)	Required amount of jth resource for current commuters' available in zone i

Table 3 – Notations used in prediction system and their meanings.

Notation	Description
$p^i(n_c, R)$ and $q^i(n_v, R)$	Probability of finding n_c number of commuters' and n_v number of vehicles in zone i
β and α	Poisson point process with commuters' and vehicles' density
$\Delta TV^i_{c,x,t}$ and $\Delta TV^i_{v,x,t}$	Predicted commuters and vehicles traffic density in zone i at time t
$\Delta C_{i,x,t}$ and $\Delta V_{i,x,t}$	Commuters and vehicles traffic density growth in zone i at time t
m and n	Number of sub-zones and zones

$$\Delta TV^i_{c,x,t} = \frac{\lambda_i(t)R}{\Delta x \overline{v}_i} + \frac{(\beta R)^{n_c} e^{-\beta R}}{n_c!} + \max\left\{H^i_{c,x,t}, -\left[N^i_{c,x,t} + p^i(n_c, R)\right], 0\right\} \tag{16}$$

The prediction of commuters' density in zone i at time t is sum of commuters' density in all m number areas denoted as $\Delta C_{i,x,t}$ and is called as "commuters' density prediction model", and is given as

$$\Delta C_{i,x,t} = \frac{1}{|Z_i|} \int_{x=1}^{m} TV^i_{c,x,t} \Delta TV^i_{c,x,t} dx \tag{17}$$

The commuters' density prediction in the region l is the sum of the commuters' density in all zones (n), and is given as

$$\Delta C_{l,x,t} = \frac{1}{|R_l|} \int_{i=1}^{n} \Delta C_{i,x,t} dx \tag{18}$$

4.6.2. *Prediction of vehicles' traffic density*

The total number of vehicles in zone i at time t is estimated using Eq. (2). The vehicles' arrivals are Poisson point process with density $\propto$. The probability of finding n_v number of vehicles in R range of zone i is given by

$$q^i(n_v, R) = \frac{(\propto R)^{n_v}}{n_v!} \tag{19}$$

The predicted vehicles' traffic density at xth in zone i is sum of total number of vehicles' available at zone i at time t, probability of n_v number of vehicles' in the zone i and unexpected number of vehicles' arrival density as compare to history database.

$$\Delta TV^i_{v,x,t} = N^i_{v,x,t} + q^i(n_v, R) + \max\left\{H^i_{v,x,t} - \left[N^i_{v,x,t} + q^i(n_v, R)\right], 0\right\} \tag{20}$$

where $H^i_{v,x,t}$ is the historical vehicle's traffic density prediction in x of zone i at time t.

$$\Delta TV^i_{v,x,t} = \frac{\mu_i(t)R}{\Delta x \overline{s}_i} + \frac{(\propto R)^{n_v}}{n_v!} + \max\left\{H^i_{v,x,t} - \left[N^i_{v,x,t} + q^i(n_v, R)\right], 0\right\} \tag{21}$$

The prediction of vehicles traffic density in zone i at time t is the sum of vehicles' density in all m number areas and is as $\Delta V_{i,x,t}$, and is called as "vehicles traffic density model", and is given as

$$\Delta V_{i,x,t} = \frac{1}{|Z_i|} \int_{x=1}^{m} TV^i_{v,x,t} \Delta TV^i_{v,x,t} dx \tag{22}$$

The prediction of vehicles traffic density in region l at time t is sum of the vehicles traffic density in all zones (n), and is given as

$$\Delta V_{l,x,t} = \frac{1}{|R_l|} \int_{i=1}^{n} \Delta V_{i,x,t} dx \tag{23}$$

Algorithm 2 presents the procedure of commuters and vehicles traffic density prediction in zones and regions of metropolitan area (Fig. 5).

4.6.3. *Prediction of travel times of vehicles*

The travel time prediction refers to measuring travel times for future (or unknown) traffic conditions on a particular route. In

Algorithm 2 Prediction of commuters and vehicles' traffic density in zones and regions

Begin
Input data: $\lambda_i(t), \mu_i(t), \overline{v}_i, R, \overline{s}_i, \beta, n_v, n, \Delta TV^i_{c,x,t}, H^i_{c,x,t}, \Delta TV^i_{v,x,t}$ *and* $H^i_{v,x,t}$
for l=1 to N **do**
  Static agent (SA) is deployed in l^{th} region
  for i=1 to n **do**
    SA creates and dispatches Mobile agents (MAs) to i^{th} zone
    RSU in each zone estimates total number of commuters and vehicles in zones.
    RSU provides this information to the MA during interaction with it.
    The MA provides collected information from RSU of zone i to SA.
    SA estimates $\Delta C_{i,x,t}$ *and* $\Delta V_{i,x,t}$
  end for
  The SA estimates the expected patterns of commuters and vehicles traffic density in l^{th} region
  $\Delta C_{l,x,t}$ *and* $\Delta V_{l,x,t}$
end for
End

Fig. 5 – Algorithm 2.

Table 4 – Notations and their meanings in section 4.6.3.

Notation	Description
$n_v(t)$	Number of vehicles observed by RSU at time t on route r
T_b	Time required for broadcasting
$l(t)$	Effective length of vehicle during the time period T_b
$o(t)$	Percent of time required for the RSUs to detect the vehicles
$v(t)$	Velocity of vehicle
$v(i,d,t,r)$	Velocity of vehicles detected by RSU i on route r at time t on day d
$T(d,t,r)$	Travel time on route r at time t on day d
T^I, T^H and T^D	Instantaneous travel time, historical travel time and delay involved on route r
m_v	Total number of times the vehicle stopped at different stops between RSU i and i+1

real time, the prediction of travel time is more important than the latest measured travel time for commuters in a metropolitan area. More precisely, to predict the expected travel time of vehicles we need to consider the delays involved during the traveling period along the routes. As we know at each intersection a RSU is installed to collect the vehicle density at different time periods in a day. Notations and their descriptions used in this subsection are presented in the Table 4.

Let $n_v(t)$ be the number of vehicles observed by RSU at time t on route r, T_b is the time required for broadcasting, $l(t)$ is the effective length of vehicle during the time period T_b and $o(t)$ is the percent of time required for the RSUs to detect the vehicles. The velocity of vehicle is given by

$$v(t)=\frac{l(t)n_v(t)}{T_b o(t)} \tag{24}$$

Let $v(i,d,t,r)$ is the velocity of vehicles detected by RSU i on route r at time t on day d. The travel time on route r at time t on day d and is denoted by $T(d,t,r)$ between the traveling segment from RSU i to $i+1$, and is given by

$$T(d,t,r)=(\mathrm{dist}_{i+1}-\mathrm{dist}_i)\Big/\left[\frac{v(i+1,d,t,r)+v(i,d,t,r)}{2}\right] \tag{25}$$

where numerator part of Eq. (25) is the distance from RSU i to $i+1$ and denominator part is the typical speed in the segment i to $i+1$.

The travel time prediction on route r is the sum of instantaneous travel time (T^I), historical travel time (T^H) and delay involved (T^D) on route r at different stops between the RSUs.

T^I is instantaneous travel time for prediction at $t+\delta$ on day d and route r, which is we have assumed that traffic will not change during short interval of time, and is given as

$$T^I(d,t+\delta,r)=T(d,t,r) \tag{26}$$

The historical travel time is the average value of past travel time data at time $t+\delta$ on route r and is denoted as $T^H(d,t+\delta,r)$, and is used to predict future travel time, and is given as

$$T^H(d,t+\delta,r)=T^H(d,t,r) \tag{27}$$

The average travel time delay, at $t+\delta$ on route r and day d, involved in the segment i to $i+1$ is given as

$$T^D(d,t+\delta,r)=\frac{1}{m_v}\sum_{i=0}^{m_v}[T_{i+1}(d,t,r)-T_i(d,t+\delta,r)] \tag{28}$$

where $T_0(d,t+\delta,r)=0$ and m_v is the total number of times the vehicle stopped at different stops between RSU i to $i+1$.

The prediction model of travel time on route r at time $t+\delta$ on day d is given by

$$\begin{aligned}T^p(d,t+\delta,r)=&\zeta(t,\delta)T^I(d,t+\delta,r)\\&+\eta(t,\delta)\max\left[T^H(d,t+\delta,r)-T^I(d,t+\delta,r),0\right]\\&+\gamma(t,\delta)T^D(d,t+\delta,r)+\epsilon\end{aligned} \tag{29}$$

where $\zeta(t,\delta)$, $\eta(t,\delta)$ and $\gamma(t,\delta)$ are the three varying co-efficient and are time dependent, δ is future time prediction and random fluctuation, and ϵ is measurement error.

5. Analysis of resource, traffic density and travel time in zones and regions of metropolitan area

In this section, we present analysis of each zone and region at different time periods in a metropolitan area. The analysis of each zone is based on the above mentioned estimated information.

Analysis at zone i and time t is denoted as $z_{i,t}$ and is given by

$$z_{i,t}=\alpha\left(w_{t,x}O_{i,t,x}\right)+\beta\left(w_{t-\delta,x}O_{i,t-\delta,x}\right) \tag{30}$$

where $\alpha(w_{t,x}O_{i,t,x})$ is the current observation and $\beta(w_{t-\delta,x}O_{i,t-\delta,x})$ is the past observation at zone i, w, α and β are weights, and $w_{t,x}$ is weight assignment to the place x at time t.

The choice of these weights are crucial issue in spatial and time. Typically, these weights are chosen a priori to reflect geographical characteristics of regions and zones under certain conditions (e.g., workplaces, commercial activities, educational institutes, hospitals, etc.). The value of $\alpha>\beta$ for giving more importance to current observation than past. The following properties satisfy for the weight assignment:

- $w_{t,x}\geq 0, \alpha\geq 0$ and $\beta\geq 0$.

Algorithm 3 Analysis of zones and regions in a metropolitan area

```
Begin
Input data: ΔC_{i,x,t}, ΔV_{i,x,t}, O^R_{i,x,t}, r^i_{j,x,t}(avail), R^i_{j,x,t}(surp), R^i_{j,x,t}(break), H_{c,x,t}, H_{v,x,t}, H_{j,x,t}.
for l = 1 to R do
  SA is deployed in l^th region
  for i = 1 to n do
    SA creates and dispatches MAs to i^th zone
    for j = 1 to m do
      RSU of i^th zone estimates N^i_{c,x,t}, N^i_{v,x,t}, and R_a(t) and provides to MA during interaction
    end for
    MA provides collected information from RSUs of zone i to SA
    MA estimates O_{i,x,t} and Z_{i,t}.
  end for
  Using each zone pattern the SA analysis the region and whole metropolitan area
  SA estimates R_{l,t}
end for
End
```

Fig. 6 – Algorithm 3.

· $\sum_{x \in X} w_{x,t} = 1$ and $\alpha + \beta = 1$

$O_{i,t,x}$ is the observations at place x and time t and is given as

$$O_{i,t,x} = \begin{cases} \dfrac{O^{R}_{i,x,t}}{H^{I}_{j,x,t}} \\ \dfrac{T^{p}_{d,t+\delta,r}}{T^{H}_{d,t+\delta,r}} \\ \dfrac{\Delta C_{i,x,t}}{H_{c,x,t}} \\ \dfrac{\Delta V_{i,x,t}}{H_{v,x,t}} \end{cases} \tag{31}$$

where $O^{R}_{i,x,t}$, $O^{T}_{i,x,t} = \frac{T^{p}_{d,t+\delta,r}}{T^{H}_{d,t+\delta,r}}$, $\Delta C_{i,x,t}$, and $\Delta V_{i,x,t}$ are the observations of pattern of resource, travel time, traffic of commuters and vehicles, respectively in zones.

The resource observation is the function of commuters' arrival, resource breakdown and resource availability at place x and time t in zone i, and is given by

$$O^{R}_{i,x,t} = N^{i}_{c,x,t} \frac{R^{i}_{j,x,t}(\text{surp}) - R^{i}_{j,x,t}(\text{break})}{r^{i}_{j,x,t}(\text{avail})} \tag{32}$$

where $R^{i}_{j,x,t}(\text{break})$ is the breakdown of resource j in the zone i. The Eq. (32) gives the resource pattern in zone i.

The complete analysis of zone i at time t is denoted as $Z_{i,t}$ and is given by

$$Z_{i,t} = \frac{1}{|Z_i|} \int_{k=1}^{m} z_{i,t} \mathrm{d}x \tag{33}$$

where $k = 1, 2, \cdots, m$, and m is the different areas in the zone i.

The Eq. (33) gives the analysis of the zone i, i.e., average resource utilization, travel time and traffic density pattern in a zone i at different time periods in a metropolitan area. Similarly, the complete analysis of region l at time t is denoted as $R_{l,t}$, and is given by

$$R_{l,t} = \frac{1}{|R_l|} \int_{i=1}^{n} Z_{i,t} \mathrm{d}x \tag{34}$$

where $l = 1, 2, \cdots, N$, N is the total number of regions in a metropolitan area, and n is the total number of zones in a region l.

The complete analysis of zones and regions in a metropolitan area is explained in Algorithm 3 (Fig. 6).

6. Emergent intelligence based traffic management

In this section, we discuss intelligent traffic management system in a metropolitan area. The traffic management provides guidance to commuters and operators about the

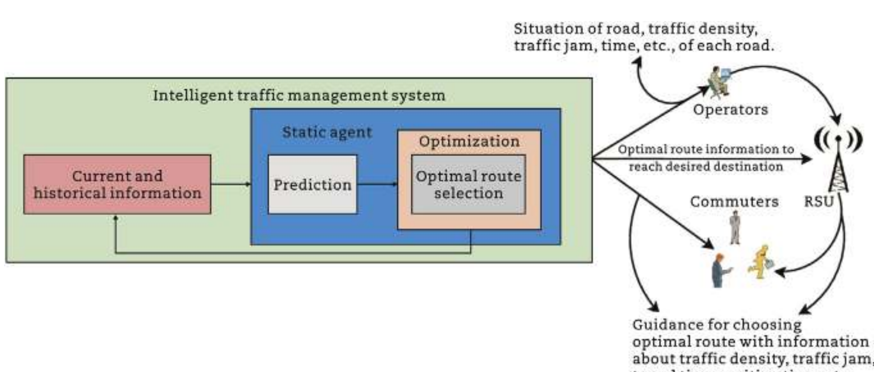

Fig. 7 – Intelligent traffic management system at a depot.

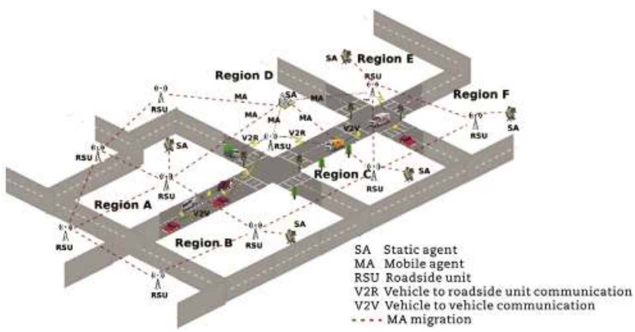

Fig. 8 – Scenario of metropolitan area for traffic management.

situation on roads, zones and regions in a metropolitan area to ensure smooth flow of traffic. To achieve smooth traffic flow, we make use of the historical and current data, predicted traffic density and travel time. The traffic management in a metropolitan area consists of entities like vehicles, RSUs, pedestrians and agents, and there exists communications between them, such as vehicle to vehicle, vehicle to RSUs, etc., and vice-versa.

The EI technique along with the above mentioned communications is used for collecting, estimating, monitoring and sharing traffic and resource related information in zones and regions of metropolitan area. Fig. 7 shows intelligent traffic management system, which is available at every depots in a metropolitan area. The intelligent traffic management system diverts the traffic, reduces the frequency of occurrence of traffic congestion and avoids the traffic density growth on a particular routes in a metropolitan area.

The EI technique is an intelligence of group, which uses following decision making steps to manage traffic in a metropolitan area.

(1) Initiator depot's agents form groups, which consists of neighborhood agents, RSUs, and vehicles, and continuously and periodically collects and shares traffic and resource related information.
(2) Agents analysis each zone and region of metropolitan area with respect to traffic density, resource utilization pattern and travel time on each route.
(3) Agent uses historical, collected and analyzed information for predicting the traffic density and travel time on each route in each zone and region of metropolitan area.
(4) Agent optimizes traffic density in each zone and travel time on each route of zone.
(5) Agent finds total number of routes (N_r) using optimized and analyzed information to divert the traffic.
(6) Agent computes a route which is having shortest travel time (optimal route) among N_r, and diverts the traffic to these routes.

Fig. 4(c) shows different communications in a region of metropolitan area, which are extended to the whole metropolitan area for better analysis and improving traffic efficiency as shown in Fig. 8.

The SA deployed at depot (in the region) creates and dispatches MAs to each zone as shown in Fig. 8. The migrated MAs to zones with EI technique forms group and interacts continuously among neighborhood RSUs, MAs, pedestrians and vehicles. During interaction they collect and share estimated information (as discussed in the sections 4 and 5). The EI technique at SA gets these collected and shared information of zones periodically and spontaneously. The SA analyzes and predicts growth/decline of traffic density, resource utilization, and travel time in zones and regions in a metropolitan area. The SA optimizes the analyzed and predicted information to find an optimal route to divert traffic for management as shown in Fig. 7, and are discussed in the following subsections.

6.1. *Minimization of traffic density*

The minimization of traffic density, improves the efficiency of traffic flow in a metropolitan area. The predicted information (as discussed in the section 4) and their threshold values along with the analyzed traffic information are used to minimize growth of traffic densities in a metropolitan area. We have built an objective function, which characterizes performance of the system to be optimized by taking into account, the current and expected behavior of system. The objective of following optimization problem is to minimize the growth of traffic density in zone i, and is given by

$$\min\left(\frac{Q_i + AD_i}{2}\right) \tag{35}$$

subject to

$$\begin{cases} \Delta V_{i,x,t} \le \Delta V^{T}_{i,x,t}\,, \quad x \in m \\ w_{x,t} \ge 0,\ \alpha \ge 0,\ \beta \ge 0 \\ \sum_{x \in X} w_{x,t} = 1 \\ \alpha + \beta = 1 \end{cases}$$

where $Q_i = \sum_{x \in m}(\Delta V_{i,x,} - \Delta V^{T}_{i,x,t})$ is the predicted traffic density in zone i, $AD_i = f(Z_{i,x,t})$ is the function which gives analyzed traffic density pattern in zone i, m is the total number of areas in zone i, $\Delta V^{T}_{i,x,t}$ is the threshold value of traffic density in zone i, which is chosen in such a way that even at deteriorated conditions the system must be in a stable state.

Similar to a single zone optimization problem, the optimization problem for multiple zones (is also called single region) can be computed as

$$\min\left(\frac{Q_1 + AD_1}{2}, \frac{Q_2 + AD_2}{2}, \cdots, \frac{Q_n + AD_n}{2}\right) \tag{36}$$

subject to

$$\begin{cases} \Delta V_{i,x,t} \le \Delta V^{T}_{i,x,t}\,, \ i \in n \\ w_{x,t} \ge 0,\ \alpha \ge 0,\ \beta \ge 0 \\ \sum_{x \in X} w_{x,t} = 1 \\ \alpha + \beta = 1 \end{cases}$$

where $Q_l = \sum_{i \in n}(\Delta V_{i,x,t} - \Delta V^{T}_{i,x,t})$ is the predicted traffic density

Algorithm 4 Emergent Intelligence based traffic management in a metropolitan area

Begin
Initiator SA creates zones and sub-zones using Algorithm 1.
SA analyzes resource, travel time and traffic density (both commuters and vehicles) pattern using Algorithm 3.
SA predicts traffic densities in every zones and regions using Algorithm 2.
SA predicts the travel time on route r:
$T^P(d,t+\delta,r) = \zeta(t,\delta)T^I(d,t+\delta,r) + \eta(t,\delta)max(T^H(d,t+\delta,r) - T^I(d,t+\delta,r),0) + \gamma(t,\delta)T^D(d,t+\delta,r) + \epsilon$
SA optimizes the traffic density in region l: $\Delta V_r^{opt} = \frac{Q_{l_j}+AD_{l_j}}{2}$
SA Optimizes travel time error on route r: $T^e(d,t+\delta,r) = \left(\frac{T^P(d,t+\delta,r)+AT_i}{2}\right) - T^T(d,t+\delta,r)$.
SA estimates set of routes available to reach the destination $N_s = \sum_{r=1}^{R^T}\left(T^e_{opt}(d,t+\delta,r) \le T^{eT}(d,t+\delta,r)\right)$
SA estimates the relevant routes $R_t = \sum_{r=1}^{N_s} P_{t+d,r}\left(T^e_{opt}(d,t+\delta,r) \le T^{eT}(d,t+\delta,r)\right)$
SA selects optimal routes $R_{opt} = min\left(\sum_{r=1}^{R_t}\left(T^e_{opt}(d,t+\delta,r), \Delta V_r^{opt}\right)\right)$.
SA manages traffic effectively by diverting traffic to their desired destination through these estimated optimal routes.
End

Fig. 9 – Algorithm 4.

in region l, $AD_l = \sum_{i\in n} f(Z_{i,x,t})$ is the analyzed traffic density pattern in region l, and n is total number of zones in a region l.

Similar to a single region optimization problem, the optimization problem for multiple regions (complete metropolitan area) can be computed as

$$\min\left(\frac{Q_{l_1}+AD_{l_1}}{2}, \frac{Q_{l_2}+AD_{l_2}}{2}, \dots, \frac{Q_{l_n}+AD_{l_n}}{2}\right) \tag{37}$$

subject to

$$\begin{cases} \Delta V_{l,x,t} \le \Delta V^T_{l,x,t}, \ l\in N \\ w_{x,t} \ge 0, \ \alpha \ge 0, \ \beta \ge 0 \\ \sum_{x\in X} w_{x,t} = 1 \\ \alpha + \beta = 1 \end{cases}$$

where $Q_{l_j} = \sum_{l\in N}(\Delta V_{l,x,t} - \Delta V^T_{l,x,t})$ is the predicted traffic density in region l, $AD_{l_j} = \sum_{l\in N} f(Z_{l,x,t})$ is the analyzed traffic density pattern in region l, $\Delta V_{l,x,t}$ is the threshold value of traffic density in region l, N is total number of regions available in a metropolitan area.

6.2. Minimization of travel time

The travel time minimization makes traveler to take more comfortable journey in a metropolitan area. The estimation of travel time error on route r using the predicted, analyzed and threshold travel time is given by

$$T^e(d,t+\delta,r) = \frac{T^p(d,t+\delta,r)+AT_i}{2} - T^T(d,t+\delta,r) \tag{38}$$

where $AT_i = g(Z_{i,x,t})$ is the function which is analyzed travel time (as discussed in the section 5), $T^T(d,t+\delta,r)$ is the travel time threshold value. The value of $T^e(d,t+\delta,r)$ indicates the reliability of routes, i.e., the minimum value indicates more reliability and vice versa. We have formulated an objective function, which minimizes the travel time error on route r at time t in day d, and is given by

$$\min \sum_{r\in R,\ d\in D} T^e(d,t+\delta,r) \tag{39}$$

subject to

$$T^p(d,t+\delta,r) \le T^T(d,t+\delta,r)$$

where R is the set of routes to a destination, and D is the set of days.

6.3. Optimal route selection for diverting traffic

In this subsection, we discuss the estimation of optimal routes using predicted information and available number of routes information.

Optimal route is the route which has the highest quality, which means least travel time and is the best among the available routes. The SA computes a set of routes available (N_s) to reach the desired destination S using optimized travel time error value and threshold travel time error value at time $t+\delta$ on route r, and is given as

$$N_s = \sum_{r=1}^{R^T}\left(T^e_{opt}(d,t+\delta,r) \le T^{eT}(d,t+\delta,r)\right) \tag{40}$$

where R^T is the total number of routes available, $T^e_{opt}(d,t+\delta,r)$ is the optimized travel time error value given by Eq. (39) and $T^{eT}(d,t+\delta,r)$ is the threshold travel time error on the route r.

SA estimates the total number of relevant routes available among the N_s to reach the destination S, and is given as

$$R_t = \sum_{r=1}^{N_s} P_{t+d,r}\left(T^e_{opt}(d,t+\delta,r) \le T^{eT}(d,t+\delta,r)\right) \tag{41}$$

The SA analyzes the predicted traffic density on all R_t and optimizes the predicted traffic density, and finds an optimal route (which is having least travel time) among them to reach the desired destination S, and is given as

$$R_{opt} = \min\left[\sum_{r=1}^{R_t} T^e_{opt}(d,t+\delta,r), \Delta V_r^{opt}\right] \tag{42}$$

where ΔV_r^{opt} is the optimized predicted traffic densities on route r given by Eq. (35) (or Eqs. (36) or (37)). The EI technique shares these predicted information and optimal routes among group of neighbor vehicles, pedestrians, agents and RSUs. The SA uses these predicted and optimal information to manage the traffic by diverting the traffic to the desired destination through an optimal route.

Algorithm 4 shows the complete procedure of emergent intelligence based traffic management in a metropolitan area (Fig. 9).

Table 5 – Simulation parameters.

Parameter	Value
Simulation time (s)	6000
Number of regions	6
Number of zones	36
Number of static agents	6
Number of mobile agents	36
Static agent size (KB)	1000
Mobile agent size (KB)	500
Number of depots	6
Number of RSUS	12
Number of vehicles	5000
Transmission range of RSU (m)	300
Transmission range of OBU (m)	200
Communication technology	IEEE 802.11p
Frequency band used (GHz)	5.9
Bit rate (Mbps)	18
Beacons rate (Hz)	2
Number of repetitions	30
Confidence interval (%)	95

7. Simulation and analysis results

In this section, we describe the scenario and performance assessment of the EI technique for traffic prediction by means of simulated experiments by integrating NS2 with SUMO, OpenStreatMap (OSM) and MOVE tool to enable the realistic VANET environment simulation in a metropolitan area in Fig. 8. The creation of road map, zones, regions, deployment of various number of RSUs and vehicles, and are configure with different communication range capabilities. Fuel consumption of vehicles is estimated using EMIT model, which is integrated with SUMO. In the subsequent subsection, we describe simulation scenarios and the comparison with conventional methods results obtained.

7.1. Simulation scenario

We have considered 1000, 2000, 3000, 4000 and 5000 vehicles per kilometers square traffic conditions in the simulated scenario of metropolitan area. These vehicles are move randomly in all the created streets with having speed range from 25 to 55 km per hour. Vehicles mobility is done using random way point mobility model, which is the inbuilt model in NS2. Simulation time of 6000 s is considered, which is enough to measure the performance of the proposed system. This simulation time makes all vehicles to move around streets. In the simulation scenario there exists communications, including vehicle to vehicle, vehicle to roadside units, agent to roadside units and vice versa and are supported by IEEE 802.11p protocol and are the inbuilt protocol in NS2. This protocol works in the licensed frequency band at 5.9 GHz and is called as wireless access in wireless environments (WAVEs).

In the program, we have set 2 Hz as beacon shipping frequency to avoid the overloading of network with this wide dense of vehicles and at every 1 s programme updates the frequency of propagation efficiency. The results of EI technique obtained are the average value of 30 repetitions with the 95% confidence interval of each point in the graphs. Table 5 gives a summary of simulation and configuration parameters that are considered during the simulation run.

The performance evaluation of the proposed system were carried out on a dual-CPU Intel Core i5-2400 at 3.10 GHz Desktop computer with 12-GB RAM running Fedora version 25.

The simulated scenario of metropolitan area, consists of regions A to F. The Region A is the residential area. Region B is the industrial area. Region C is the wholesale market area for agriculture production in the city. Region D has more temples, hotels and educational institutes. Region E consists of many educational institutes, shopping malls, companies and market area. We have analyzed traffic density in zones of region E at different time periods in a day.

7.2. Results analysis

Table 6 shows traffic density in zones of region E in a metropolitan area, and these information are provided by the spatio-temporal module.

Fig. 10(a) shows pattern of growth or decline of traffic density at different time periods in a day. In the zone 1, due to shopping malls, companies, etc., the traffic densities in the morning (8 AM–10 AM) and evening (4 PM–6 PM) are more i.e., between 60% and 80%. Similarly, in the afternoon (12 AM–2 PM) periods are moderate i.e., between 55% and 65%. But during the night times there are no growth of traffic densities.

In zone 2, the patterns of traffic density growth are more between 10 AM and 8 PM time period. The traffic densities are almost 90% in between 1 PM and 5 PM time period and are shown in Fig. 6(a). But in the night time traffic density pattern is approximately 5%–10%. Similarly, the patterns of growth or decline of traffic density in the zone 3 are interpreted.

Table 7 shows the traffic densities in regions A, B, C, and D of metropolitan area, and these information are given by the spatio-temporal module. Fig. 10(b) shows pattern of growth or decline of traffic densities at different time periods in a day in the metropolitan area. The region A is a residential area, hence growth of traffic density is more in morning time (7:30 AM to 10:30 AM) and evening time (4:00 PM to 9:30 PM) than in afternoon and night time. Similarly, for regions B to D the patterns of traffic densities are interpreted.

Overall, in Fig. 10, traffic densities witnesses highest points during peak periods (of respective areas) and reaches its lowest point at non-peak periods (of respective areas) and night time.

In our simulation, we have created some abnormal traffic situations, like sudden occurrence of accidents and lane blockage at different time periods in a particular location in zones of regions in a metropolitan area to test the proposed

Table 6 – Traffic density (%) at zones 1, 2 and 3 in region E.

Zone	Traffic density (%)		
	Morning	Afternoon	Evening
Zone 1	40–70	30–60	35–65
Zone 2	40–60	68–85	80–87
Zone 3	40–80	62–65	35–65

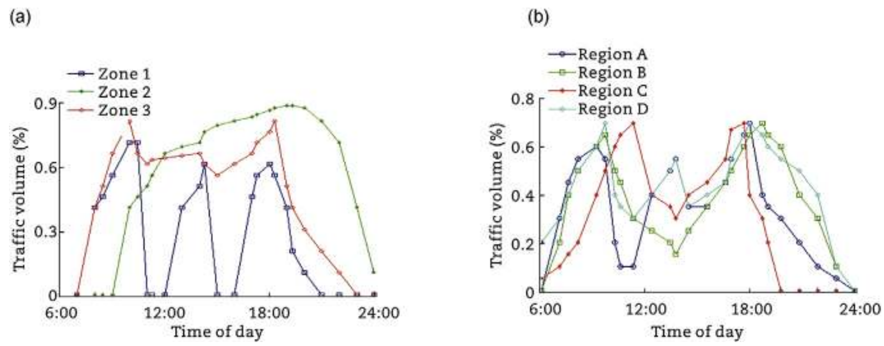

Fig. 10 – Pattern of growth or decline of traffic density at different time periods of a day. (a) In zones. (b) In regions.

system behavior. In zone 2, we have created 100 to 150 vehicles and these vehicles movements are started from 10:00 AM to 6:30 PM, and created the following situations to observe the traffic pattern.

(1) Accident

We have created the accident scenario at 11:00 AM to 12:15 AM, the existing methods during this situation may come across the missing of some important data and resulting into wrong traffic prediction. In order avoid the wrong prediction, the proposed system guesses the missing information using the historical data of similar situation in that place and time periods in the zone 2. Hence, in Fig. 11, shows how exactly the traffic flow pattern varies with respect to time.

(2) Lane blockage

We have again created the scenario of lane blockage in the zone 2 at 12:30 AM to 1:15 PM and 2:15 PM to 3:00 PM, and shown in Fig. 11 how the proposed system predicts the exact traffic using historical and spatio-temporal data.

(3) Free flow

Fig. 11 shows that the free flow traffic density with constant pattern of traffic (i.e., constant increment and decrements of traffic flow) from 4:40 PM to 6:15 PM.

Fig. 12 presents, output of the proposed traffic optimization and prediction models of typical roads at each zone and region with low, medium, and high traffic densities. We have included the observed traffic for comparison with the predicted and optimized traffic in a metropolitan area. The observed, optimized and predicted traffic have similar traffic patterns as shown in Fig. 12(a)-(c). The proposed optimization and prediction model performs well in high and medium traffic densities but it is inefficient at low traffic densities. Because in congested conditions the average traffic densities in metropolitan area become stable.

The proposed method behaves like existing method when the traffic density is low, because small variations in the predicted and observed value results into bigger error. Therefore, the proposed method becomes inefficient during low traffic density in a metropolitan area. In a metropolitan area, most of the time medium and high traffic densities will occur and there will be the possibility of occurrence of small variation between predicted and observed traffic density value, and the variation produces negligible error which can be avoided. Hence, the proposed optimization and prediction model for traffic density provides more efficient and promising solution for traffic management in a metropolitan area.

Fig. 13 presents the proposed travel time optimization and prediction models output for typical roads at each zone and region with low, medium, and high traffic densities. We have included the observed travel time for comparison. The observed, optimized and predicted travel time has similar patterns as shown in Fig. 13. The proposed travel time prediction and optimized model becomes more efficient and accurate at high and medium traffic density in a metropolitan area, because in congested conditions the average travel time becomes stable. When we consider the low traffic density our proposed method becomes inefficient and behaves like existing methods. The main reason behind is small amount of differences observed in predicted and observed travel time makes bigger error.

Table 7 – Traffic density (%) in regions A, B, C, and D in a metropolitan area.

Region	Traffic density (%)		
	Morning	Afternoon	Evening
Region A	30–50	20–55	30–60
Region B	20–65	15–20	30–70
Region C	10–60	30–55	40–70
Region D	30–70	30–55	38–70

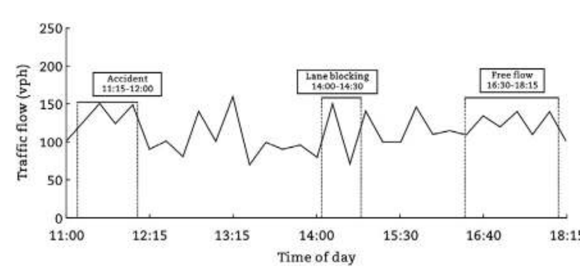

Fig. 11 – Traffic prediction under normal and abnormal traffic conditions.

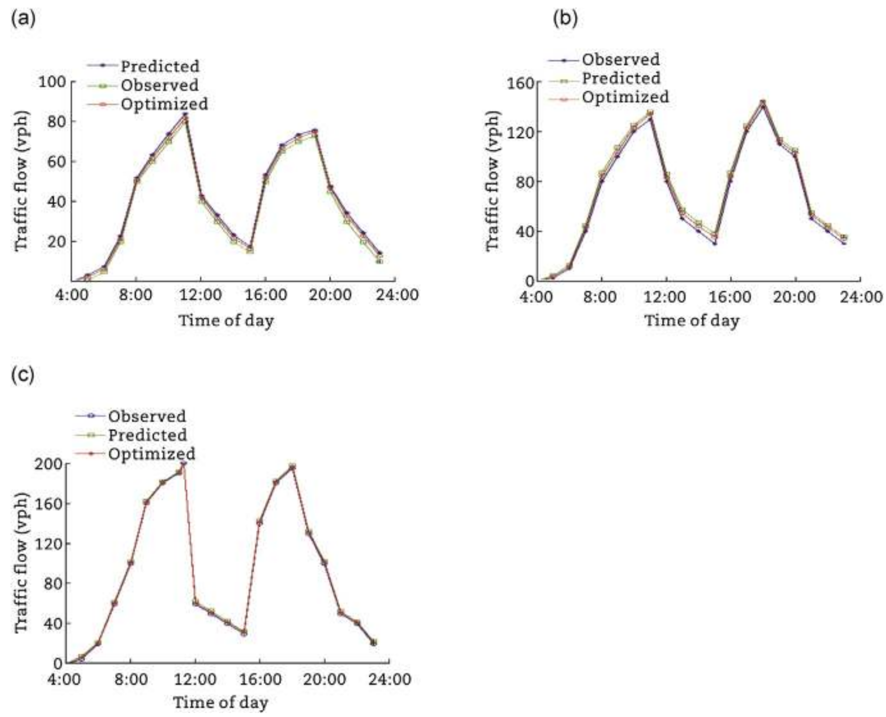

Fig. 12 – Traffic prediction on roads in zones and regions. (a) Low traffic density. (b) Medium traffic density. (c) High traffic density.

Overall, in Figs. 12 and 13, the proposed optimization and prediction models of traffic density and travel time are more efficient during medium and high traffic density and results witnesses the highest points during peak hours and lowest points during non-peak hours and night times. At these time periods and traffic densities there will be the possibility of data missing and jamming which results in traffic jam and congestion in metropolitan area. To avoid these consequences in our proposed model we used historical and spatio-temporal modules data. These modules provide accurate traffic density and travel time required at particular place and time periods. Therefore, in results our proposed predicted graph is very close with the observed graph.

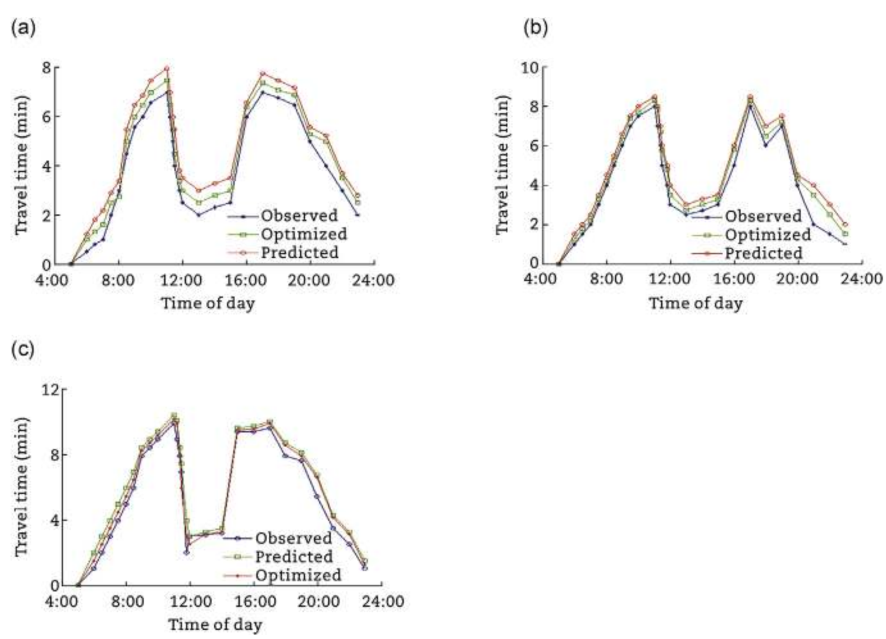

Fig. 13 – Travel time prediction on roads in zones and regions. (a) Low traffic density. (b) Medium traffic density. (c) High traffic density.

For measuring performance of the proposed model with the existing models, we use mean absolute error (MAE). The MAE is one of the ways of comparing predictions with their actual outcomes.

$$AE = \frac{1}{N}\sum_{j=1}^{N}|OT_j - PT_j| \tag{43}$$

where OT and PT are observed and predicted traffic respectively.

We have calculated the total MAE at peak hours of each model. Peak hours are the time interval from 7:30 AM to 11:00 AM and 4:30 PM to 9:00 PM. During peak hours there will be more traffic congestion and likely to increase the estimation error and hence estimation at peak hours is more important than other duration. Therefore, peak hours MAE is considered as a major evaluation factor for the performance evaluation of proposed model. The Table 8 shows different prediction models performance evaluation results.

The proposed prediction model using traffic flow parameters (speed and density), historical and spatio-temporal data shows good results at different time periods in a day compared to the existing models, namely ANN, SVM and KNN, with their error values in terms of MAE as shown in Fig. 14.

The EI technique involves hybrid communication mode, i.e., combination of both infrastructure and infrastructure-less based network. The time required collecting and share event related information in infrastructure based communication (e.g., cellular network) is usually very small and whose value depends upon the type of cellular technology is going to use. The time needed in GPRS and GSM networks is in the range 0.1–0.45 s as mentioned in Desai et al. (2011). Hence, communication network may need less than 1 s time for collecting and sharing traffic and resource related information. In the case of ad-hoc network communication, time required for collecting and sharing event related information depends upon topology and mobility of vehicles. Therefore, we assume that few seconds delay required distributing event information. The hybrid communication mode takes at most few seconds for collection and distributing information.

The average time taken required to take a decision by the swarm intelligence (SI) and EI techniques is shown in Fig. 15. Here, event is considered as traffic congestion, accident, deficit resources and so on. During the event at 10:00 AM, the following behaviors of SI and EI techniques have observed for traffic management in a metropolitan area.

In SI approach (with hybrid communication) following behaviors occur.

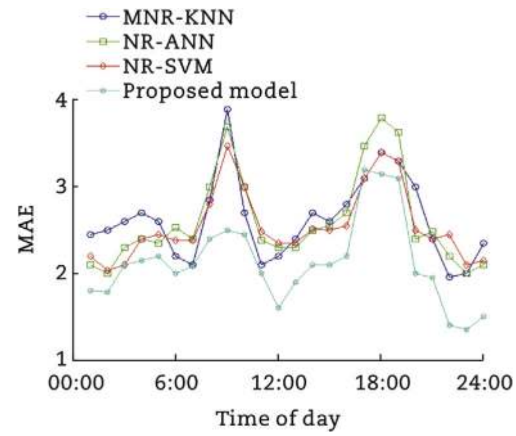

Fig. 14 – Comparison of prediction models with their MAE values.

- Soon after event, affected vehicles sends message to nearby vehicles (V2V) and RSUs (V2Rs).
- At $t = 2$ s, agents resided in vehicles and RSUs forms group and starts communicating with each other, i.e., A2V and A2R.
- At $t = 5$ s, during group communication they collect and share their traffic related information.
- At $t = 7$ s, complete overview of zone or region traffic situation information is shared among nearby commuters (vehicles and people).
- At $t = 9$ s, commuters take decisions according to the shared information of complete zone/region traffic situation information and process will stop.

In EI technique (with hybrid communication) following behaviors occur.

- Soon after event, affected vehicles send message to the nearby vehicles (V2V) and RSU (V2R) at $t = 1$ s.
- At $t = 2$ s, agents resided in vehicles and RSUs forms groups and starts communicating with each other, i.e., A2V and A2R.
- At $t = 4$ s, one groups information is shared with nearby group with the help of migrated mobile agents.
- At $t = 5$ s, in each group there exists communications such as V2V, V2R, A2V, A2R and vice-versa, and during

Table 8 – Performance comparison of MAE of rush hours and prediction time of different prediction models.

Prediction Model	Total MAE	MAE in rush hours	Prediction time (s)
MNR-KNN	2.5820	2.9847	75,435.33
NR-ANN	2.6050	3.1697	7.66
NR-SVM	2.4485	2.9797	187.45
Proposed model	2.2185	2.4970	7.10

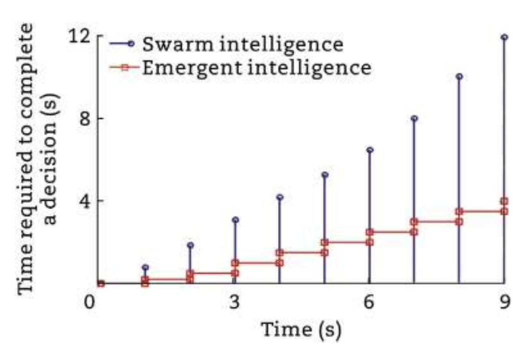

Fig. 15 – Average time required for taking a decision by swarm intelligence and emergent intelligence techniques.

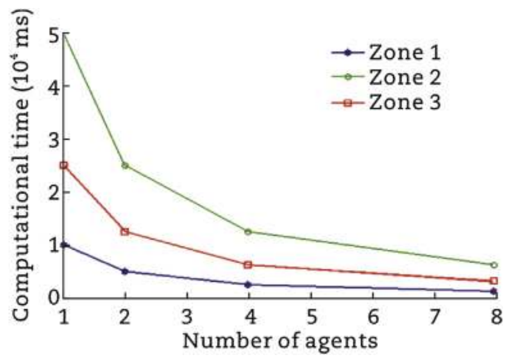

Fig. 16 – Computational time of agents in zones.

communication they collect and share their respective traffic related information.

- At $t = 7$ s, complete overview of traffic situation in metropolitan area is shared among all these groups.
- At $t = 9$ s, an accurate decision is taken according to the shared information of traffic situation in a metropolitan area and the process will stop.

Following simulation parameters are considered for the comparative purposes. We assume that the events affected vehicles move 20 km/h, distance between RSUs is 1000 m, distance between vehicles is 100 m, message size is 300 bits, mobile agent size is 500 KB, GSM data rate transmission is 9.6 Kbps, inter-vehicle communication data rate is 6 Kbps, and data rates during V2R and R2V are in the range [2.5, 14] Kbps.

Soon after t is 9 s from the occurrence of event, the EI technique takes 4 s and the SI technique takes 12 s for taking an accurate decision are presented in Fig. 15. The reduction of average time required for taking decisions in EI technique is possible because multiple new routes information is given after the commuters have been received traffic situation information from nearby zones/regions and entire metropolitan area which caused the traffic congestion. Similarly, in SI technique commuters have been received traffic situation of event occurred zone not nearby zone. Therefore, EI technique's average time required for taking decisions is less than the SI technique in a metropolitan area.

We have analyzed the computational time required in the zones 1, 2, and 3 of region E. In each of these zones, we have considered 1, 2, 4, and 8 number of mobile agents in a group, and computational time required in these zones are computed by the static agent at region E. We have ran the simulation 30 times for each group size and taken the mean value of them. Fig. 16 shows that as the population of mobile agents increases in the zones the time required for analyzing, processing, sharing and predicting traffic related information decreases.

8. Discussion

Overall, the purpose of this paper is to divide metropolitan area into regions and zones using SA; analyze and predict exact behavior of traffic, resource and travel time on routes in each zone and region of metropolitan area using emergent intelligence technique with agents; and predicted, historical and current available data are used to manage the traffic efficiently.

We have evaluated the proposed traffic management system model performance. As expected the existing models, such as MNR-KNN, NR-ANN and NR-SVM, predicted output showed better results. These existing models have not used spatio-temporal data, historical information and EI technique with agents. Among these models, the proposed prediction model for traffic management performance in a metropolitan area was the best.

The proposed model is compared with other models with respect to MAE and prediction time (Table 8). The time needed to calculate the prediction values for all given data sets are the prediction time. The obtained results of proposed model showed the least prediction time. This is because it used EI technique with agents and it provides the parallel computing in a synchronized group of agents. Hence, prediction time has reduced at the step of prediction.

For MNR-KNN, prediction accuracy shows the first longest prediction time at the prediction step and it requires a longer time for finding k number of neighboring points in the database. The similar performance has shown by NR-SVM, compared to other methods and it had a long user defined parameters optimization time. Hence, MNR-KNN and NR-SVM's prediction times are delayed. The NR-ANN shows second least prediction time, because the learning data is executed with parallel computing technique.

The proposed prediction model's prediction time was 7.10 s and which indicates that it provides more satisfactory performance compared to other models, and it is the first least prediction time among the above mentioned models.

9. Conclusions

In this paper, we proposed emergent intelligence technique based traffic management using prediction information in a metropolitan area. The proposed analysis and prediction model considered the traffic flow parameters (speed and density), historical data and spatio-temporal correlated data as inputs. The proposed method reduced the frequency of occurrence of traffic congestion, growth of traffic density and travel time in each zone and region at different time periods in a day. The EI technique efficiently collected, analyzed, shared and predicted traffic densities and travel times in zones and regions. This technique provides autonomy, flexibility, adaptiveness, robustness and self-organization to avoid traffic system's randomness and non-linearity. We compared EI and SI techniques with respect to their properties and capabilities for traffic management in a metropolitan area. The prediction method is exhaustively evaluated and compared with existing methods, such as KNN, ANN and SVM. The simulation results show that the EI technique achieved significant level in traffic management than SI, by efficiently managing traffic to reduce time taken for taking accurate decisions and reduces computational time complexity.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

Acknowledgments

The authors would like to acknowledge Chandana, Suman and research scholars of PET Unit and also the valuable comments of the reviewers, which made the overall presentation better.

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