International Journal of Computer and Information Technology (ISSN: 2279 – 0764)
Volume 03 – Issue 06, November 2014

An Agent Model with Adaptive Weight-based Multi-objective Algorithm for Road-network Congestion Management

Bin Jiang
Department of Computational Intelligence and Systems Science
Tokyo Institute of Technology
Yokohama, Japan
College of Computer Science and Electronic Engineering
Hunan University
Changsha, China
Email: jiangbin {at} trn.dis.titech.ac.jp

Chao Yang
Department of Computational Intelligence and Systems Science
Tokyo Institute of Technology
Yokohama, Japan
Business School
Hunan University
Changsha, China

Takashi Yamada
Department of Computational Intelligence and Systems Science
Tokyo Institute of Technology
Yokohama, Japan

Takao Terano
Department of Computational Intelligence and Systems Science
Tokyo Institute of Technology
Yokohama, Japan

Abstract—**This paper proposes an agent model with adaptive weight-based multi-objective algorithm to manage road-network congestion problem. Our focus is to construct a quantitative index series to describe the road-network congestion distribution, and use such indexes as weights in the multi-objective algorithm to shunt vehicles on those congested links. First, a multi-agent system is built, where each agent stands for a vehicle that adapts its route to real-time road-network congestion status by a two-objective optimization process: the shortest path and the minimal congested degree of the target link. The agent-based approach captures the nonlinear feedback between vehicle routing behaviors and road-network congestion states. Next, a series of quantitative indexes is constructed to describe the congested degree of nodes, and such indexes are used as weights in the two-objective functions which are employed by the agents for routing decisions and congestion avoidance. In this way, our proposed agent model with adaptive weight-based multi-objective algorithm could achieve congestion distribution evaluation and congestion management at the same time. The simulation results show that our proposed approach has successfully improved those seriously congested links of road-network. Finally, we execute our model on a real traffic map, and the results show that our proposed model reduce the congestion degree of road-network, thus have its significant potentials for the actual traffic congestion evaluation and management.**

Keywords-adaptive weight; agent model; multi-objective optimization; road-network congestion management

I. INTRODUCTION

In the field of Intelligent Transportation System (ITS), traffic congestion management has become one of the key applications, and has always been a hot topic for green cities. For instance, effective management of traffic congestion results in an even distribution of traffic on arterial roads, decreasing travel and wait times, and reducing vehicle emissions and probability of road hazards [1]. Although a wide variety of approaches such as physics methods [2, 3], mathematical programming methods [4] and adaptive dynamic programming [5] have been proposed to improve road-network congestion problem, there has been recently an increasing interest in the application of agent-based approaches. The autonomous and distributed nature of multi-agent system (MAS) makes it suitable to capture the dynamic and geographically distributed features of transportation system. Using MAS approaches, vehicles are defined as agents and traffic congestion is regarded as an emergent result of nonlinear feedback between agent behaviors and traffic status. Thus, with a bottom-up perspective, agent models can relate microscopic vehicle routing behavior and macroscopic traffic evolving situation to address the real world congestion problem.

There have been many contributions that apply agent-based models to ease the traffic congestion problem. In this paper, we divide these approaches into three categories:

(1) Infrastructure-based agent approach, which provides traffic guidance by regulation of the traffic flow on infrastructures such as signals and intersections. For example, Hoar et al. build a MAS-based evolutionary algorithm which achieves an efficient traffic flow by adjusting the timing sequences of the traffic lights. The simulation results show an overall decrease in waiting time of 26% for complex routes [6]. As some researches attempt to employ machine learning

models, Arel et al. present a Q-learning algorithm for multi-intersection traffic signal scheduling and the simulation results show greater reduction of wait times by compared with longest-queue-first algorithm [7]. And, Roozemond elaborates a multi-layered MAS model to implement urban traffic control. The model consists of agents with different roles at various levels, where Intelligent Traffic Signaling Agents cooperate and coordinate to resolve traffic conflicts by using information from Roadside agents [8]. Chen et al. also present an adaptive and cooperative traffic light agent model which shows obvious reduction of delay time compared with the fixed sequence traffic signal control case [9]. Onieva et al. build an agent-based traffic simulator to study the traffic flow controlled with independent agent-based traffic signals, in order to manage traffic congestion problem [10]. Besides, Tahilyani et al. propose a MAS model which decides route diversion to solve the traffic congestion problem by utilizing a cognitive radio system for traffic flow information [11].

(2)Vehicle/Driver-based agent approach, which proposes appropriate control measures with an individual-level perspective to avoid traffic congestions. Some papers use bio-inspired techniques such as ant pheromone [12-14], bird flocking [15] and honey-bee foraging [16]. For example, Ando et al. propose a car agent model which deposits ant pheromone based on various semantics and uploads the traffic-related information to a probe server, so as to predict traffic congestion [12]. And Narzt et al. establish self-organizing congestion evasion strategies using ant-based pheromones [13]. Sur et al. also build an agent-based model with multi-breeded mean-minded ant colony optimization for vehicle routing management, the results show the vehicle has near uniform distribution thus implementing congestion avoidance [14]. Besides, Astengo-Noguez et al. set up a bird flocking based agent model, where vehicle agents form groups and coordinate together to achieve effective optimization of traffic flow [15]. And, Wedde et al. develop *BeeJamA* algorithm for traffic jam avoidance based on the analogy of honey-bee foraging, and the simulation results show decrease in average travel time and traffic density as compared to Dijkstra shortest path algorithm [16]. Other contributions are found in the approaches which consider driver behaviors for route selection. For example, Buscema et al. simulate various scenarios by varying driver's feedback, and the results show decrease in travel time with increase in the feedback [17]. Zolfpour-Arokhlo et al. establish a multi-agent system which uses Q-learning algorithm to help vehicles make route decisions, and confirm the effectiveness of the model by case studies on road-network in Malaysia [18]. Arnaout et al. also describe an IntelliDriver application for reducing traffic congestions using an agent-based approach [19]. Ito et al. build an anticipatory stigmergy model for decentralized traffic congestion management, and the simulation results demonstrate its effectiveness and robustness [20]. Desai et al. present a multi-agent based approach for congestion avoidance and route allocation with virtual agent negotiation, and the simulation results show an improvement for travel time as compared to shortest path algorithm [21]. And, our group proposes an agent-based model with a multi-objective optimization algorithm, which considers shortest path and congestion avoidance simultaneously for vehicle routing selection [22]. The simulation results show an effectiveness of our proposed multi-objective routing selection method in balancing the road-network congestion distribution.

(3) Hybrid-perspective-based agent approach, which provides traffic guidance by integrating and processing diverse information from infrastructure units and vehicle drivers. Among these works, Weyns et al. establish a Delegate MAS model, where vehicle agents generate exploration ants to traverse the road-network and gather route information, and then choose a particular route which satisfies the driver preference to either shortest travel distance or wait time or both. Then infrastructure predicts the queuing time. The simulations show better results for reduction in travel distance and wait time [23]. Kammoun et al. develop a joint hierarchical fuzzy multi-agent model to deal with the route choice problem, and the simulation results show better road-network management by accounting for environmental factors, vehicle states and driver preferences [24]. Yang et al. realize an algorithm based on ant colony optimization, using the principles of the trunk road loop with high priority and real-time traffic information, to avoid congested roads [25]. Gao et al. also elaborate a multi-layered agent approach which coordinates the system optimum for road-network and the user optimum for user preference to ensure route selection [26]. Vasirani et al. propose a distributed, market-inspired approach for intersection management in urban road traffic networks by using multi-agent models [27]. And, our group proposes an adaptive weight model which constructs a quantitative index series to describe the network congestion distribution, and uses such index sequence as weights of the two-objective functions in [22] for shunting vehicles [28]. The simulation experiments on the same predefined road-network topology show obvious reduction of congested degree on those seriously congested roads compared with the fixed weight congestion control case. Such method needs further validation on real road maps.

Based on the above literature review, an infrastructure-based agent approach processes global traffic information to optimize the macro-level traffic flow, but it does not consider driver's behaviors and preferences. And, vehicle/driver-based agent approach takes into account the micro-level vehicle control and the driver's preference, while it does not possess a global view on traffic state. Hybrid-perspective-based agent approach involves not only global traffic flow information but also considers local driver preference for making route decisions. In this paper, following our previous work, we propose an adaptive agent model to study the road-network congestion problem with a hybrid perspective. In our model, each vehicle agent makes its routing decision at an individual-level by a two-objective optimization process: the shortest path and the minimal congested degree of the target link. The agent-based model captures the nonlinear feedback between vehicle routing behaviors and road-network congestion states. Next, we construct a series of quantitative indexes to measure the real-time congestion distribution of road-network at each node, and use such indexes as weights in the two-objective functions to shunt vehicles on those congested links. An adaptive node weight algorithm is proposed based on variations of adjacent link's passage time. In this way, our agent model with adaptive weight-based multi-objective optimization algorithm could achieve congestion distribution evaluation and congestion management at the same time. At each simulation step, the vehicle agents autonomously move towards their destination nodes according to the optimization result, through which the improvement and control of those congested links of road-network is realized. Finally, the proposed agent model are further validated on a real road map.

The rest of this paper is organized as follows: Section II describes the definition, design concepts and implementation details of the agent model, then next, Section III explains the simulation experiments and settings based on the different simulation purposes; Section IV discusses and analyzes the experimental results; and finally, Section V summarizes the work of this paper, and presents the future work.

II. Model Description

Below, we present the agent model following the ODD (Overview, Design concepts, Details) protocol proposed by Grimm et al. [28].

A. *Purpose*

In this paper, we describe an agent model with adaptive weight-based multi-objective algorithm to improve the road-network congestion problem in ITS. In our model, each vehicle agent considers shortest path and congestion avoidance as two objectives in his/her routing selection. We focus on constructing a quantitative index series to measure the road-network congestion distribution with system-level perspective, and employ such indexes as weights of the two-objective function for agent routing decision at an individual-level. In this way, our proposed agent model could achieve congestion distribution evaluation and congestion management at the same time. The proposed approach may provide a dynamic diversion idea from the vehicles perspective with the help of GPS devices or Route Guidance System with global traffic information of road-network, rather than vehicle shunt in single intersections in most applications.

B. *Entities, State Variables and Scales*

The model includes three types of entities: vehicle entity, node entity and network link entity, as described in Table I.

TABLE I. Entities and Descriptions

Entities	Descriptions	Identification
Vehicle	The vehicle individuals of the road-network	*agentId*
Node	The physical nodes with fixed coordinates of the road-network	*nodeId*
Network Link	The links that connect two nodes of the road-network	*linkId*

Next, the state variables are explained in order as they appear in Table II, which are Source Node (*SN*), Destination Node (*DN*), Vehicle Path (*VP*), Node Weight (*NW*), Link Length (*LL*), Link Situation (*LS*), Link Congestion Index (*LCI*), and Link Travel Time (*LTT*).

TABLE II. State Variables and Descriptions

Entities	Descriptions	Identification
Source Node	The predefined departure node when a vehicle is added into the road-network	*startNode*
Destination Node	The predefined target node where a vehicle supposed to eventually reach	*endNode*
Vehicle Path	A list of nodes where vehicles passed by, which describes the movement trajectory of the vehicles	*pathMap*
Node Weight	The weight of a node, which reflects an integrated congestion impact from connected links	*nodeWeight*
Link Length	The physical length of the link, approximately calculated by the linear distance between two nodes	*linkLength*
Link Situation	The current status of the link, either congested or un-congested	*linkSituation*
Link Congestion Index	A quantitative indicator used to describe the dynamic congested degree of the road-network links with their link situation congested	*linkCon*
Link Travel Time	The passage time of a vehicle passing through a link	*linkTravelTime*

Of the eight variables, source node and destination node are represented by the node ID, and vehicle path is represented by a list of node IDs. Next, we define equations to calculate the rest of variables. The first important variable is node weight, whose design principles come from the Proportional Regulator (*P* Regulator) of automatic control field [29, 30]. The main idea of *P* regulator is to balance the travel time of different ways that connects the same start and destination.

We use this idea to shunt vehicles to different ways when they reach at a node of the road-network. When a vehicle passes one node and changes the state of the target link from uncongested to congested, or from congested to uncongested, it affects all the agents travel time on this target link. We therefore propose an adaptive node weight algorithm based on iterative operations on the real-time passage time of adjacent links, through which the model achieves congestion distribution evaluation and congestion management at the same time. By assuming the road-network has one node *a* and a link (*a*, *b*) connects to it, the node weight is adaptively updated by the following equation (1) and (2):

$$NW_a^t = NW_a^{t-1} - K\Delta T_{(a,b)}, \quad where \;\; NW_a^t \in (0,1], \tag{1}$$

$$\Delta T_{(a,b)} = \frac{T_{(a,b)}^t - T_{(a,b)}^{t-1}}{T_{(a,b)}^t}, \tag{2}$$

where NW_a^t and NW_a^{t-1} are shown by the weight of node a at time step t and $t-1$ respectively, $T_{(a,b)}^t$ and $T_{(a,b)}^{t-1}$ are the expected travel time of a vehicle on link (a,b) at time step t and $t-1$ respectively, K is the model parameter. According to the equations, the node weight is adjusted iteratively according to the difference between vehicle's passage times on the target link in two consecutive time steps. As NW_a^t gets smaller in magnitude, the more seriously congested degree of the node becomes. As the real-time link situation affects the agents travel distance at each simulation step, we discuss the calculation of $T^t_{(a,b)}$ in two cases. Assume that the travel time of an agent on passing an uncongested link is T_{uncon}, when the simulation proceeds and the link situation changes into congested, the expected travel time of the agent on the rest of this link is represented by T^t_{con}. The calculation of T^t_{con} is presented by equation (3), which originates from the result of investigation and regression analysis of a large number of road traffic data by the Bureau of Public Roads (BPR) of the US [31].

$$T^t_{(a,b)} = \begin{cases} T_{uncon} = \dfrac{LL_{(a,b)}}{V}, & where \quad LS^t_{(a,b)} = Uncongested, \\ T^t_{con} = T_{uncon}(1+\alpha(LCI^t_{(a,b)})^{\beta}), & where \quad LS^t_{(a,b)} = Congested \end{cases} \quad (3)$$

where $LL_{(a,b)}$ is the physical length of link (*a*, *b*), V is the velocity of the vehicle agent, $LCI^t_{(a,b)}$ is the congested degree of link (*a*, *b*), $LS^t_{(a,b)}$ is the link status, either congested or uncongested, α and β are two parameters of the equation which are set to 0.15 and 4 respectively according to the suggestion in [31]. Furthermore, assume that a link (*a*, *b*) has its largest traffic capacity as $e^{\max}_{(a,b)}$ and the current number of vehicles on link (*a*, *b*) at time step t is $n^t_{(a,b)}$, we then calculate *LS* and *LCI* of link (*a*, *b*) in equation (4) and (5) respectively:

$$LS^t_{(a,b)} = \begin{cases} Congested & where \quad n^t_{(a,b)} >= e^{\max}_{(a,b)}, \\ Uncongested & where \quad n^t_{(a,b)} < e^{\max}_{(a,b)} \end{cases} \quad (4)$$

$$LCI^t_{(a,b)} = \frac{n^t_{(a,b)}}{e^{\max}_{(a,b)}} \; where \quad LS^t_{(a,b)} = Congested. \quad (5)$$

C. Process and Scheduling

At the initial stage of the simulation process, agents are added into the road network at different time steps. When the simulation proceeds and the agents arrive at a node, they make route choices. An agent is removed from the network when it arrives at a predefined target node. During the simulation, the agent aggregation will cause link congestions and thus affect other agents' route decisions. The following pseudo-code in Fig.1 describes the process and the scheduling of the agent-based model. The details of two sub-models that agent select a target link and travel a distance on the link are to be explained in section II.F.

```
Start
    Initialize the nodes and links of the road-network
    for simulation step=1 to MaxSimulationStep
      for agent number=1 to MaxAgentNumber
          if (the simulation step == the time stamp an vehicle to be
                added)
            add the vehicle to the road-network
        end if
        if (the agent reaches a node)
          if (the agent arrives at its predefined destination)
              remove the agent from the road-network
          else
              the agent selects a target link
                update the agent number and link situation of the
                involved links
              update the node weight based on the link situation
          end if
        else
          the agent travels a distance on the link
        end if
          update the state varibles of the agent
      end for
    end for
End
```

Figure 1. Pseudo-code of the agent simulation model.

D. Design Concepts

Basic principles: The general concepts underlying the model design come from the urban road-network traffic optimization theory proposed by Sheffi [4]. In his theory, congestion is one of the most important mechanisms, directly affecting the vehicles passage time, and it is associated with the number of vehicles through the nodes. With a predefined road-network structure and traffic data, Sheffi points out that link function, represented by the travel time function of the traffic flow of network links, is one of the most important factors that affect the traffic flow in the urban road-network congestion control problem. It reflects the degree of traffic congestion. Meanwhile, he proposes a user-equilibrium theory in which no driver can shorten his/her journey time by changing the path to realize an equilibration state, and such ideal situation is difficult to achieve in practice. Furthermore, Sheffi proposes several approaches to approximate this equilibrium state; and the Label-Connecting algorithm which is a shortest path tree approach has been proved as one of the most effective methods. According to Sheffi's theory and methods, we choose shortest path and congestion avoidance as two objectives of the road-network congestion control and set up our agent model with parameters based on his theories.

Emergence: The traffic flow of the road-network is formed and evolved when vehicle agents continuously move toward their destinations, and the network links appear different congestion degree, especially those show serious congestion.

Adaptation: In the model, the link selection strategy and the node weight are adaptively updated based on the real-time congested degree of connected links.

Objectives: The objective of the model is defined as a utility function, which is implemented by operating the agent's link selection process by a two-objective optimization algorithm, where shortest path and congestion avoidance are considered as two objectives for routing optimization.

Stochasticity: When the simulation starts, the model randomly generates the departure and destination nodes of each vehicle agent. With the simulation proceeds, vehicle agents which arrive at a node need to determine their next target link based on the sub model of link selection. When agents face multiple candidate links, a utility function helps them to make the link selection decision. The utility function not only considers the two main factors of shortest path and congestion avoidance, but also takes into account the stochastic disturbances like traffic incidents or drivers preferences in the real life, which is implemented by Gaussian function.

Observation: The observations from the agent-based model are the reduction in Link Congestion Index (*LCI*) and Link Congestion Time (*LCT*) of congested links, which reflect the effectiveness of our proposed agent model and algorithms on improving road-network congestion problems.

E. Initialization

For the initialization, the model randomly generates a group of vehicle agents with their departure and destination nodes. They are gradually added into a predefined road-network at different time steps that follow a uniform distribution with 1 to 50. The weight of each node of road-network is initialized to 1. When the simulation proceeds, the weights of some nodes are adaptively updated based on equation (1). In this paper, we define those nodes with their weights not equal to 1 as congestion feedback nodes.

F. Sub-models

Two sub models are additionally defined for the operation of link selection and agent travel process. First, we describe the pseudo-code of link selection model in Fig.2.

```
Start
    if (the node connects to an unique link)
        Choose this link as the target link
    else  if (the link situation on shortest path == uncongested)
            Choose shortest link as the target link
          else
            Calculate the utility values of all connected links
            Choose a link with the minimum utility value as the target link
          end if
    end if
End
```

Figure 2. Pseudo-code of the link selection model.

As stated in Fig.2, each vehicle agent changes its link selection strategies according to his/her real-time congested degree of connected links. When multiple links can be selected, the agent chooses one based on a utility function. The utility function of link (*a*, *b*) at simulation step t is given in equation (6).

$$U_{(a,b)}^{t} = NW_{a}^{t} * g_{(a,b)} + LCI_{(a,b)}^{t} * (1 - NW_{a}^{t}) + Gauss, \quad (6)$$

where the first term $g(a, b)$ represents the strength which attracts agent moving towards its destination node, calculated by Floyd shortest path algorithm[32]; the second term $LCI_{(a,b)}^{t}$ reflects the congested degree of link (a, b) at simulation step t, calculated by equation (5); and the parameter NW_{a}^{t} is used as a weight to simultaneously optimize the two objectives (the shortest path and the congestion avoidance). Furthermore, in order to reflect randomness in agent's motion, we add Gaussian stochastic disturbance as the third term of the utility function. We set the two parameters as mean and variation of Gaussian function equal to 0 and 1, respectively. In the following, we present the pseudo-code of the agent travel process in Fig.3.

G. Evaluation criteria

In order to compare and analyze the simulation results, we define three evaluation criteria: First, the Link Congestion Index (*LCI*), which reflects the congested degree of a link at different time steps (which is also taken as a state variable given in Table II), calculated by equation (5); second, the Link Congestion Time (*LCT*), which is a quantitative indicator to describe the regulated congestion time of a link when the simulation is terminated, given by equation (7); and third, the number of congestion feedback nodes (*N_CFN*), which refers to those nodes with their weights less than 1. As the weight of each node is initialized as 1, and such values are updated when the congestion situation of connected links change, therefore, those nodes with their weights less than 1 indicate a feedback to the dynamic congestion situation of road-network.

```
Start
    if (the current link situation == uncongested)
        the agent moves forward a predefined distance on
        current link
    else
        calculate the rest of the link distance S to the next node
        calculate the expected travel time t_exp for passing the rest of the
link
        the agent move forward a S/t_exp distance on current link
    end if
End
```

Figure 3. Pseudo-code of the agent travel model.

$$LCT_{(a,b)} = \frac{\sum_{t=1}^{t=st} LCI_{(a,b)}^{t}}{st} * ct \quad (7)$$

In the above equation, *st* shows the total simulation time steps and *ct* is the sum of the congestion time of link (*a*, *b*). We summarize the three evaluation criteria in Table III.

TABLE III. ENTITIES AND DESCRIPTIONS

Criteria	Description	Name
Link Congestion Index	The congested degree of different links	*LCI*
Link Congestion Time	The regulated link congestion time	*LCT*
Number of Congestion Feedback Node	The number of congestion feedback nodes with their node weight less than 1	*N_CFD*

III. EXPERIMENTS

A. Experiment Design and Setups

In this paper, we conduct three groups of simulation experiments to examine the applicability and effectiveness of our model in improving the road-network congestion problem. The purposes and evaluation criteria of each group of experiments are summarized in Table IV.

To conduct the experiments, we define two types of agents: one type of agent is the Floyd agent that uses shortest path strategy, and the other agent type is the autonomous agent that uses hybrid strategy. Hybrid strategy refers to executing the shortest path strategy and the two-objective optimization strategy in turn according to the real-time congestion situation. The autonomous agent using hybrid strategy adapts its routing selection strategies to the real-time congestion environment of nearby links. In other words, the agents will use either shortest path strategy or the two-objective optimization strategy in link

TABLE IV. SUMMARY OF THE PURPOSES AND EVALUATION CRITERIA OF SIMULATION EXPERIMENTS

No.		Purpose	Evaluation Criteria
Group1	Experi-ment 1	Validation of the model on congestion evaluation and control.	*LCI*, *LCT*, the weight distribution of congestion feedback nodes
Group2	Experi-ment 2	Sensitivity analysis of the parameter *K* on congestion control.	*N_CFN*
	Experi-ment 3	The effect of the number of agents on congestion control	*N_CFN*
Group3	Experi-ment 4	Verification of the model on a real road map	*LCI*, *LCT*, *N_CFN*

selection, depending on the real-time congested degree of nearby links of road-network (See Fig.2 link selection model). On this basis, we execute simulation experiments with different composition of these two types of agents, and compare the simulation results by using the three evaluation criteria in Table III.

Table V presents the different composition of agents in the above four experiments. And, the experiments set the default value of K equal to 0.2.

TABLE V. THE DIFFERENT COMPOSITION OF AGENTS IN THE EXPERIMENTS

No.		Agent Composition
Group1	Experi-ment 1	3000 Floyd vs. 1500 Floyd and 1500 Autonomous.
Group2	Experi-ment 2	1500 Floyd and 1500 Autonomous.
	Experi-ment 3	1500 Floyd and 1500 Autonomous; The agent number scales in {1500, 2000, 2500, 3000, 3500, 4000, 4500}.
Group3	Experi-ment 4	6000 Floyd vs. 3000 Floyd and 3000 Autonomous 8000 Floyd vs. 4000 Floyd and 4000 Autonomous 10000 Floyd vs. 5000 Floyd and 5000 Autonomous

At the initial stage, the two types of agents travel along the shortest routing according to equation (6). When the simulation proceeds, some roads become congested, and the connected nodes would adjust their weights based on equation (1). Then the agent model adaptively shunts vehicles by using such weight sequences as weights in a two-objective function based on equation (6). In this way, the developed model constructs a set of dynamic evaluation indexes for describing the real-time congested degree of road-network, and achieving congestion reduction based on such index sequences simultaneously.

B. *Experimental Results*

1) *Validation of the model on the congestion control*

Given a predefined road-network topology in Fig.4, we simulate a road-network consisting of 39 nodes with their IDs ranging from 0 to 38, and 146 links represented by a pair of nodes. The coordinates of the nodes are defined in the same way as in [33].

The first experiment examines how our model using adaptive weight-based two-objective optimization algorithm reduces the road-network congestion. We focus on the improvements of those congested links. In this experiment, we execute trial one with 3000 Floyd agents using shortest path strategy, and trial two with 1500 Floyd agents using shortest path strategy and 1500 autonomous agents using hybrid strategy. We choose *LCI* and *LCT* of those congested links as the evaluation criteria to measure the simulation results. The simulation runs are terminated at step 200 since there were no more obvious variations in the simulation results after 200 steps.

Fig.5 presents the results of *LCI* and *LCT* of all congested links in the predefined network by two trials with different setup of agents.

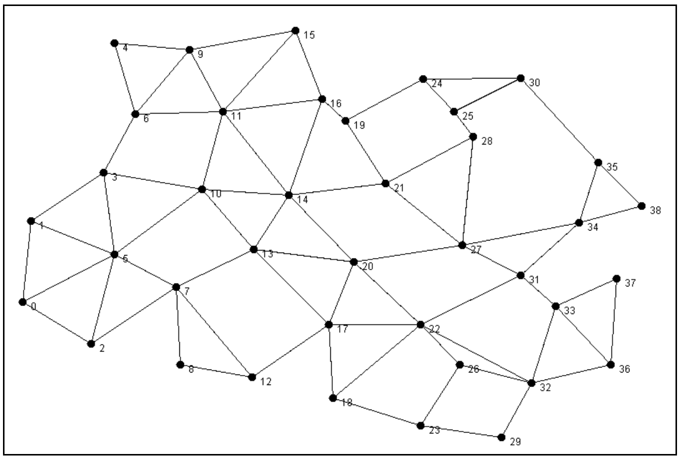
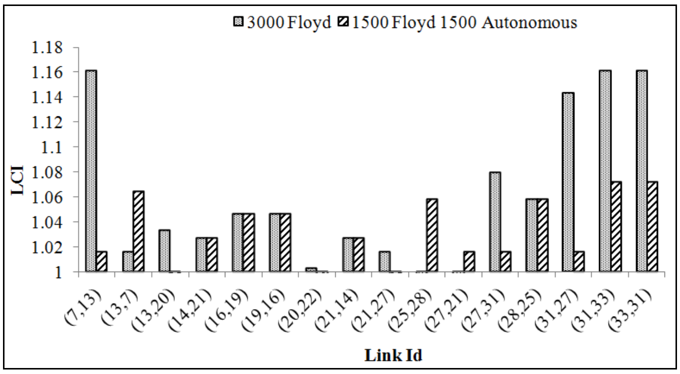
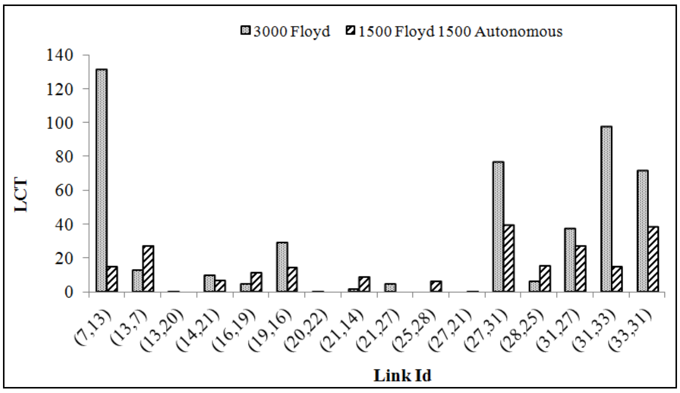


Figure 4. *The predefined road-network topology.*



(a) *LCI*



(b) *LCT*

Figure 5. *LCI* and *LCT* of congested links under different setup of agents.

The results in Fig.5 (a) showed that those seriously congested links, like link (7, 13) and (31, 27), had their values of *LCI* decreased from 1.16, 1.15 to 1.02. Other severely congested links such as link (31, 33) and (33, 31) had their values of *LCI* decreased from 1.16 to 1.07. Especially, some congested links became uncongested, like link (13, 20) and (21, 27), meanwhile there were new congestions formed in link (27, 21). Besides, *LCI* of some links appeared slightly increased, such as link (13, 7) and (25, 28). The results in Fig.5 (b) showed that most congested links had their *LCT* decreased, two seriously congested links as link (7, 13) and (31, 33) had their values of *LCT* decreased from 130,110 to 18. There also had congested links (13, 20), (20, 22) and (21, 27) turned to be uncongested, meanwhile new congestion appeared in link (25, 28). And, *LCT* of links (13, 7), (16, 19) and (21,14) appeared slightly increased.

Further, Fig.6 illustrates the weight distribution of congestion feedback nodes after applying our proposed agent-based model with adaptive weight algorithm. It is interesting that we find the IDs of congestion feedback nodes just corresponding to the end nodes of congested links in Fig.5. Especially, the seriously congested links like (7, 13), (31,27), (31, 33) and (33, 31), their connected end nodes 7, 31 and 33 have their weights as 0.068, 0.002 and 0.055, which are much smaller than other nodes.

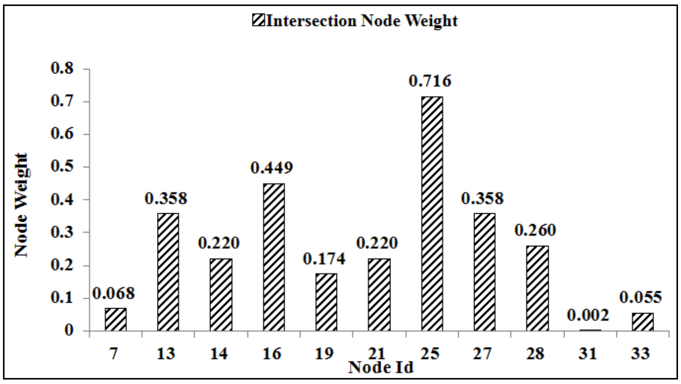


Figure 6. *The weight distribution of congestion feedback nodes.*

2) The Effect of Parameter K and the Number of Agents on the Congestion Control

The second group of simulation experiments includes two parts: Experiment 2 conducts sensitivity analysis of parameter *K* on congestion control and Experiment 3 examines the effect of the number of agents on congestion control. In both experiments, we keep road-network topology as the one in Experiment 1.

First, we execute Experiment 2 for sensitivity analysis of parameter *K* on congestion control. The experiment sets the agent-based model consisting of 1500 Floyd agents and 1500 Autonomous agents, and the values of parameter *K* changing from 0.2 to 2. As the number of congestion feedback nodes directly reflects the effect of our agent model on congestion management and control, we therefore calculate the number of congestion feedback nodes under different *K* values and present the results in Fig.7.

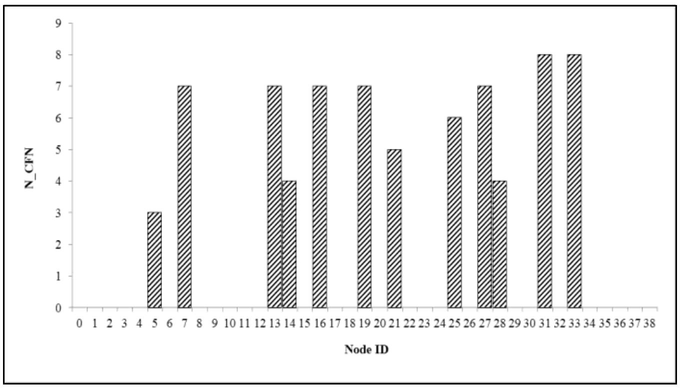


Figure 7. *The number of congestion feedback nodes under different K.*

As shown in Fig. 7, the number of congestion feedback nodes was getting smaller with an increasing *K*. More concretely, the value of *N_CFN* was decreased from 9 (*K*=0.2) to 1 (*K*=1.45). And, there was no more congestion feedback nodes in the network when *K* was bigger than 1.45.

Next, we conduct Experiment 3 to examine how the number of agents influences the improvement of road-network congestion. We first execute eight trials of the simulation model with 1500 Floyd agents and 1500 Autonomous agents, and the agents are initialized with randomly generated start and destination nodes. Fig.8 presents the number of occurrences of congestion feedback nodes of the given road-network.

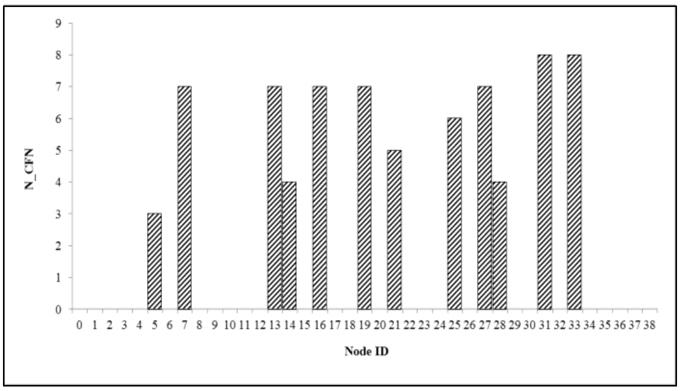


Figure 8. *The number of occurrences of congestion feedback nodes of the predefined network.*

As shown in Fig.8, even though the eight trials generated the agents with different start and destination nodes, congestion feedback nodes were located on some specific nodes 7, 13, 16, 19, 27, 31 and 33. These nodes appeared 7 or 8 times as congestion feedback nodes in eight trials. Of the seven nodes, the node 7, 31 and 33 are corresponding to the end nodes of congested links in Fig.5.

Then, we execute Experiment 4 to test our model under different number of agents, ranging in the collection of {1000, 1500, 2000, 2500, 3000, 3500, 4000, 4500}. Fig.9 presents the number of congestion feedback nodes after simulation when the number of agents scales from 1000 to 4500. As shown in Fig.9, the number of congestion feedback nodes increases with the number of agents.

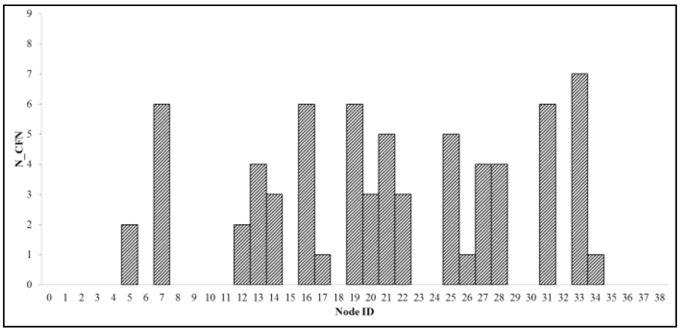


Figure 9. *The number of congestion feedback nodes under different number of agents.*

Further, Fig.10 lists the distribution of number of congestion feedback nodes among the 39 nodes of the road-network. In Fig.10, we find similar results where the congested nodes are still concentrated on certain nodes, such as node 7, 13, 16, 19, 31 and 33.

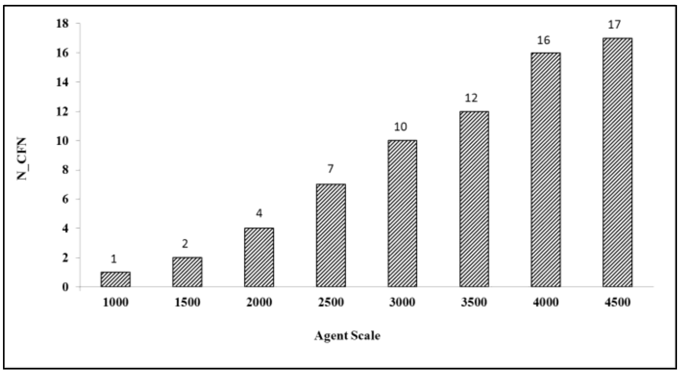


Figure 10. *The distribution of number of congestion feedback nodes under different number of agents.*

3) The effectiveness of the model on a real road map

Finally, the third group of simulation experiments runs to verify the applicability and effctiveness of our agent model on a real traffic map. We preprocess the GIS map data of a Medium-sized city in China from ArcMap, and get a directed graph consisting of 514 nodes and 791 links. First, we examine the efficiency of the model under different traffic flows by increasing the number of agents. Table VI gives the result number of congestion feedback nodes under a growing number of agents.

TABLE VI. THE NUMBER OF CONGESTION FEEDBACK NODES WITH DIFFERENT NUMBER OF AGENTS

The number of Agents	***N_CFN***
6000	38
8000	73
10000	106

The results in Fig.7 showed that the number of congestion feedback nodes increased from 38 to 106, with the number of agents changing from 6000 to 10000. Since the number of congestion feedback nodes reflects an ability of the model in improving congestion, therefore, such results confirmed the efficiency of our model on congestion control. Next, we fix the number of agents to 6000, and sort the links by their *LCI* values in a descending order and the top ten links are found and summarized in Table VII.

TABLE VII. THE LIST OF THE TOP TEN LINKS SORTED BY *LCI*

Link Id	**6000 Autonomous**	**3000 Floyd 3000 Autonomous**	**Improvement Rate**
(385,386)	1.6546	1.5041	9.09%
(103,104)	1.6008	1.0440	34.78%
(56,570)	1.4610	1.1083	24.14%
(379,380)	1.3823	1.0367	25.00%
(57,58)	1.3457	1.1128	17.31%
(258,257)	1.3379	1.0946	18.18%
(110,109)	1.3359	1.0312	22.81%
(380,110)	1.2899	1.0279	20.31%
(378,379)	1.2591	1.0301	18.18%
(244,243)	1.2560	0.0000	100.00%

As described in Table VII, nine of the top ten congested links had improved their *LCI* values more than 17%. The most seriously congested link (385, 386) had its *LCI* value improved 9%, and the congestion in link (244, 243) disappeared. By using the two-objective optimization algorithm in our model, the average value of *LCI* of all congested links was decreased from 1.1601 to 1.0755.

Then, we fix the number of agents to 6000, and sort the links by their *LCT* values in a descending order. Table VIII lists the top ten links with larger *LCT* values.

TABLE VIII. THE LIST OF THE TOP TEN LINKS SORTED BY *LCT*

Link Id	**6000 Autonomous**	**3000 Floyd 3000 Autonomous**	**Improvement Rate**
(379,380)	338.6683	165.8784	51.02%
(380,110)	149.6260	49.3379	67.03%
(56,57)	130.0289	56.5255	56.53%
(378,379)	119.6103	85.5013	28.52%
(57,58)	98.2352	20.0300	79.61%
(58,59)	60.5380	0.0000	100.00%
(396,395)	44.8691	19.8438	55.77%
(52,56)	40.7229	27.3767	32.77%
(258,257)	38.7987	25.1766	35.11%
(109,110)	34.1477	28.2182	17.36%

As shown in Table VIII, most links with bigger values of *LCT* were greatly decreased, such as link (379,380) (380,110), (56, 57), (57, 58) and (396,395). The improvement rates of these links were over 50%. Especially, the congestion no longer occurs on link (58, 59). By using the two-objective optimization algorithm with adaptive weight in our model, the average value of *LCT* of all congested links was decreased from 31.8819 to 16.3685.

Further, Fig.11 gives the weight distribution of those seriously congested links in Table VII and VIII. The black dashed line in Fig.10 represents the average weight of all congestion feedback nodes of the road-network, which was 0.3264. According to the results in Fig.10, most nodes had their weights much smaller than the average value. Particularly, the two end nodes, 379 and 380 that belong to the most congested link (379,380), have their weights that are modified to 0.0713 and 0.1085, respectively.

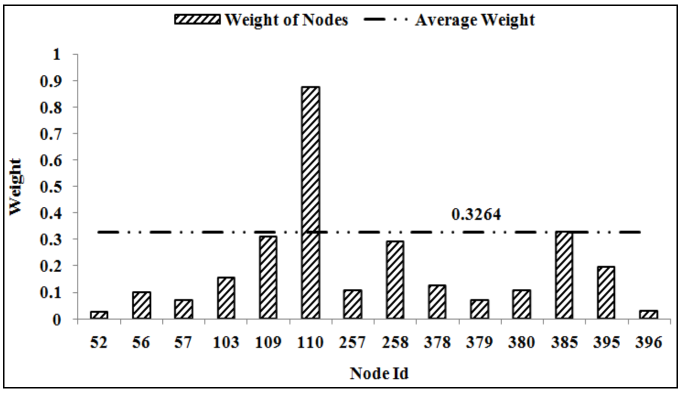


Figure 11. *The weight distribution of those seriously congested links.*

For a more intuitive display with congestion feedback nodes to describe the distribution of congestion, we mark the locations of the congestion feedback nodes on the real road map in Fig.12. In this figure, the nodes with more dark red color indicate smaller values of the weight, which also mean more severe congestion of connected roads.

Figure 12. *The distribution of congestion feedback nodes on the real road map.*

IV. DISCUSSION

From the experimental results above, we draw the following discussions:

(1) In the first group of simulation experiments, the results of *LCI* and *LCT* showed that our proposed model helped to decrease the congested degree of those congested links, especially those seriously congested links like (7, 13) and (31, 33). But the simulation results showed *LCI* and *LCT* of some links (e.g. (13, 7)) had a slight increase. This exactly explained the model effect on vehicle shunting and congestion equilibration. Additionally, the achieved adaptive weight sequence confirmed that the value of node weights could reflect the non-uniform road congestion degree in a quantitative way. When the simulation starts, the weight of nodes are initialized to 1. At the early stage of the simulation, Both Floyd agent using shortest path strategy and autonomous agent using hybrid strategy travel along the shortest routing according to equation (6). When the simulation proceeds, some roads become congested, and the connected nodes would adjust their weights based on equation (1) and implement vehicle shunt via the two-objective optimization by equation (6). During the simulation process, the extremely small weight of nodes meant a seriously congested situation with those connected links while the nodes with higher values of weight approximating to or more than one meant less congestion or never congestion. Therefore, the results in experiment one showed that our model successfully constructed a new quantitative index of nodes for evaluating the real-time congestion distribution of the road-network, and use such index sequences as weights in a two-objective function for vehicle shunt and congestion control simultaneously.

(2) The results in the second group of simulation experiments showed that the performance of our proposed approach was affected by the values of parameter *K* and the number of agents. The result in Experiment 2 found that the number of congestion feedback nodes decreased with a growing value of parameter *K*. Such results indicated that the congested nodes and related links were also decreased and the network congestion was greatly improved. And, the simulation results achieved best performance when *K* equal to 0.2. On the contrary, the result that no more congestion feedback nodes appeared when *K* was bigger than 1.45 indicated a threshold for *K* in the process of node weight adjustment. That is because too large values of parameter *K* would lead to an over-modification of node weight and a coarseness of the congestion evaluation. In this case, our model was unable to accurately measure the congestion distribution of the road-network. Furthermore, the results in Experiment 3 indicated that congestion locations of a road-network mainly depended on the network topology. Although eight trials of the simulation were executed by setting the different start and destination nodes of agents, the congestion feedback nodes were mainly located on some specific nodes, just like the road-network junction and the intersection of the arterial link. The results also showed that the number of congestion feedback nodes increased with a growing number of agents, which indicated that bigger traffic flow would cause more serious congestion status. This shows that the node weight affected by the agent quantity to a certain

degree. Further, the distribution of congestion feedback nodes under different amounts of agent again proved that the congestion nodes mainly depended on the network topology.

(3) The results obtained from the third group of simulation experiments showed that the agent model with adaptive weight-based two-objective optimization algorithm had successfully reduced the traffic congestion on the real road map. The increased amount of congestion feedback nodes denoted that the performance of the agent model was affected by the different traffic scales, and also indicated the effect of different traffic scales on the nodes weights. The improvement rate of those seriously congested links with higher values of *LCI* and *LCT* confirmed the shunting effect of our proposed model on congestion control. The node weights exactly provided a quantitative index for describing and evaluating the network congestion distribution with a global perspective. Meanwhile, according to the simulated results of distribution of congestion feedback nodes on the real traffic map, we found most nodes located at the road junction or near the unique road connecting the east and west urban area. Because these nodes connected traffic arteries, most agents of the simulated traffic system had to pass such nodes to go through the regions and finally reached their destinations. Although we did not set agents according to the real traffic flow in the city map, the simulation results reflected the same congested node with the real map in actual life. Also, the improvement made by our model on those seriously congested links provided a dynamic balancing diversion idea from the vehicles perspective, which had its significant potentials for guiding actual operation of the congestion control. Therefore, the simulation results verified the applicability and effectiveness of our proposed model executing on the real traffic map.

V. CONCLUSION

In this paper, we have developed an agent model with adaptive weight-based multi-objective algorithm to manage the road-network congestion problem. In this way, a series of quantitative index to describe the road-network congestion distribution is built. And these indexes are used as weights in the multi-objective algorithm of agent-based model to shunt vehicles on those congested links. We therefore implement a multi-agent system, and execute three groups of simulation experiments to examine the applicability and effectiveness of our model on improving road-network congestion problem.

The simulation results show that the model realizes a real-time road congestion control, thus reduces the road congestion and promots traffic capacity of the transport network. Especially, the validation of the model with a real traffic map of a Medium-sized city in China turned out that our proposed model could balance and reduce the congestion in the road-network. The simulation results also confirmed an applicability and effectiveness of the node weight as a new quantitative index sequences to describe the road-network congestion distribution, and shunt vehicles on those congested roads based on that index simultaneously.

Such a hybrid-perspective-based agent approach based on a multi-objective optimization algorithm with adaptive weight will have its significant potentials for actual traffic congestion control by considering the global congestion distribution and the local vehicle routing selection at the same time. With the help of GPS devices, the proposed agent model has a theoretical value and practical significance for both vehicle navigation and route selection used in the field of ITS. In the future work, we plan to test the effectiveness and accuracy of our model based on an exact traffic flow data. We also consider the implementation of this idea to a real world traffic environment.

ACKNOWLEDGMENTS

This work was supported by the Natural Science Foundation of Hunan Province, China, grant no. 13JJ3049.

REFERENCES

[1] P. Desai, S. W. Loke, A. Desai, and J. Singh, “Multi-agent based vehicular congestion management”, in IEEE Proceedings of Intelligent Vehicles Symposium (IV’11), pp. 1031-1036, 2011.

[2] G. Liao and P. J. Shang, “Scaling and complexity-entropy analysis in discriminating traffic dynamics”, Fractals, vol. 20(03-04), pp. 233-243, 2012.

[3] D. Helbing, “Traffic and related self-driven many-particle systems”, Reviews of Modern Physics, vol. 73(4), pp. 1067-1141, 2001.

[4] Y. Sheffi, Urban Transportation Networks: Equilibrium Analysis with Mathematical Programming Methods. New Jersey, USA: Prentice-Hall, 1985.

[5] Y. J. Dai and D. B. Zhao, “A traffic signal control algorithm for isolated intersections based on adaptive dynamic programming”, in IEEE Proceedings of 2010 International Conference on Networking Sensing and Control (ICNSC 2010), pp. 255-260, 2010.

[6] R. Hoar, J. Penner, and C. Jacob, “Evolutionary swarm traffic: if ant roads had traffic lights”, in IEEE Proceedings of Congress on Evolutionary Computation (CEC’02), pp. 1910-1915, 2002.

[7] I. Arel, C. Liu, T. Urbanik, and A. G. Kohls, “Reinforcement learning based multi-agent system for network traffic signal control”, Intelligent Transport Systems, vol. 4(2), pp. 128-135, 2010.

[8] D. A. Roozemond, “Using intelligent agents for pro-active, real-time urban intersection control”, European Journal of Operational Research, vol. 131(2), pp. 293-301, 2001.

[9] R. S. Chen, D. K. Chen, and S. Y. Lin, “ACTAM: Cooperative multi-agent system architecture for urban traffic signal control”, IEICE Transaction on Information and Systems, vol. E88-D(1), pp. 119-126, 2005.

[10] E. Onieva, V. Milanés, J. Pérez, J. Alonso, T. Pedro, R. García, J. Godoy, and J. Villagra, “Study of traffic flow controlled with independent agent-based traffic signals”, in Proceedings of the 13th International Conference on Computer Aided Systems Theory (EUROCAST 2011), pp. 382-389, 2011.

[11] S. Tahilyani, M. Darbari, and P. L. Shukla, “A new multi agent cognitive network model for lane-by-pass approach in urban traffic control system”, International Journal of Advanced Research in Artificial Intelligence, vol. 1(3), pp. 32-36, 2012.

[12] Y. Ando, Y. Fukazawa, O. Masutani, H. Iwasaki, and S. Honiden, “Performance of pheromone model for predicting traffic congestion”, in Proceedings of the fifth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS’06), pp. 73-80, 2006.

[13] W. Narzt, U. Wilflingseder, G. Pomberger, D. Kolb, and H. Hortner, “Self-organising congestion evasion strategies using ant-based pheromones”, Intelligent Transport Systems, vol. 4(1), pp. 93-102, 2009.

[14] C. Sur, S. Sharma, and A. Shukla, “Analysis & modeling multi-breeded mean-minded ant colony optimization of agent based road vehicle routing management”, in IEEE Proceedings of 2012 International

Conference for Internet Technology and Secured Transactions (ICITST 2012), pp. 634-641, 2012.

[15] C. Astengo-Noguez and R. Brena-Pinero, "Flock traffic navigation based on negotiation", in Proceedings of the 3rd International Conference on Autonomous Robots and Agents (ICARA 2006), pp. 159-164, 2006.

[16] H. F. Wedde, S. Lehnhoff, B. van Bonn, Z. Bay, S. Becker, S. Bottcher, C. Brunner, A. Buscher, T. Furst, A. M. Lazarescu, E. Rotaru, S. Senge, B. Steinbach, F. Yilmaz, and T. Zimmermann, "A novel class of multi-agent algorithms for highly dynamic transport planning inspired by honey bee behavior", in Proceedings of IEEE Conference on Emerging Technologies and Factory Automation (ETFA 2007), pp. 1157-1164, 2007.

[17] D. Buscema, M. Ignaccolo, G. Inturri, A. Pluchino, A. Rapisarda, C. Santoro, and S. Tudisco, "The impact of real time information on transport network routing through intelligent agent-based simulation", in Proceeding of 2009 IEEE Toronto International Conference on Science and Technology for Humanity (TIC-STH 2009), pp. 72-77, 2009.

[18] M. Zolfpour-Arokhlo, A. Selamat, S. Z. M. Hashim, and H. Afkhami, "Modeling of route planning system based on Q value-based dynamic programming with multi-agent reinforcement learning algorithms", Engineering Applications of Artificial Intelligence, vol. 29, pp. 163-177, 2014.

[19] G. M. Arnaout, M. T. Khasawneh, J. Zhang, and S. R. Bowling, "An IntelliDrive application for reducing traffic congestions using agent-based approach", in Proceedings of 2010 IEEE Systems and Information Engineering Design Symposium (SIEDS'10), pp. 221-224, 2010.

[20] T. Ito, R. Kanamori, J. Takahashi, I. M. Maestre, and E. D. L. Hoz, "Effect of anticipatory stigmergy on decentralized traffic congestion control", in Proceedings of the 15th International Conference on Principles and Practice of Multi-Agent Systems (PRIMA 2012), pp. 214-217, 2012.

[21] P. Desai, S. W. Loke, A. Desai, and J. Singh, "CARAVAN: Congestion avoidance and route allocation using virtual agent negotiation", IEEE Transaction on Intelligent Transport Systems, vol. 14 (3), pp. 1197-1207, 2013.

[22] B. Jiang, X. Xu, C. Yang, R. F. Li, and T. Terano, "Solving road-network congestion problems by a multi-objective optimization algorithm with Brownian agent model", in Proceedings of 13th International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS 2013), pp. 36-48, 2013.

[23] D. Weyns, T. Holvoet, and A. Helleboogh, "Anticipatory Vehicle Routing using Delegate Multi-Agent Systems", in IEEE Proceedings of Intelligent Transportation Systems Conference (ITSC'07), pp. 87-93, 2007.

[24] H. M. Kammoun, I. Kallel, and A. M. Alimi, "A joint hierarchical fuzzy-multi agent model dealing with route choice problem RoSFuzMAS", in Proceedings of the 4th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2007), pp. 394-397, 2007.

[25] J. R. Yang, "A dynamic route guidance algorithm based on modified ant colony optimization", in Proceedings of 1st International Symposium on Computer Network and Multimedia Technology (CNMT 2009), pp. 1-3, 2009.

[26] P. Gao, Z. S. Yang, and D. Hong, "Notice of retraction research on the solution method of Braess paradox based on multi-agent system", in Proceedings of 2010 3rd IEEE International Conference on Computer Science and Information Technology (ICCSIT 2010), pp. 187-191, 2010.

[27] M. Vasirani and S. Ossowski, "A market-inspired approach for intersection management in urban road traffic networks", in Proceedings of the 8th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2009), pp. 617-624, 2009.

[28] B. Jiang, X. Xu, C. Yang, R. F. Li, and T. Terano, "Vehicles Congestion Control in Transport Networks Using an Adaptive Weight Model", in Proceedings of 2014 International Conference on Internet of Vehicles (IOV2014), pp. 99-109, 2014.

[29] V. Grimm, U. Berger, D. L. DeAngelis, J. G. Polhill, J. Giske, and S. F. Railsback, "The odd protocol: A review and first update", Ecological Modelling, vol. 221(23), pp. 2760-2768, 2010.

[30] A. Messmer and M. Papageorgiou, "Automatic control methods applied to freeway network traffic", Automatica, vol. 30(4), pp. 691-702, 1994.

[31] Y. Pavlis and M. Papageorgiou, "Simple decentralized feedback strategies for route guidance in traffic networks", Transportation science, vol. 33(3), pp. 264-278, 1999.

[32] Bureau of Public Roads, Traffic assignment manual U.S. Department of Commerce. Washington, DC, USA: Urban Planning Division, 1965.

[33] R. W. Floyd, "Algorithm 97: shortest path". Communications of the ACM, vol. 5(6), pp.345, 1962.

[34] F. Schweitzer, W. Ebeling, H. Rose, and O. Weiss, "Optimization of Road Networks using Evolutionary Strategies", Evolutionary Computation, vol. 5(4), pp. 419-438, 1997.