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Study on Agent-Based Models for Routing Selection in Road-network Congestion Management

（道路渋滞管理のためのルート選択問題に関するエージェント・ベース・モデルの研究）

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ABSTRACT

In the past decades, road-network congestion especially in urban has become more serious due to an increasing travel demand and limited traffic capacity. Congestion is known to cause travel and waiting costs, pollution emissions and even increase the probability of road hazards, which further restrict our economic prosperity and social progress. Therefore, effective congestion management mechanism as an foundation component of human society has its research and practical significance to benefit the travelers, businesses and environment. Traditional congestion management mostly emphasizes on either building more roads to expand the traffic capacity or reducing travel demand through government intervene measures. However, it is impractical to set up enough roads to completely satisfy the increasing travel demand. And, the effect of government intervention measures is always not obvious with an increasing travel demand. Besides, the recent literature has witnessed a great interest and success in designing intelligent transportation systems (ITS), such as intelligent traffic signal control and vehicle route guidance to solve the road-network congestion problem.

Under such a background, this thesis studies the congestion management issue based on vehicle route guidance of intelligent transportation system. The literature review shows that agent-based framework with bottom-up perspective has been widely used in this field because of its natural and suitable for capturing the dynamic and geographically distributed features of

transportation systems. In our study, we aim to propose agent-based models with weighted multi-objective optimization algorithm to implement vehicle route guidance. Especially, our focus is to construct a quantitative index sequence which could achieve the congestion evaluation and management of road-network at the same time. First, a multi-agent system is built, where each agent stands for a vehicle that would adapt its route to a dynamic road-network congestion condition 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 status, thus we can observe the formation and evolution of road-network congestion through agent-based simulations. Next, a series of quantitative indexes is constructed to describe the congested degree of road nodes, and such indexes are used as weights in the two-objective function employed by the agents for routing decision in a changing traffic environment. In this way, our proposed agent models with adaptive weight-based multi-objective optimization algorithm could achieve congestion distribution evaluation and congestion management at the same time. Besides, we define a set of evaluation criteria to measure the effect of our proposed agent models on road-network congestion improvement.

Intensive experiments on a generated road-network topology and a real road map have both shown an applicability and effectiveness of our proposed agent model on reducing congestion. We further examine the agent model effect with adaptive weight-based two-objective optimization algorithm. The simulation results have also confirmed an applicability and effectiveness of

the node weights as a new quantitative index sequences which describe the road-network congestion distribution, and shunt vehicles on seriously congested roads based on that index simultaneously. By comparing the distribution of those congested links or nodes on the real road map, we find that most congested locations are the unique road connecting two regions or road junction. The reason is that these locations always connect traffic arteries, thus most agents of the simulated traffic system have to pass such links or nodes to go through the regions and finally reach their destinations.

The contributions of our study in the field of congestion management could be found in the hybrid route guidance strategy which quantifies the influence of congestion avoidance and implements a two-objective function which considers both shortest path and congestion avoidance for the routing optimization; and agent-based models with weighted two-objective algorithm for understanding the formation and reduction of road-network congestion by capturing the nonlinear feedback between agent routing behaviors and road-network congestion conditions; as well as a quantitative index sequence which measures the real-time congestion distribution and also is used as weights of the two-objective function simultaneously for implementing agent routing selection function, it could achieve a good tradeoff between user satisfaction and effective utility of road-network. The proposed model and method will have their significant potentials for actual traffic congestion control. With the help of GPS devices, the proposed model and method will have their theoretical value and practical significance for both vehicle navigation and route guidance used in the field of ITS.

1. INTRODUCTION

1.1 RESEARCH BACKGROUND

In recent years, due to the pace of human work and life continue to accelerate, and the popularity of transportation tools and the expansion of transportation networks, urban transportation systems have been experienced an unprecedented flourish and outspread. But the attendant problems become more apparent. One serious problem is the congestion caused by an increasing number of vehicles and poor traffic management mechanisms with limited road passage capacity. There have already existed many different definitions of traffic congestion. In this study, we use one popular definition proposed by Turner: 'congestion is the time or the delay in excess of that normally incurred under light or free flow traffic condition' [Turner, 1996]. The sudden traffic accidents or periodical holiday events are always to cause traffic congestion when no efficient and timely emergency mechanisms work to divert vehicle groups. Traffic congestion is known to cause travel and waiting cost, the long waiting queue of vehicles exacerbates emissions and increases the probability of road hazards, it will further impact on the economic development and environmental sustainability [Desai, 2011]. Nowadays, road-network congestion especially in urban has become a major bottleneck restricting economic prosperity and social progress. Therefore, effective congestion management mechanism as an foundation component of human society has its research and practical significance to benefit the travelers, businesses and environment.

Current solutions for road-network congestion are mostly achieved by expanding the road traffic capacity and restricting the traffic flow, which can be divided into three categories: (1) building more roads and infrastructures

to increase the road traffic capacity; (2) reducing traffic demand through intervene by government management measures; and (3) scattering traffic flow by designing intelligent transportation systems (ITS), such as intelligent traffic signal control and vehicle route guidance. However, it is impractical to set up enough roads and infrastructures to completely satisfy the increasing travel demand. Furthermore, the effect of government intervention measures such as limiting vehicle travel dates to either odd or even dates according to the final figure of vehicle license plate is always not obvious with an increasing travel demand and large traffic flow.

Under such a background, Intelligent Transportation Systems (ITS) are becoming more and more widely adopted as an important solution for road-network congestion management. ITSs are advanced applications which aim to provide innovative services relating to different modes of traffic management and enable various users to be better informed and make safer, more coordinated, and smarter use of transportation networks [EU Directive, 2010]. Although ITS may refer to each possible transportation mode, we use the definition provided by EU Directive 2010/40/EU (7 July 2010), in which ITS are 'systems where information and communication technologies are applied in the field of road transportation, including infrastructure, vehicles and users, and in traffic management and mobility management, as well as for interfaces with other modes of transportation' [EU Directive, 2010]. In the application of ITS to traffic management, certain studies show that the travel time may increase 6% to 19% when users make vehicle routing selection without considering any information provided by GPS and/or route guidance system [Adacher, 2014]. Meanwhile, another challenge for conducting correct traffic management in a given road-network section is the design of right ITS, able to implement effective vehicle route guidance [Adacher, 2014].

The past decades have witnessed an increasing interest in the application of agent-based approaches to study the urban road-network congestion problem. The autonomous and distributed nature of multi-agent system (MAS) makes it suitable to capture the dynamic and geographically distributed features of transport 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.

In the literature, earlier methods mainly performs static route recommendation without updating the related road-network information, they always calculate single measures such as shortest path, travel time with exact or approximation algorithms to implement route guidance. More sophisticated route guidance systems make use of information on current traffic conditions in the road-network. In these systems, the road conditions are generally obtained through communication with a central station which connects to sensors placed in the road-network. Based on the knowledge of traffic condition of the road-network, route guidance approaches are further divided into two categories: reactive route guidance and anticipatory route guidance. The former approaches provide path to drivers at any given time based on the traffic situation at that moment, and the latter recommend path based on the prediction of future traffic conditions. However, one problem is how future conditions could be correctly predicted. In practice, there is no consensus on which of these two approaches should be used [Bottom, 2000].

Meanwhile, scientists suggest that route guidance systems should take into account the overall road usage so as to improve traffic management and

avoid road-network oversaturation phenomenon [Adler, 1998]. This can be achieved by providing the route guidance systems with multiple path routing selection embedded algorithms in order to split vehicles over several paths [Adacher, 2007] [Beccaria, 1992]. Different approaches have been proposed to handle multiple path routing problems, such as system optimum approach and user equilibrium approach. The system optimum approaches always route the vehicle along an optimum path measured by overall time or distance of the road-network; and the user equilibrium approaches aim to satisfy the individual-level optimizations such as minimal travel time or shortest path and then route the vehicle. Roughgarden and Tardos investigate the relation between these two approaches, and find that the user equilibrium approach often proposes solutions outperforming the system optimum approach [Roughgarden, 2000]. However, the route guidance systems always cause a dilemma by recommending a same path to too many drivers. In order to solve this problem, Adacher et al. propose a multiple path routing algorithm which considers both user's preferences and traffic information provided by the reference nodes to guide the vehicle routes [Adacher, 2014]. Although the results show that the proposed methodology achieves a good trade-off between single user satisfaction and global utilization of the road-network, how to correctly classify user preferences becomes another meta-problem. Besides, the definition and selection of quantitative indexes to measure road-network congestion is not an easy task and each study depending on its purpose focuses on a suitable methodological framework.

1.2 MOTIVATION OF THE RESEARCH

Vehicle route guidance as one basic method for dealing with traffic congestion problem in the road-network transportation system has always

been concerned as a hot research topic and engineering issues. In the field of study of methodology for conducting vehicle route guidance, agent-based framework with bottom-up perspective are natural and suitable for capturing the dynamic and geographically distributed features of transportation systems, thus have been widely used in the study of vehicle route guidance. As literature review shows that current route guidance systems pay rare attention to the dilemma by suggesting the same path to too many drivers, which may even exacerbate road-network congestion. On the other hand, the user equilibrium approaches have often proposed solutions outperforming the system optimum approaches over multiply paths. Therefore, we intend to design agent-based models which implement a good trade-off between single user satisfaction and global utilization of the road-network by designing right routing selection algorithm so as to implement effective route guidance of ITS.

The motivations of this thesis are: (1) to design a routing selection function which quantifies the influence of congestion avoidance and implements a two-objective algorithm which considers both shortest path and congestion avoidance for the routing optimization; (2) to propose agent-based models which could capture the nonlinear feedback between vehicle routing behaviors and road-network traffic conditions, so as to analyze the congestion formation and evolution especially focus on finding common features of those seriously congested roads; (3) to define a set of evaluation criteria, which could evaluate the performance of our proposed agent-based models for solving road-network congestion problem; (4) to construct a quantitative index sequence which describes the utilization of the road-network and evaluates the congestion distribution based on current information of road conditions obtained from the referenced intersection nodes, and also use such indexes as weights in the route selection function to

shunt vehicles on those congested roads.

1.3 OBJECTIVES OF THE RESEARCH

The objectives of this research are to formulate a comprehensive methodology for quantifying and identifying congestion characteristic based on variations in road-network congestion degree and distribution. Our focus is to build agent-based models with multi-objective optimization algorithm in order to achieve a good tradeoff between user satisfaction and effective utility of road-network.

We describe the main objectives as follows: (1) to design a routing selection function which supports vehicle agent routing decision by satisfying two objectives as the shortest path and the minimal congested degree of the target link simultaneously; (2) to define agent-based models which relate vehicle routing behaviors and road-network traffic dynamics to analyze the road-network congestion problem, especially focusing on finding common features of those seriously congested positions; (3) to construct a quantitative index sequence which describes the global congestion distribution of the road-network and are also used as weights in the multi-objective function to shunts vehicles on those congested roads; and (4) to define a group of evaluation criteria for validating the effectiveness of our proposed models and methods on road-network congestion improvement.

1.4 POSITION OF THE RESEARCH

The road-network congestion management is a key application in the field of intelligent transport system, therefore it is significant to analyze the internal mechanism of congestion formation and nonlinear feedback between different constitute units, such as infrastructures, vehicles and road-network,

and further understand the common features of those seriously congested intersections and roads in the transportation systems.

The position of this research in social science is at the methodology level, including the modeling, simulation and evaluation of road-network traffic condition so as to implement route guidance of intelligent transportation system. 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 models capture the nonlinear feedback between vehicle routing behaviors and road-network congestion states. Next, a series of quantitative indexes is constructed to describe the utilization and congestion distribution of the road-network, and such indexes are also used as weight in the two-objective function employed by the agents for routing decision 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.

1.5 ORGANIZATION OF THIS THESIS

This thesis is organized as shown in Fig 1.1:

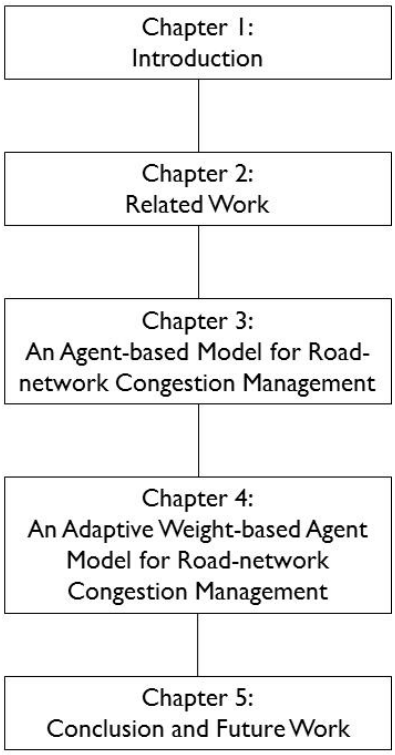


Fig 1.1 Organization of this thesis

As shown in Fig 1.1, the rest of this thesis is organized as follows: Chapter 2 makes a brief literature review of the related work; Chapter 3 proposes an agent-based model with multi-objective algorithm on routing selection and congestion management and conducts experiments on a generated road-network and a real-map to validate the effectiveness of this basic agent-based model on congestion improvement; Chapter 4 constructs a quantitative index series to measure the traffic congestion distribution, and such index sequence are also used as adaptive weights in the agent model to achieve the traffic congestion reduction, the model also validated by both generated road-network and a real road map. Finally, chapter 5 concludes the work of this study and proposes some ideas for future work.

1.6 SUMMARY

In this chapter, we have first introduced the background of this research, and

then have presented our motivations and objectives for building agent-based models for road-network congestion management. Next, we have elaborated the position of this research in social science. And finally, we have given the organization of this thesis.

2. RELATED WORK

2.1 INTRODUCTION

In this chapter, we make a brief literature review of this study. First, agent-based models for congestion management are compared and analyzed. Then, different approaches of route guidance in the application of the intelligent transportation systems are presented. And finally, routing selection algorithms for implementing vehicle route guidance in the intelligent transportation system are described.

2.2 ABMS FOR TRAFFIC CONGESTION MANAGEMENT

There have been many contributions that apply agent-based models to study the traffic congestion problem. According to the focus on different constituent units of transportation systems, we classify these works into three categories as Infrastructure-based agent approaches, Vehicle/Driver-based agent approaches and Hybrid-perspective-based agent approaches.

2.2.1 INFRASTRUCTURE-BASED AGENT APPROACHES

Infrastructure-based agent approaches provide 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 [Hoar, 2002]. 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 [Arel, 2010]. 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 [Roozemond, 2001]. 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 [Chen, 2005]. 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 [Onieva, 2011]. 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 [Tahilyani, 2012]. Li et al. propose a systematic approach to adaptively realize the vehicle routing with the real-time traffic information. It focuses on the route planning procedures for determining the optimal route based on analytical hierarchy process (AHP) and fuzzy logic theory. The AHP-FUZZY approach is a multi-criteria combination system, which can greatly simplify the definition of decision strategy and represent the multiple criteria explicitly [Li, 2012a].

2.2.2 VEHICLE/DRIVER-BASED AGENT APPROACHES

Vehicle/Driver-based agent approaches propose appropriate control measures with an individual-level perspective to avoid traffic congestions. Some papers use bio-inspired techniques such as ant pheromone [Ando, 2006][Narzt, 2010] [Sur, 2012], bird flocking [Astengo-Noguez, 2006] and honey-bee foraging [Wedde, 2007]. 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 [Ando, 2006]. And Narzt et al. establish self-organizing congestion evasion strategies using ant-based pheromones [Narzt, 2010]. 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 [Sur, 2012]. 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 [Astengo-Noguez, 2006]. 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 [Wedde, 2007]. 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 [Buscema, 2009]. Arnaout et al. also describe an IntelliDriver application for reducing traffic congestions using an agent-based approach [Arnaout, 2010]. Ito et al. build an anticipatory stigmergy model for decentralized traffic congestion management, and the simulation results demonstrate its effectiveness and robustness [Ito, 2012]. Olusina et al. present empirical solutions to transportation problems in the Lagos Metropolis using the bottom-up approach, from transaction-based at local government level to multimodal at the metropolitan level. The stochastic user utility model is adopted to estimate the appropriate representation of human heterogeneity, flexibility and variability on mode choice relative to route travel times. The use of Assisted GPS Cameras provides some level of intelligence on the transportation routes [Olusina, 2013]. 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 [Desai, 2013]. 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 [Zolfpour-Arokhlo, 2014].

2.2.3 HYBRID-PERSPECTIVE-BASED AGENT APPROACHES

Hybrid-perspective-based agent approaches provide traffic guidance by integrating and processing diverse information from infrastructure units and vehicle drivers. 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 traffic management by accounting for environmental factors, vehicle states and driver preferences [Kammoun, 2007]. 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 [Yang, 2009]. And, Vasirani et al. also propose a distributed, market-inspired approach for intersection management in urban road traffic networks by using multi-agent models [Vasirani, 2009]. Gao et al. 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 [Gao, 2010].

2.3 ROUTE GUIDANCE APPROACHES OF ITS

The route guidance approaches in ITSs are mainly reactive guidance approaches and anticipatory guidance approaches. In reactive guidance, it is possible to respond quickly to demand changes or sudden incidents because only real-time traffic information is utilized and no predictions are used. The

anticipatory guidance recommends user's route based on prediction of future demands and traffic conditions, which meets the problem of how future could be predicted. Both approaches are widely used in practice.

2.3.1 REACTIVE GUIDANCE APPROACHES

Among the contributions of reactive guidance approaches, Wang et al. present real-time feedback route guidance in large-scale express ring-roads, where the results indicate that real-time feedback route guidance can help alleviate and dissolve heavy non-recurrent traffic congestion, and establish dynamic user equilibrium [Wang, 2006]. And, Park et al. propose an adaptive route choice model for intelligent route guidance using a rule-based approach, where the route choice model is combined with a user interface, enabling the efficient collection of user feedback [Park, 2007]. Hawas et al. also construct an inter-vehicular communication (IVC)-based algorithm for real-time route guidance in urban traffic networks, where the algorithm are evaluated by network congestion levels, link speeds and link lengths [Hawas, 2008]. Besides, Zhang et al. investigate the factors such as the position of vehicles, the information on road conditions, the free parking spaces, etc., and build a significant-subordinate relationship between these factors to determine their relative weights for route guidance [Zhang, 2008]. And, Kumagai et al. elaborate a traffic-pattern based pre-routing method that provides an approximation of the precise route with real-time traffic data [Kumagai, 2012]. Li et al. also implement a systematic approach to adaptively realize the vehicle route guidance with the real-time traffic information [Li, 2012a].

2.3.2 ANTICIPATORY GUIDANCE APPROACH

For the contributions of anticipatory guidance approaches, 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 [Ando, 2006]. Weyns et al. also establish a multi-agent system where vehicle agents generate exploration ants to traverse the road-network and gather route information, and then choose a particular route satisfying the driver preference to either shortest travel distance or wait time or both. On this basis, the infrastructure predicts the queuing time. The simulated results show reduction in travel distance and wait time [Weyns, 2007]. And, Claes et al. elaborate a decentralized approach for anticipatory vehicle routing using multi-agent systems [Claes, 2011]. Besides, Ito et al. build an anticipatory stigmergy model for decentralized traffic congestion management, and the simulation results demonstrate its effectiveness and robustness [Ito, 2012]. Naja et al. set up a preventive congestion control mechanism applied at highway entrances and devised for ITS systems, which integrates different types of vehicles and copes with vehicular traffic fluctuations due to an innovative fuzzy logic ticket rate predictor. The proposed mechanism efficiently detects road traffic congestion and provides valuable information for the vehicular admission control [Naja, 2014].

2.4 ROUTING SELECTION ALGORITHM IN ROUTE GUIDANCE OF ITS

Different approaches have been proposed to handle routing selection problem over multiply paths, which can be divided into system optimum approach and user equilibrium approach. The system optimum approaches always route the vehicle along an optimum path measured by overall time or distance of the road-network; and the user equilibrium approaches aim to satisfy individual-level optimization of users such as minimal travel time or shortest path and route the vehicle.

2.4.1 SYSTEM OPTIMIZATION APPROACHES

Among the contributions of system optimization approaches, Dai et al. present a hierarchical intelligent control and coordination conceptual architecture to make full use of road-network resources and realize efficient transportation. In their work, a system optimum equilibrium flow model is described with minimizing the total delay of the road networks, getting optimal traffic volume on a link, then calculating the signal timing parameters and optimal route so as to make full use of road network resources and realize efficient transportation [Dai, 2005]. Hawas et al. also implement an inter-vehicular communication (IVC)-based algorithm which is built on information sharing among vehicles with same destination and within a specific communication range, through which the algorithm provides real-time route guidance in urban traffic networks [Hawas, 2008]. And, Chen suggests a dynamic route guidance method based on Particle Swarm Optimization algorithm [Chen, 2009]. Wu et al. present a threshold-based restricted searching area algorithm which uses the spatial distribution feature of the real road network to restrict the searching area by setting up a reasonable threshold value that reduces its searching size, so as to enhance its efficiency [Wu, 2010]. Besides, Zolfpour et al. set up a self-adaptive multi-agent algorithm for managing the shortest path routes, which improve the acceptability of the costs between the origination and destination nodes. Compared with Dijkstra algorithm, the experimental results show a reduction of the cost in vehicle routing problem [Zolfpour-Arokhlo, 2011].

2.4.2 USER EQUILIBRIUM APPROACH

In the field of intelligent traffic control, Sheffi proposes the 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[Sheffi, 1985]. Further, Sheffi elaborates 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. In the field of study of user equilibrium approaches in route selection, for example, Wang and his colleagues present real-time feedback route guidance in large-scale express ring-roads, where the results indicate that real-time feedback route guidance can help alleviate and dissolve heavy non-recurrent traffic congestion, and establish dynamic user equilibrium [Wang, 2006]. Another contribution can be found in Du's work. Du et al. build a coordinated online in-vehicle routing mechanism for smart vehicles with real-time information exchange and portable computation capabilities. The proposed coordinated routing mechanism incorporates a discrete choice model to account for drivers' behavior, and is implemented by a simultaneously updating distributed algorithm. This study shows the existence of an equilibrium coordinated routing decision for the mixed-strategy routing game and the convergence of the distributed algorithm to the equilibrium routing decision, assuming individual smart vehicles are selfish players seeking to minimize their own travel time[Du, 2014]. Besides, Adacher et al. propose a multiple path routing algorithm, where each vehicle computes its own route on the basis of its specific settings reflecting user's preferences and traffic information provided by the reference station. This algorithm explores a solution that represents a good tradeoff between single user satisfaction and system optimum [Adacher, 2014].

2.5 SUMMARY

In this chapter, we have reviewed the related work from three aspects: the agent-based approaches in congestion management, the route guidance in

intelligent transportation system and the routing selection algorithms in route recommendation.

In the field of study of methodology for congestion management, agent-based framework with bottom-up perspective have been widely used because of its natural and suitable for capturing the dynamic and geographically distributed features of transportation systems. However, it is not so easy to design the agent-based models to avoid too complex or too simple in practice. Literature review also shows that recent route guidance systems pay more attentions to anticipatory approaches than reactive approaches, while how to predict the future traffic flow is a problem. And among the contributions of routing selection algorithms, user equilibrium approaches especially in dynamic traffic conditions have attracted more concerns than the systemic optimum approaches over multiply paths.

On the basis of literature review, this thesis intends to design agent-based models with multi-objective based routing selection algorithms to achieve a good trade-off between single user satisfaction and global utilization of the road-network in a dynamic traffic environment.

3. AN AGENT-BASED MODEL FOR ROAD-NETWORK CONGESTION MANAGEMENT

3.1 INTRODUCTION

In this chapter, we first give the design of the agent-based model with multi-objective algorithm for road-network congestion management. Next, we elaborate the model through ODD protocol. And then, we describe the definition of evaluation criteria. Finally, we execute simulation experiments to validate the applicability and effectiveness of our proposed model on road-network congestion management.

3.2 PROPOSAL OF AN AGENT-BASED MODEL FOR ROAD-NETWORK CONGESTION MANAGEMENT

In this study, we propose an agent-based model with a hybrid vehicle routing strategy to improve the road-network congestion problem in the applications of ITS. In our model, each vehicle agent considers shortest path and congestion avoidance as two objectives in his/her routing selection. We focus on finding common features of those seriously congested links and reducing the congested degree of such links by a hybrid strategy. We also focus on the methodology: the adaptive agent model based on a hybrid strategy to analyze the congestion control problem, where the hybrid strategy may provide a dynamic diversion idea from the vehicles perspective with the help of GPS devices or Route Guidance System, rather than vehicle shunt at single intersections in most applications.

3.3 MODEL DESCRIPTION THROUGH ODD PROTOCOL

Below, we present the agent model following the ODD (Overview, Design

concepts, Details) protocol proposed by Grimm et al. [Grimm, 2010].

3.3.1 PURPOSE

The agent-based model is designed to investigate the effectiveness of vehicle route guidance strategy on congestion control, by managing shortest path and congestion avoidance simultaneously. Under such a consideration, the road-network congestion problem is studied by relating different strategies and congestion distribution result of the overall road network to address the real-world transportation problem. The purpose of this study is to find common features of those seriously congested links through agent-based simulations, and validate the effectiveness of our proposed routing selection strategy with multi-objective algorithm on improving the traffic condition on those congested links.

3.3.2 ENTITIES, STATE VARIABLES AND SCALES

The model includes three types of entities: vehicle entity, link entity and node entity, as described in Table 3.1.

Table 3.1 Entities and descriptions

Entities	Descriptions
Vehicle	The vehicle individuals of the road-network
Link	Immobile links of the road-network where vehicle passes
Node	The physical nodes with fixed coordinates of the road-network

Next, the state variables are explained in order as they appear in Table 3.2, which are Origination Node (*ON*), Destination Node (*DN*), Vehicle Path (*VP*), Link Length (*LL*), Link Capacity (*LC*), Link Traffic (*LT*), Link State (*LS*), Link Congestion Degree (*LCD*) and Link Travel Time (*LTT*).

Table 3.2 State variables and descriptions

Entity	Variables	Descriptions
Vehicle	Origination Node (*ON*)	The predefined departure node when a vehicle is added into the road-network
	Destination Node(*DN*)	The predefined target node where a vehicle supposed to eventually reach
	Vehicle Path(*VP*)	A list of nodes where vehicles passed by, which records the movement trajectory of the vehicles
Link	Link Length(*LL*)	The physical length of the link, approximately calculated by the linear distance between two end nodes
	Link Capacity(*LC*)	The largest number of vehicles on this link
	Link Traffic (*LT*)	The current number of vehicles on this link
	Link State(*LS*)	The current status of the link, either congested or un-congested
	Link Congestion Degree(*LCD*)	A quantitative indicator used to describe the dynamic congested degree of the road-network links with congested link states
	Link Travel Time(*LTT*)	The passage time of a vehicle passing through a link

Of the above nine variables, origination node and destination node are represented by the node ID, and vehicle path is represented by a list of node IDs. Link length is approximately measured by the linear distance between two end nodes, given in equation (3-1):

$$LL(r) = \frac{1}{2}\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}, \tag{3-1}$$

where x_i and y_i are the coordinates of the node i in a two-dimensional plane. And, link capacity and link traffic respectively describe the largest vehicle passage ability and current vehicle numbers on the link. Next, we define equations to calculate the rest variables as *LS*, *LCD* and *LTT*. Assume that a link r has its largest traffic capacity as $C(r)$ and the current number of vehicles at time step t on this link is $n(r,t)$, we then calculate *LS* and *LCD* of

link r in equation (3-2) and (3-3) respectively:

$$LS(r,t)=\begin{cases} Congested, & where \quad n(r,t)>=C(r), \\ Uncongested, & where \quad n(r,t)<C(r). \end{cases} \tag{3-2}$$

$$LCD(r,t)=\begin{cases} \dfrac{n(r,t)}{C(r)}, & where \ LS(r,t)=Congested \\ 0, & where \ LS(r,t)=Uncongested. \end{cases} \tag{3-3}$$

As the dynamics of real-time link state would affect the agents travel distance at each simulation step, we therefore discuss the calculation of *LTT* 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 state changes into congested, the expected travel time of the agent on the rest of this link is represented by T_{con}. The calculation of T_{con} is presented by equation (3-4), 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 [BPR, 1964].

$$LTT(r,t)=\begin{cases} T_{uncon}(r,t)=\dfrac{LL(r)}{V}, & where \quad LS(r,t)=Uncongested, \\ T_{con}(r,t)=T_{uncon}(1+\alpha(LCD(r,t))^{\beta}), & where \quad LS(r,t)=Congested. \end{cases} \tag{3-4}$$

where *LL(r)* is the physical length of link r calculated by equation (3-1), V is the velocity of the vehicle agent when the link is not congested, *LCD(r,t)* is the congested degree of link r, *LS(r,t)* is the link state, 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 [BPR, 1964].

3.3.3 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 3.1 describes the process and the scheduling of the agent-based model. The details of two sub-models that agents select a target link and travel a distance on the present link will be explained in section 3.3.6.

```
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 state of the involved links
          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
```

Fig 3.1 Pseudo-code of the agent simulation model

3.3.4 DESIGN CONCEPTS

Basic principles: The general concepts underlying the model design come from the urban road-network traffic optimization theory proposed by Sheffi [Sheffi, 1985]. 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 passing through the nodes. With a predefined road-network structure and traffic data, Sheffi has pointed out that link function, represented by the travel time function of the traffic flow on

network links, is one of the most important factors that affect the traffic flow in the road-network congestion control problem. It reflects the degree of road-network traffic congestion. Meanwhile, he has proposed 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 has proposed 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 to define the link selection function, and set up our agent model with two-objective algorithm to improve the road-network congestion problem.

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 certain links show serious congestion.

Adaptation: In the model, vehicle agents determine their target links based on two principles: shortest path and congestion avoidance. The link selection strategy is adaptively updated based on the integrated effect of shortest path and congestion avoidance.

Objectives: The objective of the model is defined as a routing selection function, which guides the agent's link selection process as a combined result of shortest path and congestion avoidance.

Observation: The observations from the agent-based model are the variation of Average Link Congestion Degree (*ALCD*), Average Link Congestion Time (*ALCT*), and Average Arrival Time (*AAT*) of all vehicle agents, which reflect the effectiveness of our proposed agent model and methods on improving road-network congestion problems.

3.3.5 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.

3.3.6 SUB-MODELS

In detail, two sub-models are defined for the operation of link selection and agent travel process. First, we describe the pseudo-code of link selection model in Fig3.2.

```
Start
    if (the node connects to an unique link)
        Choose this link as the target link
    else   if (the link state 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
```

Fig 3.2 Pseudo-code of the link selection model

As stated in Fig 3.2, an adaptive agent defined in our model changes its link selection strategies according to the congested degree of all connected links. When multiple links can be selected, the agent chooses one based on a utility function. The utility function of a link r at simulation step t is given in equation (3-5).

$$U(r,t,\lambda) = \lambda * g(r,t) + (1-\lambda) * LCD(r,t), \qquad \lambda \in (0,1] \qquad (3\text{-}5)$$

where the first term $g(r, t)$ represents the strength which attracts agent moving towards its destination node, calculated by the Floyd shortest path algorithm [Floyd, 1962]; the second term $LCD(r,t)$ reflects the congested

degree of link r at simulation step t, calculated by equation (3-3); and the parameter λ is used as a weight to simultaneously optimize the two objectives as shortest path and congestion avoidance. Next, we present the pseudo-code of the agent travel process in Fig 3.3.

```
Start
    if (the current link state == 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
```

Fig 3.3 Pseudo-code of the agent travel model

According to the pseudo-code in Fig3.3, the distance that an agent travels on a link depends on the real-time traffic condition of the link. When the link state changes to be congested, the expected travel time t_{exp} is calculated as in equation (3-4). Assume that the velocity of the vehicle agent on the current link with uncongested state is V, and S is the rest distance of this vehicle on the present link, we then provide the equation of agent travel distance (ATD) below:

$$ATD(r,t) = \begin{cases} V * \Delta t, & where \quad LS(r,t) = Uncongested, \\ S / T_{uncon}(1 + \alpha(LCD(r,t))^{\beta})) * \Delta t, & where \quad LS(r,t) = Congested. \end{cases} \tag{3-6}$$

3.4 EVALUATION CRITERIA

In this study, we consider the evaluation criteria for road-network congestion and model efficiency from three-levels:

(1) first, the link-level congestion are measured by the Average Link Congestion Degree ($ALCD$), the Average Link Congestion Time ($ALCT$) and the Average Link Congestion Index ($ALCI$), where the first index reflects the average congested degree of a link r throughout the simulation process, the

second index is a quantitative indicator which describes the average congested time of a link r when the simulation is terminated, and the third index is a regulated indicator which describes the congestion by combing both spatial and temporal traffic condition for evaluation. Assume that the simulation is executed st steps, the calculations of these indexes are given by equation (3-7), (3-8), and (3-9) respectively:

$$ALCD(r) = \frac{\sum_{t=1}^{t=st} LCD(r,t)}{st}. \tag{3-7}$$

$$ALCT(r) = \frac{\sum_{t=1}^{t=st} T_{con}(r,t)}{st}. \tag{3-8}$$

$$ALCI(r) = \frac{\sum_{t=1}^{t=st} LCD(r,t)}{st} * \frac{\sum_{t=1}^{t=st} T_{con}(r,t)}{st} = ALCD(r) * ALCT(r). \tag{3-9}$$

(2) Second, the node-level congestion is measured by Average Node Congestion Degree (*ANCD*), which reflects an integrated congestion degree of all the neighbor links. Assume that a node i has j links connected to it, each link r has its largest traffic capacity as $C(r)$ and the current number of vehicles on link r at time step t is $n(r,t)$, we then calculate *NCD* of node i at time step t in equation (3-10):

$$NCD(i,t) = \begin{cases} \sum_j \frac{n(j,t)}{C(j)}, & where \quad LS(j,t) = Congested \\ 0 \quad , & where\ all \quad LS(j,t) = Uncongeste\ d. \end{cases}, \tag{3-10}$$

Accordingly, *ANCD* is an average value of *NCD*. Assume that the agent simulation is executed st steps, the *ANCD* is computed in equation (3-11):

$$ANCD(i) = \frac{\sum_{t=1}^{t=st} NCD(r,t)}{st}. \tag{3-11}$$

(3) Finally, the model effect is measured by the improvement rate on those seriously congested locations of the road-network, and the Average Arrival Time (*AAT*) which represents the average arrival time of all the vehicle agents, given by equation (3-12).

$$AAT = \frac{\sum_{i=1}^{A} t_{out}^{a_i} - t_{in}^{a_i}}{A}, \tag{3-12}$$

where t_{in} and t_{out} represent the simulation time steps when an agent a_i enters and leaves the road-network respectively, A is the amount of agents. We summarize the evaluation criteria in Table 3.3.

Table 3.3 Evaluation criteria and descriptions

Criteria	Description	Identification
Average Link Congestion Degree	The average congested degree of a link	*ALCD*
Average Link Congestion Time	The average congested time of a link	*ALCT*
Average Link Congestion Index	The average congested condition of a link	*ALCI*
Average Node Congestion Degree	The average congested degree of a node	*ANCD*
Average Arrival Time	The average time that agents traveled in the network	*AAT*

3.5 EXPERIMENT ON THE BASIC ABM

3.5.1 EXPERIMENT OVERVIEW

In this section, we first conduct two groups of experiments to examine the applicability and effectiveness of our proposed agent model in improving the road-network congestion problem on a generated road-network. On this basis, we further conduct the third group of experiments to validate the model on a real road-map. The purposes and evaluation criteria of each group of simulation experiments are summarized in Table 3.4.

Table 3.4 Summary of the experimental purposes and evaluation criteria

Experiment No.	Purpose	Evaluation Criteria
Experiment 1	Sensitivity test of the parameter λ on congestion improvement	*ALCD*, *ALCT*, *ALCI*, *AAT*
Experiment 2	Validation of the model on a generated road-network	*ALCD*, *ALCT*, *ALCI* *ALCD, ALCT* and *ALCI* of each link and the congested links
	The impact of link density and agent number on congestion improvement	*ANCD*
Experiment 3	Validation of the model on a real road map	*ALCD*, *ALCT*, *ALCI* *ALCD, ALCT* and *ALCI* of the congested links

To conduct the experiments, we define two types of agents: the first type is the Floyd agent that uses the Floyd shortest path strategy in routing selection, and the second type is the adaptive agent that uses hybrid strategy. Hybrid strategy refers to execute the Floyd shortest path strategy and the two-objective optimization strategy introduced by equation (3-5) in turn, depending on the dynamic congestion conditions of the road-network. Thus, the adaptive agent using a hybrid strategy would adapt its routing selection strategies to a changing congestion environment of nearby links. On this basis, we execute simulation experiments with different composition of these two types of agents, and then compare the simulation results by using the evaluation criteria in Table 3.4.

There are three agent groups defined in the experiments: the first group includes all agents using shortest path strategy, the second mixed group includes half Floyd agents and half adaptive agents, and the third group includes unique Adaptive agents using hybrid strategy. All agents are randomly generated with their departure and destination nodes. Table 3.5 presents the different composition of agents in the above experiments.

Table 3.5 The different composition of agents in the experiments

Experiment No.	Agent Composition
Experiment 1	1000 Floyd vs. 500 Floyd & 500 Adaptive vs. 1000 Adaptive.
Experiment 2	1000 Floyd vs. 500 Floyd & 500 Adaptive vs. 1000 Adaptive. 500 Floyd & 500 Adaptive, 250 Floyd & 250 Adaptive
Experiment 3	3000 Floyd vs. 1500 Floyd & 1500 Adaptive vs. 3000 Adaptive.

Finally, we provide the topologies of both generated road-network and real road map employed in the designed experiments. As shown in Fig 3.4, the generated road-network consists of 39 nodes with their *ID*s ranging from 0 to 38, and 146 links represented by pair of nodes. The coordinates of the nodes are defined in table 3.6, consistent with [Schweitzer, 1997].

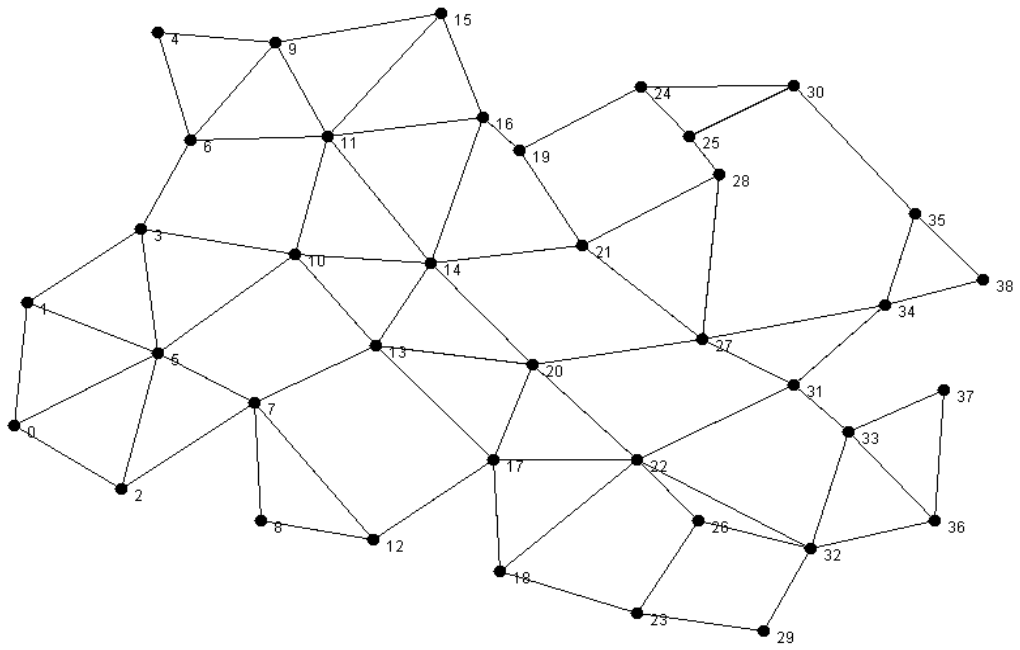


Fig3.4 The topology of a generated road-network

Table 3.6 Coordinates of the nodes in the (x, y) plane

Node	x	y	Node	x	y
0	121	388	20	518	340
1	131	291	21	556	246
2	203	438	22	598	415
3	218	233	23	598	536
4	231	78	24	601	121
5	231	331	25	638	160
6	256	163	26	645	463
7	305	370	27	648	320
8	310	463	28	661	190
9	321	86	29	695	550
10	336	253	30	718	120
11	361	160	31	718	356
12	396	478	32	731	485
13	398	325	33	760	393
14	440	260	34	788	293
15	448	63	35	811	221
16	480	145	36	826	463
17	488	415	37	833	360
18	493	503	38	863	273
19	508	171			

Further, 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, shown in Fig 3.5.

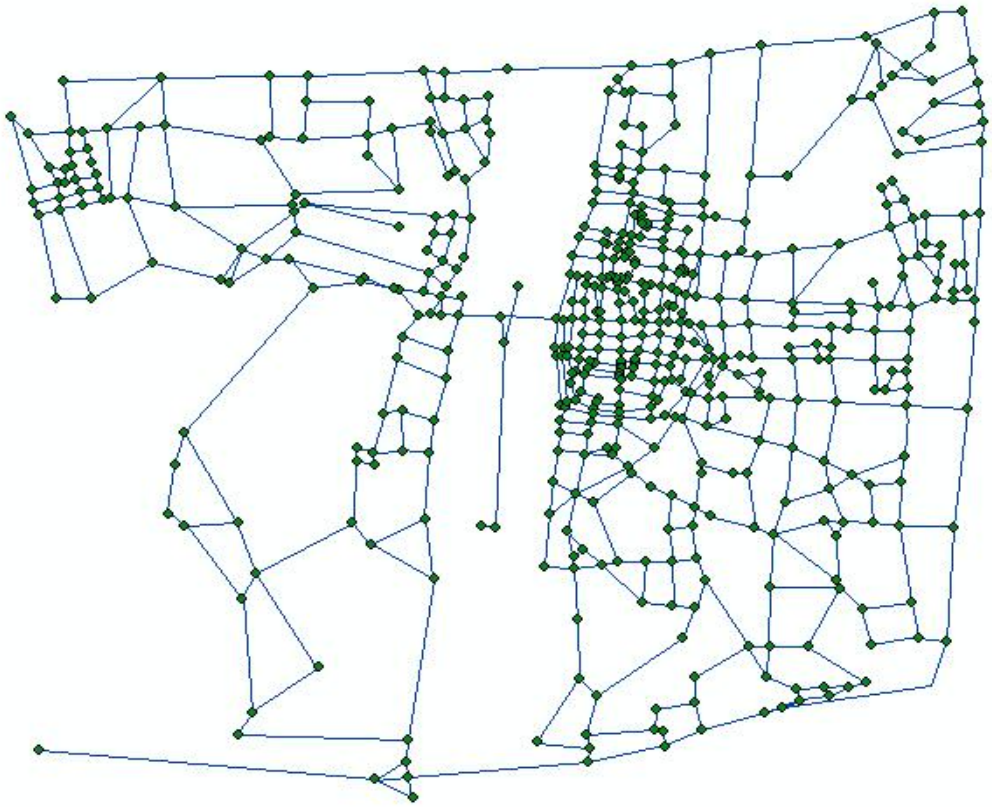


Fig3.5 The topology of a real road map

3.5.2 EXPERIMENT-1: SENSITIVITY TEST OF THE PARAMETER Λ ON CONGESTION IMPROVEMENT

Given a generated road-network topology in Fig 3.4, the first group of simulation experiments examines how the values of parameter λ affect the improvement result of congestion on this generated road-network. Among this group of simulation experiments, the values of parameter λ vary from 0.05 to 1 with an interval of 0.1, and the simulation results are evaluated by the *ALCD*, *ALCT* and *ALCI* of all links and the *AAT* of all agents under different values of λ.

Fig 3.6, Fig 3.7 and Fig 3.8 present the simulated results of the *ALCD*, *ALCT* and *ALCI* under different values of λ. The result in Fig 3.6 shows that *ALCD* increases rapidly when λ is greater than 0.85, which indicates that we should set the λ less than 0.85 to ensure the effect from congestion avoidance

represented by 1-λ in the two-objective function by equation (3-5). The results in Fig 3.6 and Fig 3.7 also show the similar trend of *ALCT* and *ALCI*. Therefore, it is important to find an appropriate value of parameter λ in order to ensure the model effect.

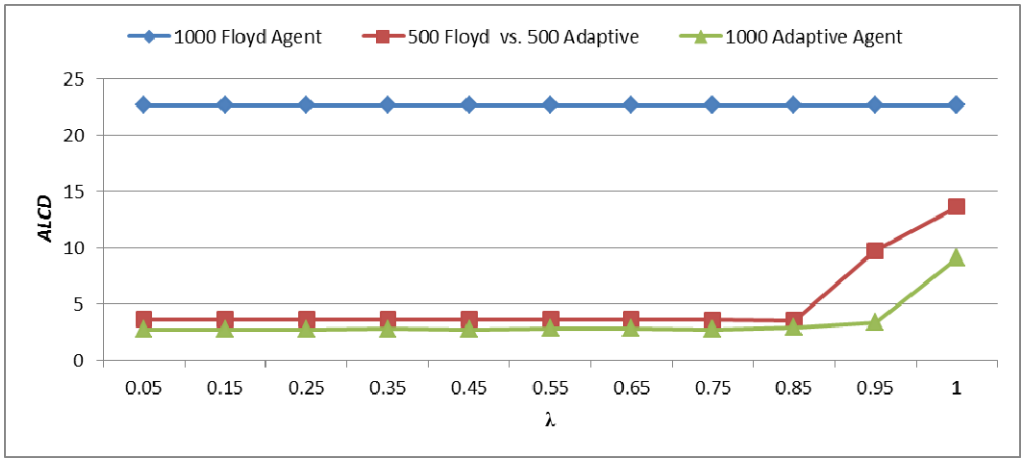


Fig 3.6 Variation of the *ALCD* under different values of λ

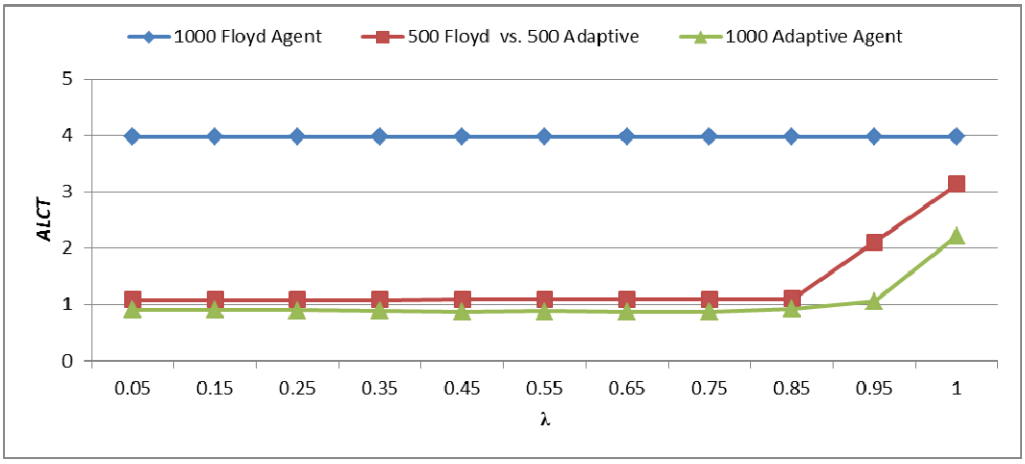


Fig 3.7 Variation of the *ALCT* under different values of λ

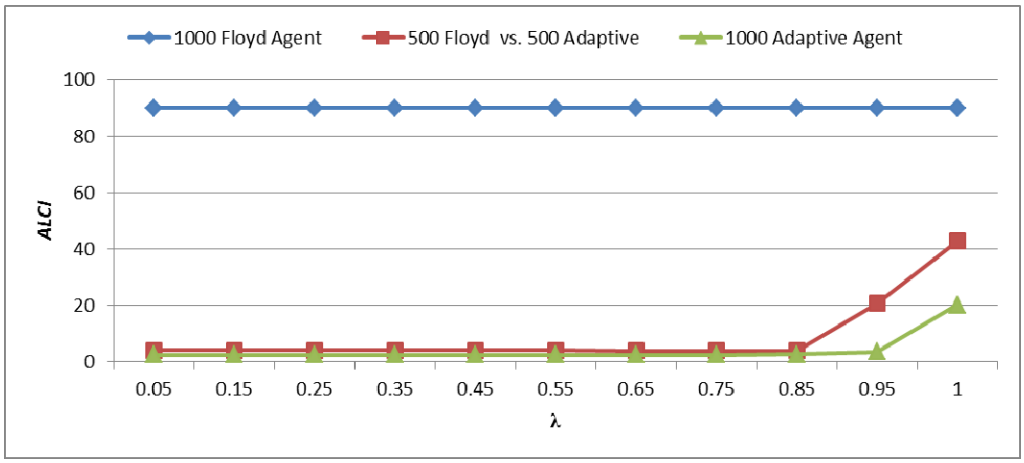


Fig 3.8 Variation of the *ALCI* under different values of λ

Further, Fig 3.9 compares the variation of *AAT* with three agent groups under different values of λ. As shown in Fig 3.9, the Floyd agent group has their *AAT* values smaller than the adaptive agent group. In the mixed agent group, although the value of λ only affects the adaptive agents' link selection process, there may exist indirect effect on the travel time of Floyd agents, which reflects a complex feedback between link congestion distribution and agent's link selection decisions. Such results also indicate the importance of finding an appropriate value of λ which could make a better improvement of the network congestion and keep the *AAT* of both agents at a lower level. We recognize that it is a better choice to set up λ to 0.85.

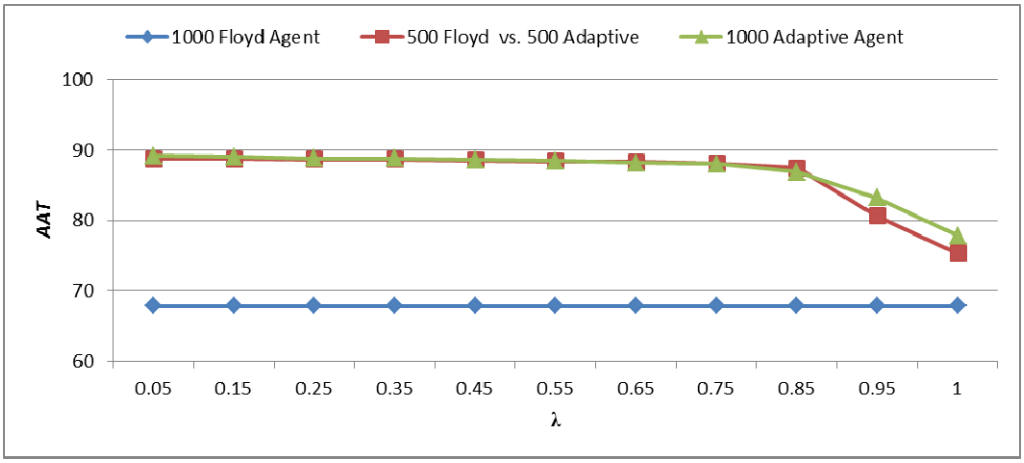


Fig 3.9 Variation of the *AAT* under different values of λ

3.5.3 EXPERIMENT-2: VALIDATION OF THE MODEL ON A GENERATED ROAD-NETWORK

The second group of simulation experiments examines how our proposed adaptive agent model with a hybrid routing selectin strategy works to improve the road-network congestion on a generated road-network. We set the same composition of three agent groups as in experiment 1. The value of parameter λ of the two-objective function for the link selection process is set to 0.85. And, we also keep the road-network topology as the same one in experiment 1. We choose *ALCD*, *ALCT* and *ALCI* as the evaluation criteria to measure the simulated network congestion results. Besides, we conduct further experiments to observe the impact of link density and agent number on network congestion distribution.

3.5.3.1 COMPARISON AND ANALYSIS ON SIMULATED RESULTS

Fig 3.10, Fig 3.11 and Fig 3.12 present the results of *ALCD, ALCT* and *ALCI* throughout the simulation period under three different agent groups, which reflect the variation of average congestion of the entire network over time. It is obvious that the adaptive agent group with hybrid strategy has obvious effect in reducing the overall network congestion after the simulation. When the simulation proceeds, agents gradually arrive at their destination nodes and then have been removed from the road-network. That is the reason why the simulated results tend to downward trends.

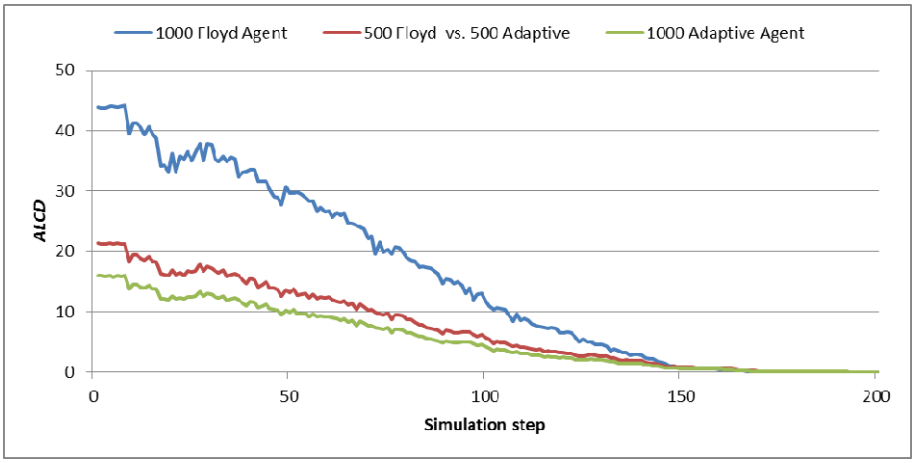


Fig 3.10 Variation of the *ALCD* under three different agent groups

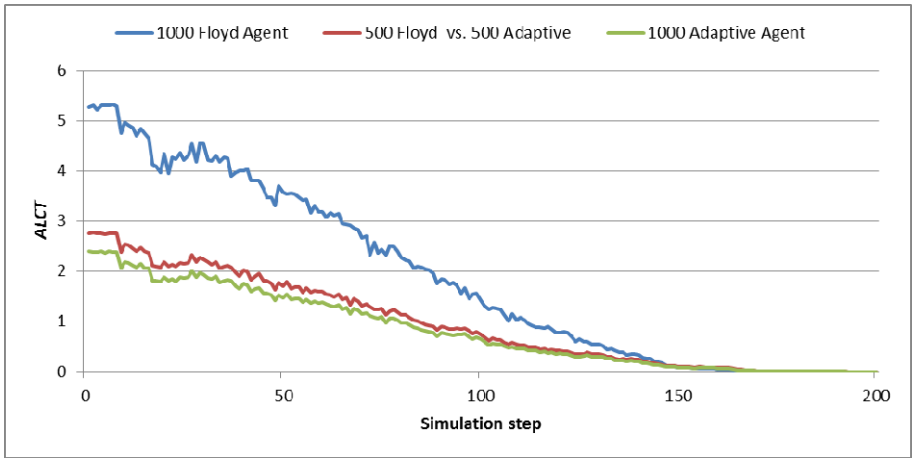


Fig 3.11 Variation of the *ALCT* under three different agent groups

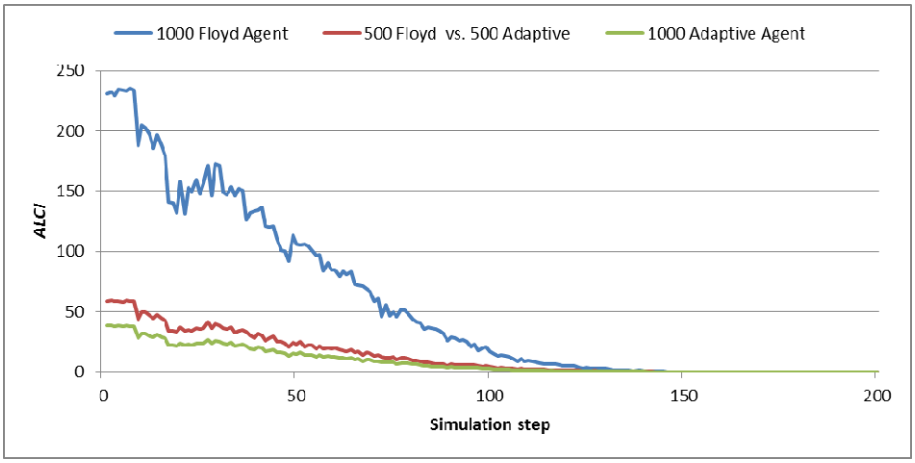


Fig 3.12 Variation of the *ALCI* under three different agent groups

We further calculate the *ALCD*, *ALCT* and *ALCI* of each congested link

over the entire simulation time, shown in Fig 3.13, Fig 3.14 and Fig 3.15.

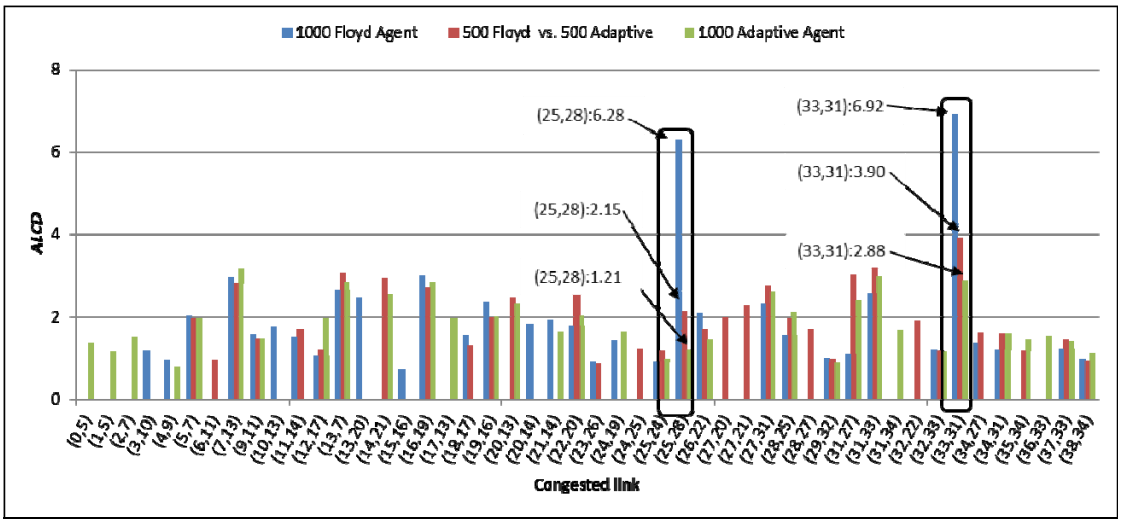


Fig 3.13 *ALCD* of congested link under different agent groups

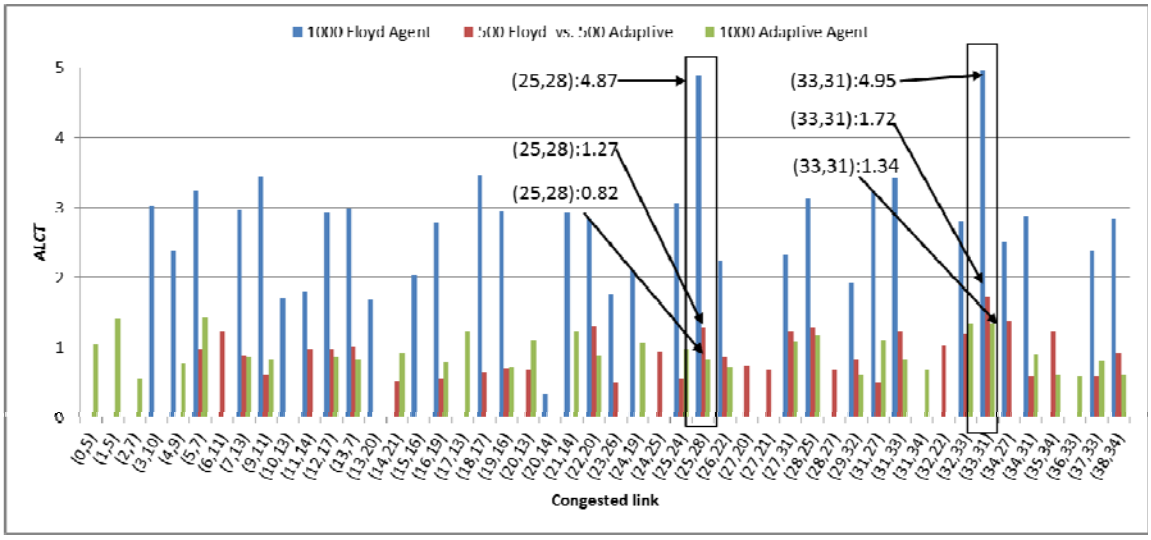


Fig 3.14 *ALCT* of congested link under different agent groups

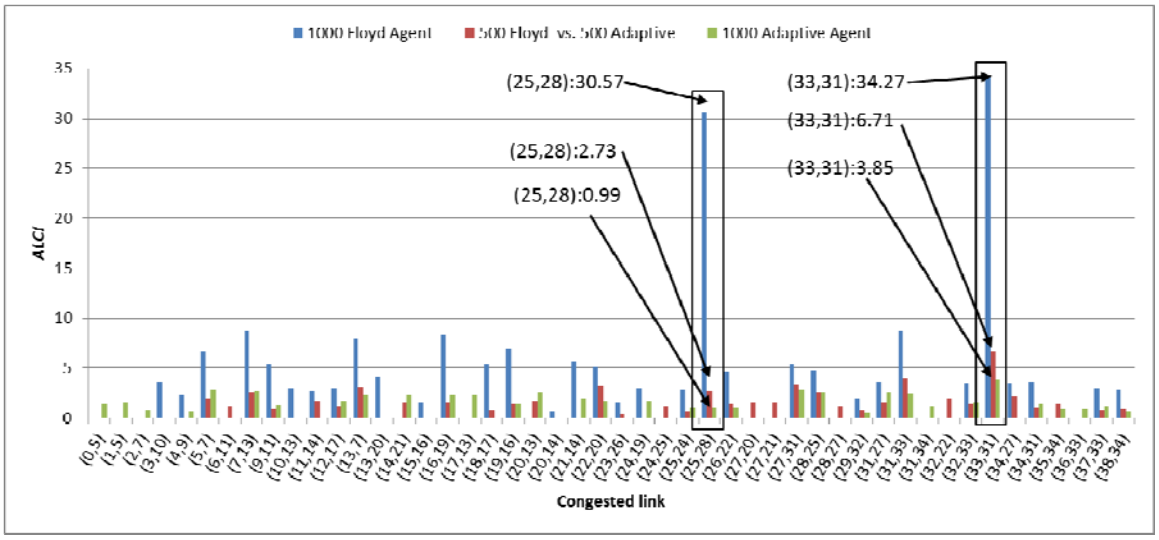


Fig 3.15 *ALCI* of congested link under different agent groups

As shown in Fig 3.13, the values of *ALCD* of most links were not obviously optimized throughout the simulation process, except some seriously congested link (25, 28) and (33, 31). The *ALCD* of these links decreased from 6.28 to 2.15, 1.21 and from 6.92 to 3.90, 2.88 respectively during the whole simulation process, marked by rectangular box in Fig 3.13. And, the simulated results in Fig 3.14 and Fig 3.15 show the reduction of *ALCT* on this two seriously congested links from 4.87 to 1.27, 0.82 and from 4.95 to 1.72, 1.34, and the reduction of *ALCI* from 30.57 to 2.73, 0.99 and from 34.27 to 6.71, 3.85 respectively during the whole simulation process, also marked by rectangular box in Fig 3.14 and Fig.3.15. The results indicate that the hybrid strategy might relieve the congestion degree of those severely congested links.

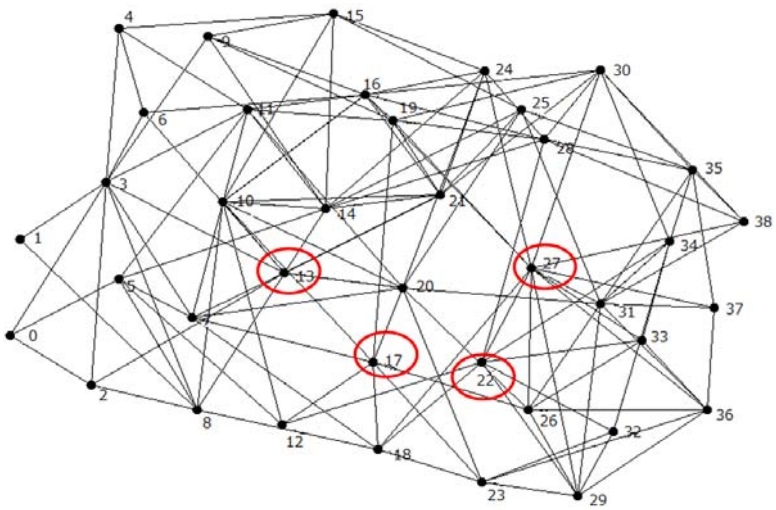
Based on the simulation results of *ALCD*, *ALCT* and *ALCI* in Fig 3.13, Fig 3.14 and Fig 3.15, we find that some congested links turn to be uncongested, like link (3, 10), (10, 13), (13, 20), (15, 16), (20,14) and (32, 22), meanwhile there are new congestion appeared in link (0, 5), (1,5), (2,7), (31, 34) and (36, 33). This phenomenon indicates a congestion transfer in the

road-network.

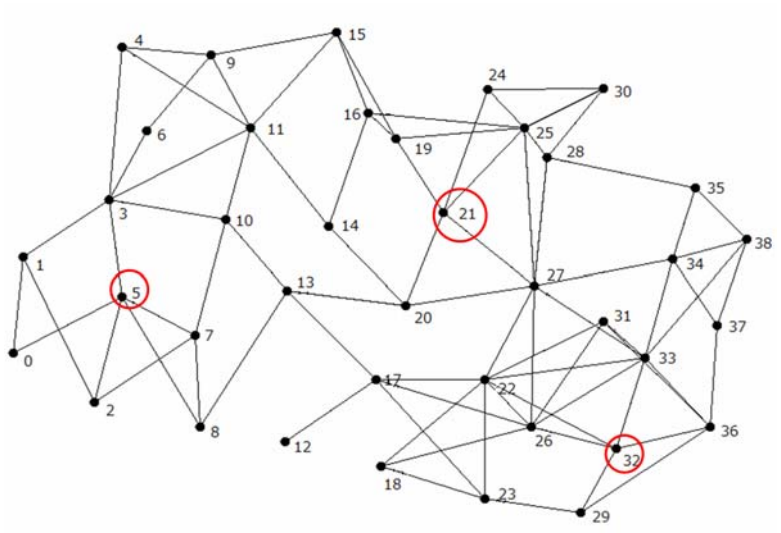
3.5.3.2 THE IMPACT OF LINK DENSITY AND AGENT NUMBER ON CONGESTION IMPROVEMENT

Further, we execute simulation experiments to examine whether and how the road-networks with different link density and different number of agents would affect the formation and evolution of road-network congestions. The experiment sets the mixed agent group with half Floyd agents and half Adaptive agents, with random departure and destination nodes. The simulation results are evaluated by *ANCD*.

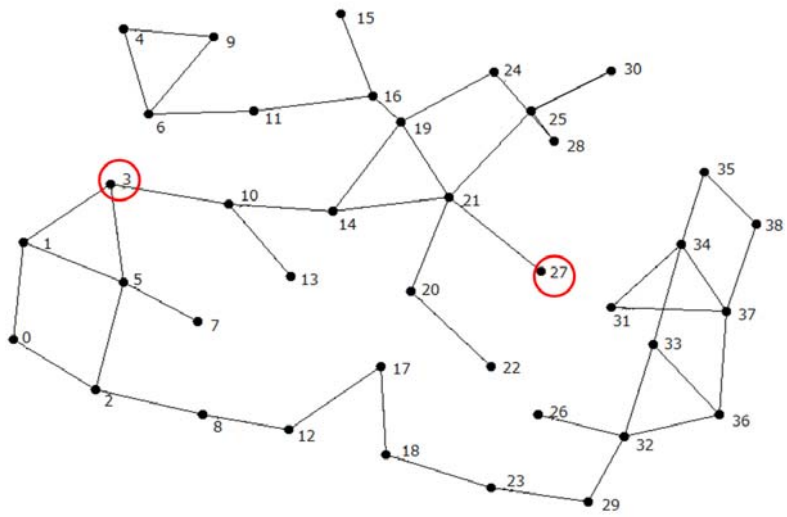
First, the experiment generates three network structures with different link density by setting the amount of links as 172, 84 and 43, respectively. The results of congestion and the distribution under each case are illustrated in Fig 3.16. Especially, those nodes marked with red circles, such as 13, 17, 22 and 27 in Fig 3.16 (a), 5, 21 and 32 in Fig 3.16 (b), and 3 and 27 in Fig 3.16 (c), represent those seriously congested positions of the road-network under each case.



(a) The congested nodes under a generated road-network with 172 links



(b) The congested nodes under a generated road-network with 84 links



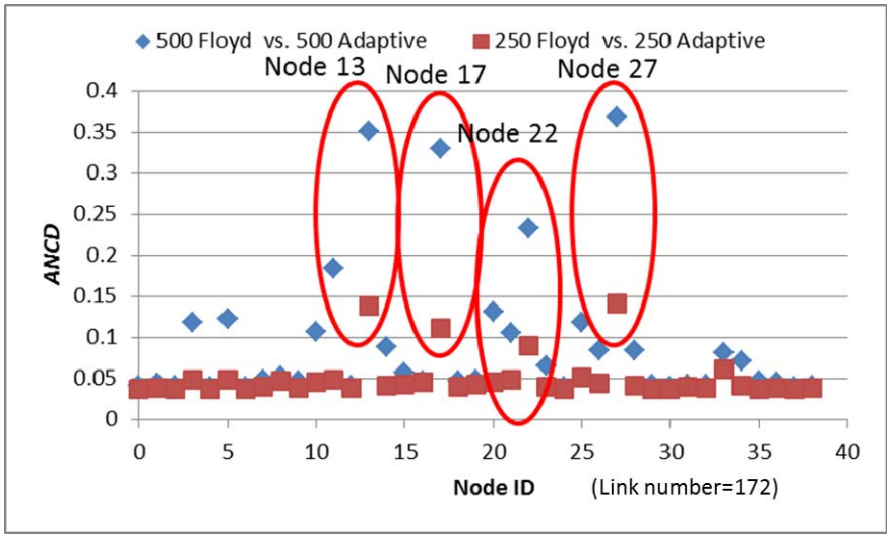
(c) The congested nodes under a generated road-network with 43 links

Fig 3.16 The congestion distribution under different link densities

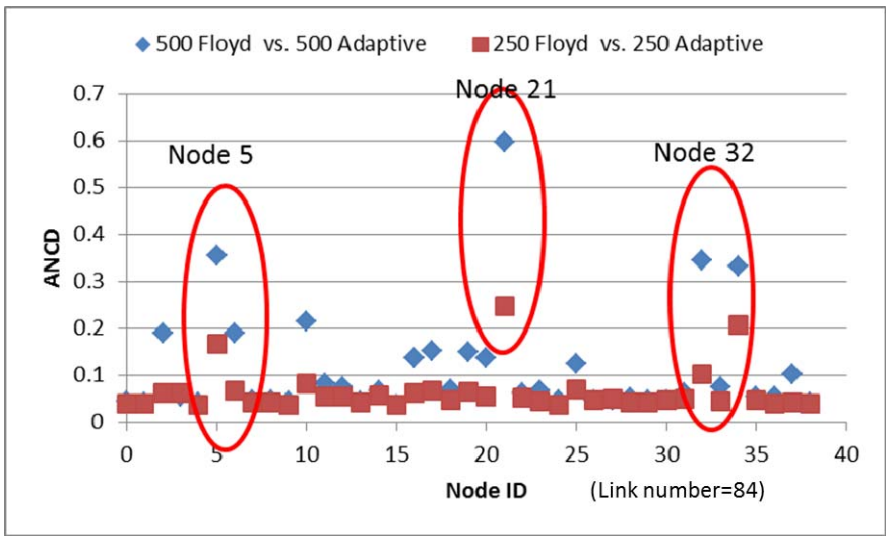
As shown in Fig 3.16, the seriously congested nodes are mostly located at junctions of the road-networks. There also exist certain peripheral isolated nodes which easily cause congestion in the road-network. Besides, the results indicate that link connection would also affect the outcomes of road congestion when all nodes of the road-network have fixed positions.

Second, the experiment sets two agent groups varying the number of agents to observe the model effect. The first group includes 500 Floyd agents

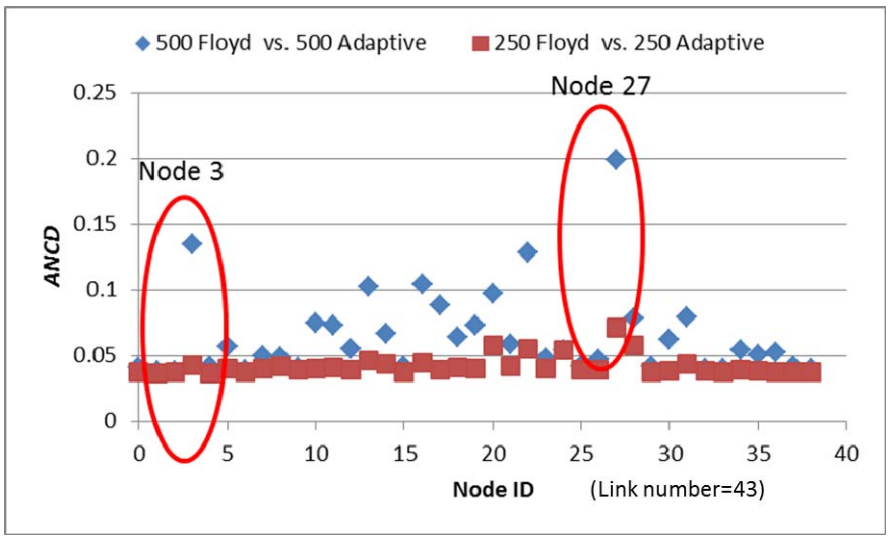
and 500 adaptive agents, and the second group consists of 250 Floyd agents and 250 adaptive agents. Both experiments set the value of parameter λ of the two-objective function for the link selection process to 0.85 and the maximum simulation step is set to 500. The simulation results are measured by *ANCD* under the above mentioned three link density, summarized in Fig 3.17. As shown in Fig 3.17, the red circles corresponding to those seriously congested nodes in Fig 3.16. It is obvious that smaller agent volume leads to light traffic congestion under all simulation scenarios. Furthermore, those seriously congested nodes show great reduction in *ANCD* values after performing our proposed agent model with multi-objective optimization algorithm in routing selection.



(a) Comparison of *ANCD* with different agent number with 172 links



(b) Comparison of *ANCD* with different agent number with 84 links



(c) Comparison of *ANCD* with different agent number with 43 links

Fig 3.17 Comparison of *ANCD* with different agent number and link density

3.5.4 EXPERIMENT-3 VALIDATION OF THE MODEL ON A REAL ROAD MAP

Finally, the third group of simulation experiments runs to verify the applicability and effectiveness of our proposed agent model on a real road 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,

shown in Fig 3.5. To compare the simulation results, we set three different agent groups as described in Table 3.5. All agents are generated with random departure and destination nodes, and added into the road-network at different time stamps. The value of λ is set to 0.85 and the maximum simulation step is set to 500. The measurements include the *ALCD*, *ALCT* and *ALCI*. We first conduct sensitivity test to find an appropriate value of parameter λ. On this basis, we focus on the comparison of improvement of those seriously congested links, and then compare and analyze the distribution of congested links over the road-network.

3.5.4.1 SENSITIVITY TEST OF PARAMETER Λ ON CONGESTION IMPROVEMENT

The variations of *ALCD*, *ALCT* and *ALCI* with three agent groups under different values of λ are given in Fig 3.18, Fig 3.19 and Fig 3.20 respectively. The simulation results show that the adaptive agent group has smaller values of *ALCD*, *ALCT* and *ALCI* than the Floyd agent groups, which indicates a better performs of the hybrid strategy in congestion control on a real road map. The simulated results also suggest that 0.85 is a better value of weight in the two-objective optimization process for routing selection.

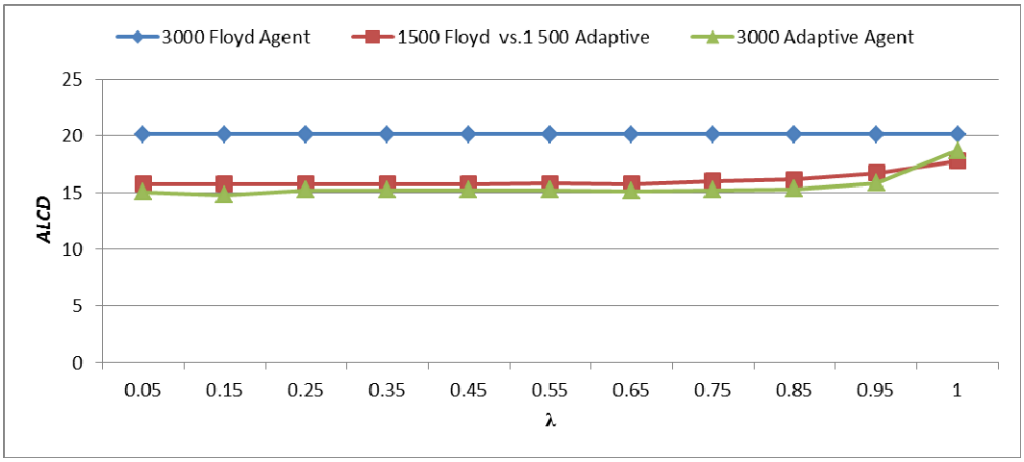


Fig 3.18 Variation of *ALCD* under different λ on a real road map

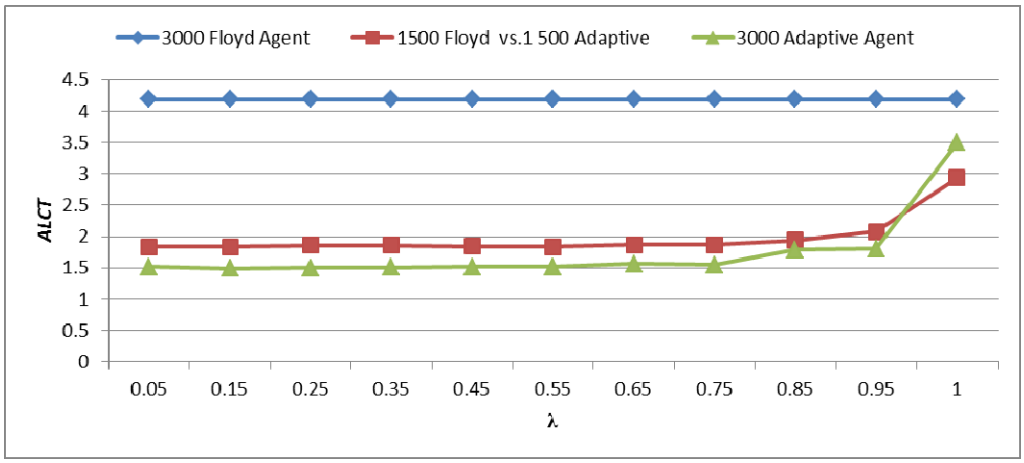


Fig 3.19 Variation of *ALCT* under different λ on a real road map

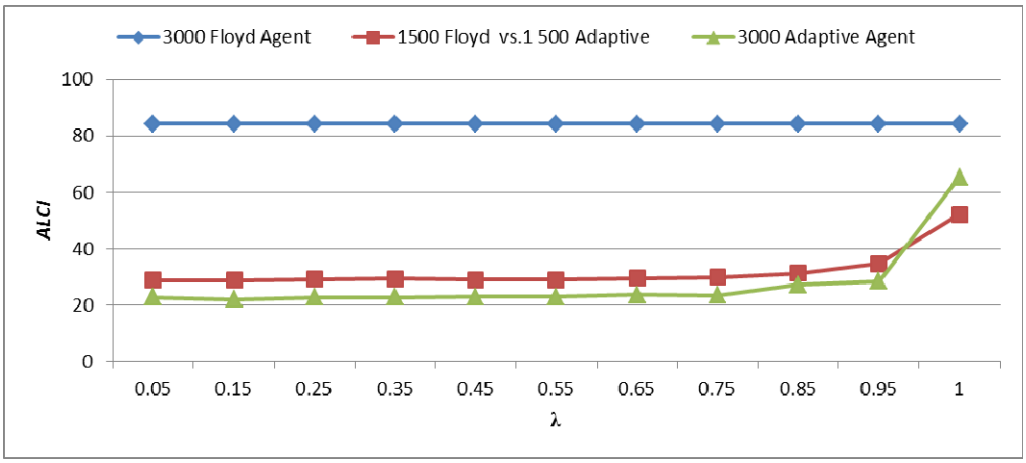


Fig 3.20 Variation of *ALCI* under different λ on a real road map

Further, Fig 3.21, Fig 3.22 and Fig 3.23 provide the results of *ALCD, ALCT* and *ALCI* throughout the simulation period under three different agent groups, which reflect the variation of average congestion of the entire network over time. It is obvious that the adaptive agent group with hybrid strategy has obvious effect in reducing the overall network congestion after the simulation. When the simulation proceeds, agents gradually arrive at their destination nodes and then have been removed from the road-network. That is the reason why the simulated results of *ALCD, ALCT* and *ALCI* show decrease trends.

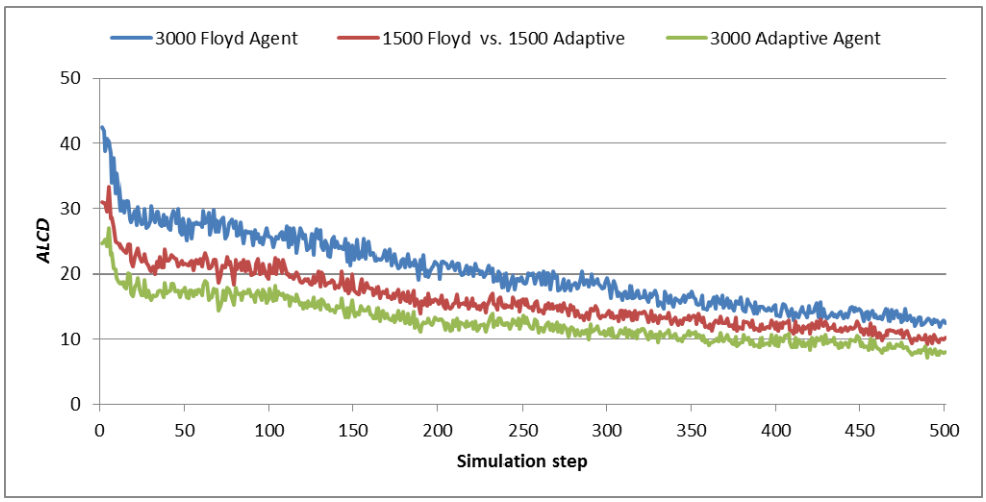


Fig 3.21 Variation of the *ALCD* under three different agent groups

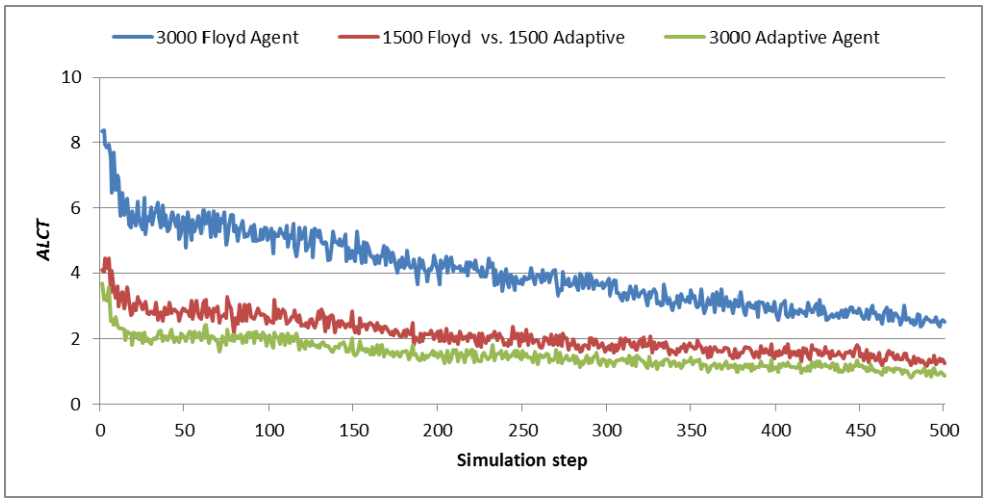


Fig 3.22 Variation of the *ALCT* under three different agent groups

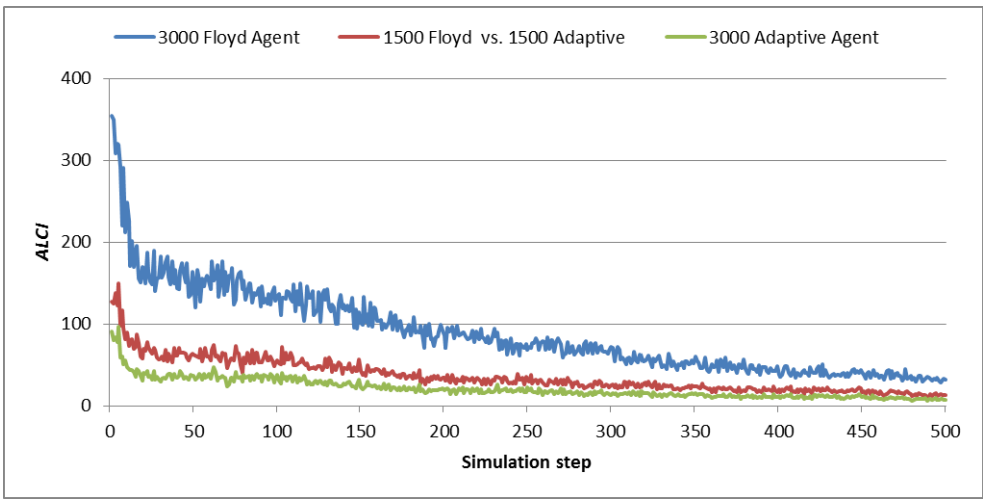


Fig 3.23 Variation of the *ALCI* under three different agent groups

3.5.4.2 IMPROVEMENT AND DISTRIBUTION OF CONGESTED LINKS

The simulated results of the sensitivity test have shown an effectiveness of our proposed agent model on reducing road-network congestion. On this basis, we focus on the model effect on decreasing congestions of those seriously congested links. With this purpose, we sort the links by their *ALCD* values in a descending order and list the top ten links with larger *ALCD* values in Table 3.7.

Table 3.7 The list of the top 10 congested links by *ALCD*

Link	*ALCD* (3000 Floyd)	*ALCD* (1500 Floyd and 1500 Adaptive)	Improvement Rate	*ALCD* (3000 Adaptive)	Improvement Rate
(380, 110)	44.28	38.73	12.53%	36.23	18.18%
(56, 57)	41.25	36.65	11.15%	33.57	18.62%
(103, 104)	38.64	33.84	12.42%	32.42	16.10%
(258, 257)	35.65	30.45	14.59%	30.02	15.79%
(385, 386)	33.34	26.75	19.77%	24.39	26.84%
(135, 136)	31.46	25.94	17.55%	24.63	21.71%
(49, 50)	28.38	24.75	12.79%	23.46	17.34%
(307, 308)	27.66	22.46	18.80%	21.94	20.68%
(186,187)	25.37	21.95	13.48%	20.71	18.37%
(226, 227)	23.47	20.15	14.15%	19.53	16.79%

As described in Table 3.7, the *ALCD* values of the top ten seriously congested links are reduced more than 15% after the adaptive agent model effect. Further, we mark the top five links on the actual road map and find their locations have some common characteristics. As shown in Fig 3.24, the most seriously congested link represented by (380, 110) is the unique road connecting the east and west urban area. Meanwhile, the rest severely congested links are located at the connection positions such as (56, 57), (103, 104), (257, 258) and (385, 386).

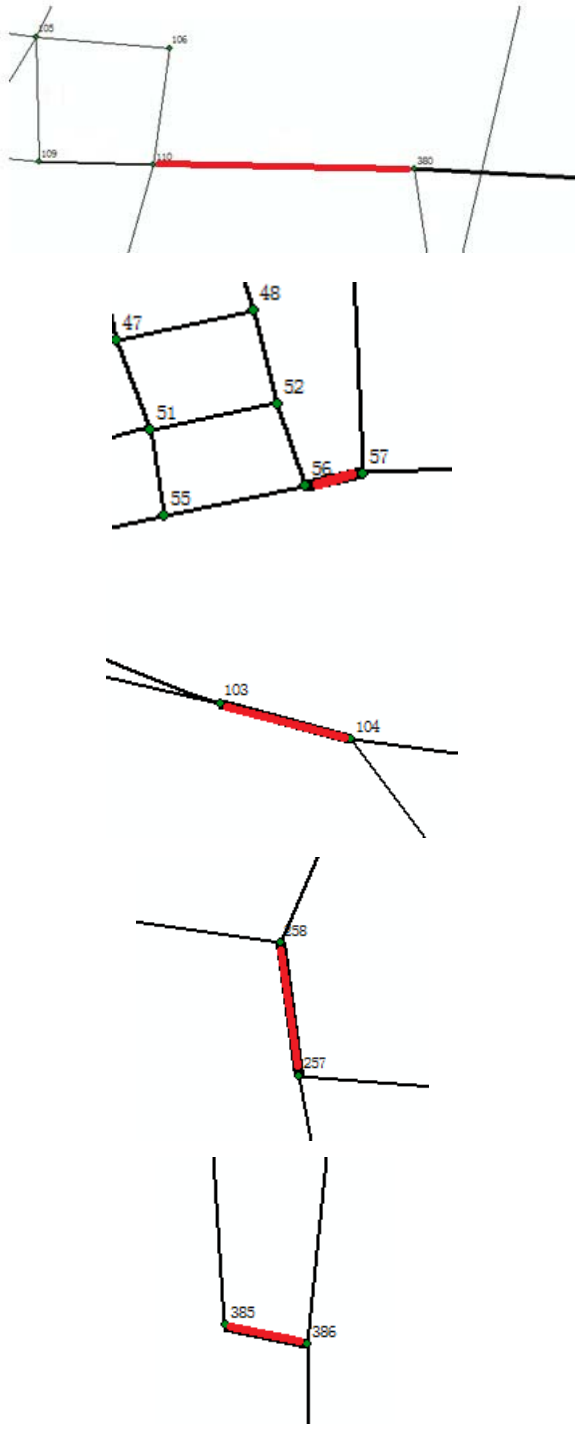
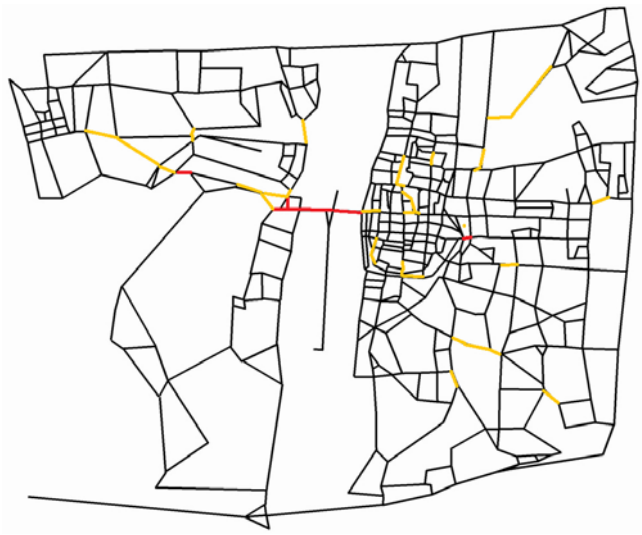


Fig 3.24 The top 5 congested links ranked by *ALCD* index on real road map

We further mark the congestion distribution on the real road map under three different agents groups, shown in Fig3.25. In these figures, the red

links mean that the two-way roads are both congested, while the yellow links represent that only one-way roads appear congested. Meanwhile the darker the color, the more serious congestion becomes. The results in Fig 3.25 denote that the adaptive agent model really reduce the congestion of the real road-network. Furthermore, the red link in the middle of the network has the most severe congestion, which corresponds to the unique bridge connecting the east and west area of the city.



(a) The congestion distribution under 3000 Floyd agents on a real road map

(b) The congestion distribution under 1500 Floyd agents and 1500 Adaptive agents on a real road map

(c) The congestion distribution under 3000 Adaptive agents on a real road map

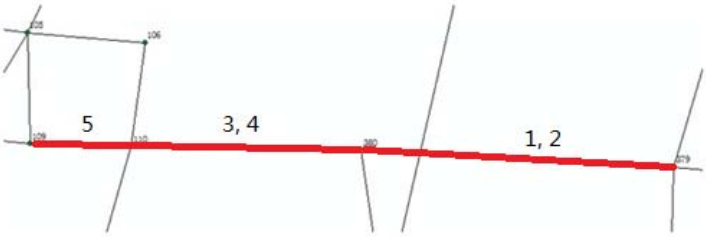
Fig 3.25 Comparison of congestion distribution under different agent groups on a real road map

To verify a robustness of congestion distribution under different congestion evaluation criteria, we again sort the links by their *ALCT* values in a descending order and list the top ten links in Table 3.8.

Table 3.8 The list of the top 10 congested links by *ALCT*

Link	*ALCT* (3000 Floyd)	*ALCT* (1500 Floyd and 1500 Adaptive)	Improvement Rate	*ALCT* (3000 Adaptive)	Improvement Rate
(379, 380)	13.46	12.25	8.99%	11.39	15.38%
(380, 379)	12.64	11.97	5.30%	10.84	14.24%
(380, 110)	11.95	10.46	12.47%	9.98	16.49%
(110, 380)	10.62	9.16	13.75%	8.47	20.24%
(109, 110)	9.13	7.35	19.50%	6.56	28.15%
(56, 57)	8.17	6.35	22.28%	5.96	27.05%
(103, 104)	8.03	6.22	22.54%	5.76	28.27%
(258, 257)	7.63	5.61	26.47%	5.44	28.70%
(385, 386)	6.94	4.38	36.89%	4.36	37.18%
(135, 136)	6.47	4.13	36.17%	4.06	37.25%

The values of *ALCT* of congested links in Table 3.8 also show great improvement of congested links. Fig 3.26 presents the distribution of the top five links on the real road map under three different agent groups. The thickness of the link represents the value of *ALCT*. That is, the thicker the link, the greater the *ALCT*. As shown in Fig 3.26, the two seriously congested links, labeled by 3, 4 are on the unique road connecting the east and west urban area, and the congested link 1, 2 and 5 are also located near the unique road. By comparing the simulation results of Floyd agent and adaptive agent, the results show obvious effect of hybrid strategy on decreasing the congested degree on those seriously congested links.



(a) The top five congested links with 3000 Floyd agents

(b) The top five congested links with 1500 Floyd agents and 1500 adaptive agents

(c) The top five congested links with 3000 adaptive agents

Fig 3.26 The distribution of the top five congested links ranked by *ALCT* under different agent groups

3.6 DISCUSSION

We discuss the simulation results as follows:

(1) The results in the first group of simulation experiments show that the values of parameter λ obviously affect the result of *ALCD*, *ALCT* and *ALCI* when its values are greater than 0.85. The changes in the value of λ reflect a variation of an agent's preference on two objectives of the utility function. On one hand, when λ becomes smaller, the agents with a hybrid strategy intend to avoid the congested link of the road-network, thus leading to a further optimization of network congestion. But the simulation results show that the *AAT* of agents increases. This is because the congestion avoidance characteristic causes some detours. Therefore, agents with hybrid strategy might travel a longer time in the network compared to those Floyd agents with only the shortest route. Such adjustment might also indirectly affect the travel time of Floyd agents in the mixed agent group under a changing traffic environment. On the other hand, when λ becomes bigger, agents with hybrid strategy prefer to travel along the shortest route. When λ continues increasing, the decreasing preference on congestion avoidance makes the congestion degree of network could not be further improved. Especially, when λ is set to 1, that is, the second part of equation (3-5) has no effect and the agents with hybrid strategy are the same as Floyd agent. Based on the analysis of simulation experiment results, we set the value of parameter λ equal to 0.85 in order to assure a balanced effect of our proposed agent model on improving road-network congestion.

(2) In the second group of simulation experiments, the results of *ALCD*, *ALCT* and *ALCI* show obvious reduction under the adaptive model effect. Furthermore, the adaptive agent model with hybrid strategy helps to decrease the congested degree of those congested links, especially seriously congested links like (33, 31). But the simulation results also show that *ALCD* of some links such as (31, 34) and (36, 33) have increased. This is exactly explained the model effect on vehicle shunting and congestion equilibration.

Therefore, the simulation results validate an effectiveness of our proposed agent model on reducing the congested time of those seriously congested links. The agent model with a hybrid routing selection strategy actually implements a dynamic congestion improvement mechanism through the nonlinear feedback between agent routing decisions and road-network congestion dynamics. Further experiments find that the link density and the agent number even the link connection would also affect the road-network congestion. Meanwhile, the seriously congested nodes emerged from simulations with different network structure show common distribution features such as junctions of the road-networks and peripheral isolated nodes. This result needs further experiment and discussion.

(3) The results obtained from the last group of simulation experiments show that the adaptive agent model with a hybrid routing selection strategy has really improved the entire road-network congestion. The agent model also has decreased the *ALCD* and *ALCT* of those seriously congested links. The reason is similar to the second group of experiments. Meanwhile, according to the simulated results of distribution of congested links in the real road map, we have found that the seriously congested links are mostly located at the connection positions or the unique road connecting two regions. Because these links are all traffic arteries, most agents of the simulated traffic system have to go through such links to pass the regions and finally reach their predefined destinations. Although we have not set agents according to the real traffic flow in the city map, the simulation results reflect the same congested road with the real map in actual life. Also, the improvement made by our model on those seriously congested links provides a dynamic balancing diversion idea from the vehicles perspective, which has its significance for guiding the actual operation of the congestion control. Therefore, the simulation results have verified the applicability and

effectiveness of our proposed model on a real road map.

Based on the above analysis, the main findings are summarized as follows: 1) both shortest path and congestion avoidance are important factors which affect the road-network congestion; 2) vehicles which adapt their route selection strategy to the real-time congested degree of surrounding roads could help improve passage capacity of road-networks; and 3) seriously congested roads have some common features, such as the connection positions or the unique road connecting two regions.

3.7 SUMMARY

In this chapter, we have proposed an agent-based model with multi-objective optimization algorithm to study the road-network congestion problem. After the proposal of the agent-based model, we have described the agent model following the ODD (Overview, Design concepts, Details) protocol. More concretely, we first describe the purpose of the study, next define three entities as the vehicle, the link and the node and their related state variables, and then present the process and scheduling of the model. We also elaborate the design concepts of the model, and further we explain two sub-models as link selection model and agent travel model. Finally, we set up the evaluation criteria for evaluating the model effect.

On this basis, we have implemented three groups of simulation experiments to conduct parameter sensitivity test, model validation under different traffic scenarios on a generated road-network topology and a real road map. The simulation results have shown that the model has realized a real-time road congestion control, it reduces the congested degree of those seriously congested links and thus promotes the traffic capacity of the transportation network. Especially, the validation of the model on a real road map of a Medium-sized city in China has turned out that our proposed model

could balance the congestion in this road-network. Therefore, the simulation results has confirmed an applicability and effectiveness of the agent model with a hybrid strategy on improving the road-network congestion problem. Besides, we also find that seriously congested roads have some common features, such as the connection positions or the unique road connecting two regions.

One limitation of the model is that the weights used in the utility function are determined by sensitivity analysis. Furthermore, it is not easy to find a suitable weight value with large-scale road-network and traffic flow. In the next chapter, we will construct a quantitative index series to describe the dynamic congestion distribution of road-network, and at the same time use such indexes as weights of the utility function to shunt vehicles on those seriously congested links.

4 AN ADAPTIVE WEIGHT-BASED AGENT MODEL FOR ROAD-NETWORK CONGESTION MANAGEMENT

4.1 LIMITATION OF THE PROPOSED AGENT-BASED MODEL

In chapter 3, we have proposed an agent-based model with multi-objective routing selection algorithm, which can reduce the number of congested links. However, the proposed agent model has two limitations. One is the road-network congestion distribution and the agents travel time is affected by the weight value of the two-objective function. For the other hand, how to find a suitable weight value with large-scale road-network and traffic flow is a difficult problem.

To solve the above weight problems, we further propose an agent model with adaptive weight-based multi-objective algorithm. We focus on construct a quantitative index series which describe and evaluate the road-network congestion distribution, and also use such indexes as weights in the two-objective function to adapt agent behaviors to the traffic dynamics.

4.2 PROPOSAL OF AN AGENT-BASED MODEL WITH ADAPTIVE WEIGHT-BASED MULTI-OBJECTIVE ALGORITHM

In this chapter, following our previous work, we propose an agent model with adaptive weight-based multi-objective algorithm to study the road-network congestion problem with a hybrid perspective. We emphasis on constructing a series of quantitative indexes to describe and measure the real-time congestion distribution of road-network at each node, and using such indexes as weights in the two-objective function to shunt vehicles on those congested links. An adaptive node weight algorithm is proposed based on the difference between the passage times on each adjacent link in two consecutive

simulation time steps. 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.

4.3 MODEL DESCRIPTION THROUGH ODD PROTOCOL

4.3.1 PURPOSE

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 process. 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 perspective. 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 embedded with the adaptive weight-based routing selection algorithm, rather than vehicle shunt in single intersections in most applications.

4.3.2 ENTITIES, STATE VARIABLES AND SCALES

The model includes three types of entities: vehicle entity, link entity and node entity, as consistent with the definition of the basic agent model in Table 3.1. The state variables are Origination Node (*ON*), Destination Node

(*DN*), Vehicle Path (*VP*), Link Length (*LL*), Link Capacity (*LC*), Link Traffic (*LT*), Link State (*LS*), Link Congestion Degree (*LCD*) and Link Travel Time (*LTT*), which are also same with the definition in Table 3.2. The unique new state variable is Node Weight (*NW*), which reflects an integrated congestion impact on a node from all its connected links. The design principles of node weight come from the Proportional Regulator (*P* Regulator) of automatic control field [Messmer, 1994][Pavlis, 1999]. 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 multiply candidate ways when they reach an intersection node of the road-network. In the case that a vehicle passes one node and selects a target link, and if such behavior changes the current state of the target link from uncongested to congested, or from congested to uncongested, this would affect the passage time of agents on the link. In consideration of the above state transitions, we define an adaptive node weight algorithm based on iterative operations on the variation of the passage time on each adjacent link in two consecutive simulation time steps. Suppose that the road-network has one node *a* connecting a link *r*, the node weight at simulation step *t* would be updated by the following equation (4-1) and (4-2):

$$NW(a,t) = NW(a,t-1) - K\Delta T(r,t), \quad where \qquad NW \in (0,1] \tag{4-1}$$

$$\Delta T(r,t) = \frac{T(r,t) - T(r,t-1)}{T\ (r,t)} \tag{4-2}$$

where $NW(a, t)$ and $NW(a, t-1)$ are the weight of node *a* at time step *t* and *t-1* respectively, $T(r, t)$ and $T(r, t-1)$ are the expected travel time of a vehicle on link *r* 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. When *NW(a, t)* gets smaller in magnitude, the more seriously congested degree of the node becomes. The other state variables are calculated in consistent with those ones in section 3.3.2.

4.3.3 PROCESS AND SCHEDULING

The process and scheduling are almost similarly as in the basic agent-based model, except those operations on node weights of the road-network. The following pseudo-code in Fig 4.1 describes the process and the scheduling of the agent model with adaptive weight-based multi-objective algorithm. The details of two sub-models as agent selects a target link and travels a distance on the link are to be explained in section 4.3.6.

```
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 into 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 states of the involved links
              update the node weight based on the link state
          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
```

Fig 4.1 Pseudo-code of the agent model with adaptive weight-based multi-objective algorithm.

4.3.4 DESIGN CONCEPTS

In the agent model with adaptive weight-based multi-objective algorithm, most design concepts are similar with in section 3.3.4, except that the observations include not only the variations of *ALCD*, *ALCT*, *ALCI*, *AAT*, but also *ANCD*.

4.3.5 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 follows a uniform distribution with 1 to 50. At the beginning of the simulation, the weight of each node in the road-network is initialized to 1. When the simulation proceeds, the weights of some nodes are adaptively updated based on equation (4-1). In this thesis, we define those nodes with their weights Less than 1 as congestion feedback nodes.

4.3.6 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 4.2.

```
Start
    if (the node connects to an unique link)
        Choose this link as the target link
    else   if (the link state 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
```

Fig 4.2 Pseudo-code of the link selection model.

As stated in Fig 4.2, each vehicle agent changes its link selection strategies according to the 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 r at simulation step t is given in equation (4-3).

$$U(r,t) = NW(a,t) * g(r) + (1 - NW(a,t)) * LCD(r,t), \tag{4-3}$$

where the first term $g(r)$ represents the strength which attracts agent moving towards its destination node, calculated by Floyd shortest path algorithm[Floyd, 1962]; the second term $LCD(r,t)$ reflects the congested degree of link r at simulation step t, calculated by equation (3-3); and the parameter $NW(a,t)$ is an adaptive weight updated by equation (4-1), which is used to simultaneously optimize the two objectives as shortest path and the congestion avoidance. The pseudo-code of the agent travel process is same with the basic agent model, shown in Fig 4.3.

```
Start
    if (the current link state == 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
```

Fig 4.3 Pseudo-code of the agent travel model.

4.4 DEFINITION OF EVALUATION CRITERIA

Besides the evaluation criteria defined in section 3.4, the number of congestion feedback nodes (*N_CFN*), which refers to those nodes with their weights less than 1 is also considered as a measurement in the study. As the

weight of each node is initialized as 1, and such values are updated when the congested degree of connected links change. Therefore, those nodes with their weights less than 1 indicate a feedback to the dynamic congestion situation of road-network. The evaluation criteria are described and listed in Table 4.1.

Table 4.1 Evaluation criteria and descriptions

Criteria	Description	Identification
Average Link Congestion Degree	The average congested degree of a link	*ALCD*
Average Link Congestion Time	The average congested time of a link	*ALCT*
Average Link Congestion Index	The average congested condition of a link	*ALCI*
Average Node Congestion Degree	The average congested degree of a node	*ANCD*
Average Arrival Time	The average time that agents traveled in the network	*AAT*
Number of Congestion Feedback Nodes	The number of congestion feedback nodes with their node weight less than 1	*N_CFN*

4.5 EXPERIMENT ON THE ADAPTIVE WEIGHT-BASED AGENT MODEL

4.5.1 EXPERIMENT OVERVIEW

Following our previous work, we first conduct two groups of simulation experiments to examine the applicability and effectiveness of the agent model with adaptive weight-based multi-objective algorithm in improving the road-network congestion on a generated road-network. On this basis, we further validate the model effect on a real road map. The purposes and evaluation criteria of each group of experiments are described in Table 4.2.

To conduct the experiments, we also define two types of agents: one type of agent is the Floyd agent using shortest path strategy, and the other agent type is the adaptive agent using hybrid strategy. Hybrid strategy refers to

executing the shortest path strategy and the two-objective optimization strategy in turn according to a changing congestion condition. The agent using hybrid strategy adapts its routing selection strategies to the dynamic congestion condition of nearby links. On this basis, we execute simulation experiments with different composition of these two types of agents, and compare the simulation results by using the evaluation criteria in Table 4.2.

Table 4.2 Summary of the experimental purposes and evaluation criteria

Experiment No.	Purpose	Evaluation Criteria
Experiment 1	Sensitivity test of the parameter K on congestion improvement	*ALCD*, *ALCT*, *ALCI*, *AAT* *ANCD*, *N_CFN*
Experiment 2	Validation of the model on a generated road-network	*ALCD, ALCT* and A*LCI* of congested links *ANCD*
	The impact of number of agents on congestion improvement	*N_CFN*
Experiment 3	Validation of the model on a real road map	*ALCD, ALCT* and A*LCI* of the top ten congested links *ANCD*
	The impact of number of agents on congestion improvement	*N_CFN*

Table 4.3 presents the different composition of agents in the experiments, with a default value of K set to 1.4.

Table 4.3 The composition of agents in the experiments

Experiment No.	Agent Composition
Experiment 1	3000 Floyd vs. 1500 Floyd and 1500 Adaptive vs. 3000 Adaptive.
Experiment 2	3000 Floyd vs. 1500 Floyd and 1500 Adaptive vs. 3000 Adaptive.
	The agent number scales in {1000, 2000, 3000, 4000, 5000}.
Experiment 3	6000 Floyd vs. 3000 Floyd and 3000 Adaptive
	8000 Floyd vs. 4000 Floyd and 4000 Adaptive
	10000 Floyd vs. 5000 Floyd and 5000 Adaptive

At the initial stage, the two types of agents travel along the shortest path according to equation (4-3). When the simulation proceeds, some roads

become congested, and the connected nodes would adjust their weights based on equation (4-1). Then the agent model adaptively shunts vehicles by using such weight sequences as weights in the two-objective function based on equation (4-3). In this way, the developed model implements a set of index sequences which describes a changing congested degree of road-network, and also use this indexes to shunt vehicles through routing selection process.

4.5.2 EXPERIMENT-1: SENSITIVITY TEST OF THE PARAMETER *K* ON CONGESTION CONTROL

The first group of simulation experiments conducts sensitivity analysis of parameter *K* on congestion control. The experiments are executed on the generated network topology given in Fig 3.4, consisting of 39 nodes with their IDs ranging from 0 to 38, and 146 links each represented by a pair of nodes. And, the experiment sets three agent groups according to Table 4.3. The values of parameter *K* change from 0.2 to 2 with an interval of 0.2. The simulation will be terminated after 1000 steps. The simulation results are evaluated by the *ALCD*, *ALCT* and *ALCI* of all links, the *AAT* of all agents and *ANCD* and *N_CFN* of all nodes under different values of *K*.

In the following, Fig 4.4, Fig 4.5, Fig 4.6, Fig 4.7 and Fig 4.8 present the results of the *ALCD*, *ALCT*, *ALCI*, *AAT* and *ANCD* under different values of *K*, respectively. As shown in Fig 4.4, the value of *ALCD* increases rapidly when *K* is greater than 1.4, which indicates that we should set the *K* less than 1.4 to ensure the effect from congestion avoidance represented by 1-*NW* in the adaptive weight-based function by equation (4-3). The results in Fig 4.5, Fig 4.6 and Fig 4.8 also show the similar variation of *ALCT, ALCI* and *ANCD*. While the resulted data in Fig 4.7 show that our proposed agent model leads to more time cost of *AAT*. Thus find a suitable value of *K* is important to ensure the model effect. By analyzing the simulation results under different

values of K, we set its value to 1.4.

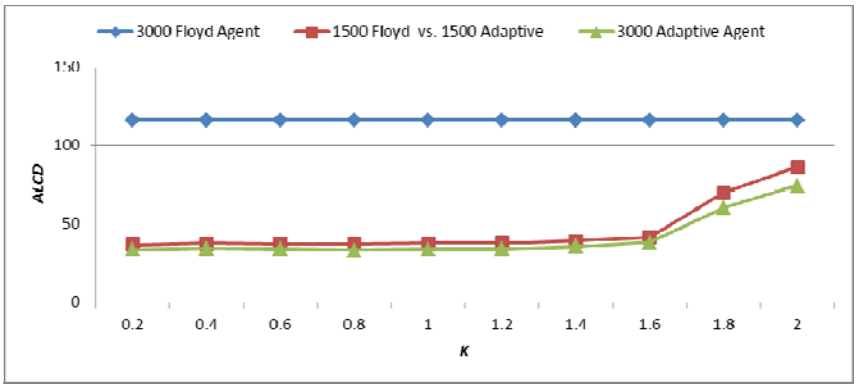


Fig 4.4 Variation of *ALCD* under different values of *K*

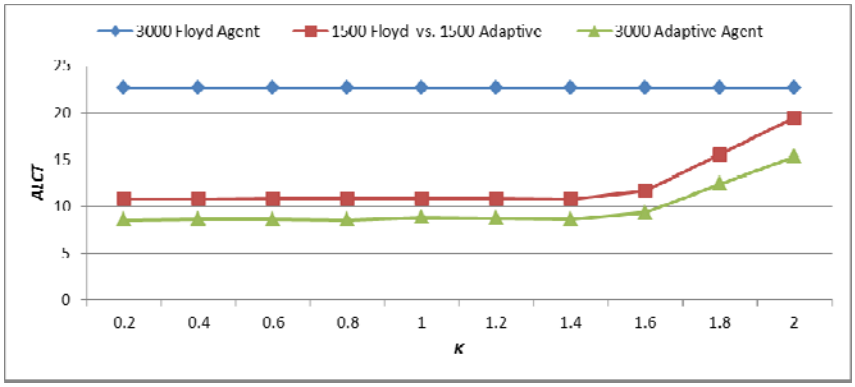


Fig 4.5 Variation of *ALCT* under different values of *K*

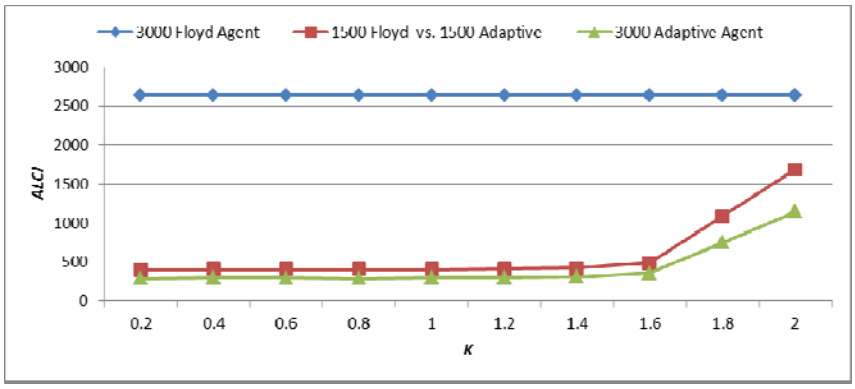


Fig 4.6 Variation of *ALCI* under different values of *K*

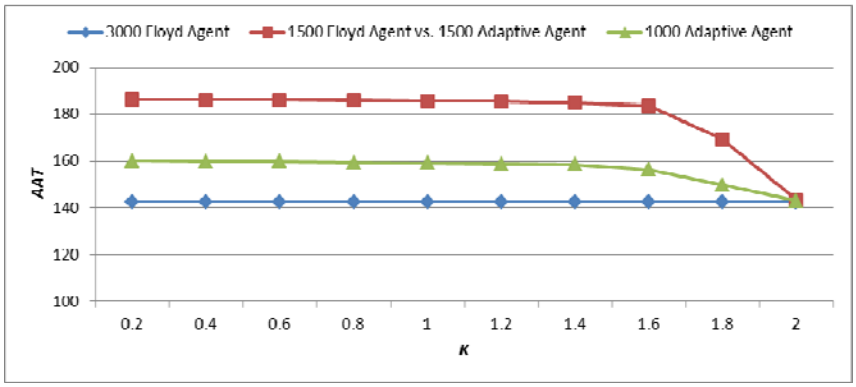


Fig 4.7 Variation of *AAT* under different values of *K*

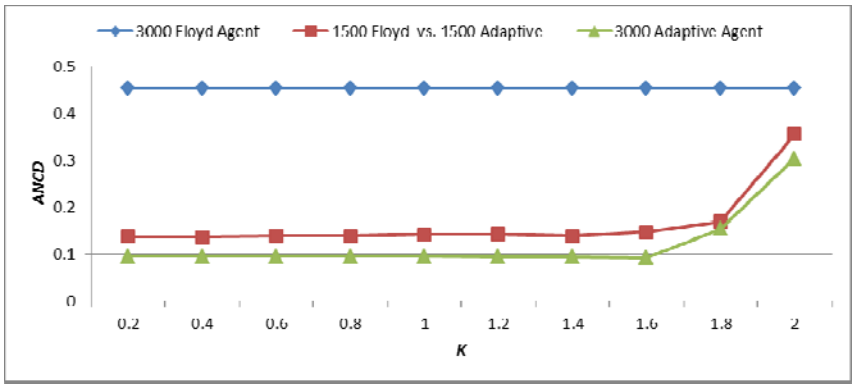


Fig 4.8 Variation of *ANCD* under different values of *K*

Further, because the number of congestion feedback nodes directly reflects the effect of our agent model on congestion management and control, we then calculate the number of congestion feedback nodes under different values of *K* and present the results in Fig 4.9.

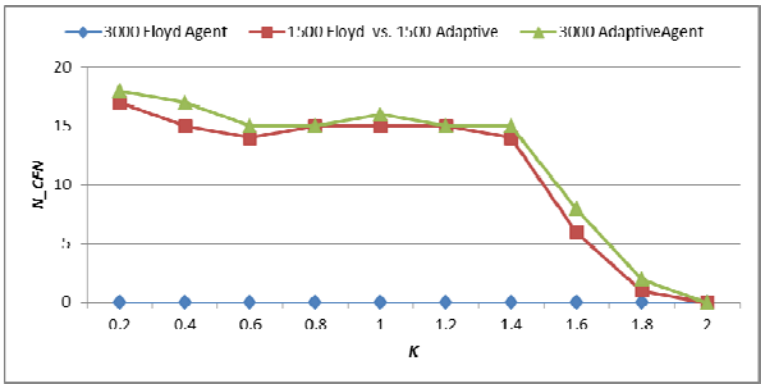


Fig 4.9 The number of congestion feedback nodes under different *K*.

As shown in Fig 4.9, the adaptive agent group and the mixed agent group

produce more congested feedback nodes than the Floy agent group, which show an obvious effect of our proposed model on congestion management. There have no obvious variation of *N_CFN* until *K* reach 1.4, which indicates we should set the value of *K* to 1.4 to ensure the model effect on congestion improvement. There is no more congestion feedback nodes in the network when *K* is bigger than 2.

4.5.3 EXPERIMENT-2: VALIDATION OF THE MODEL ON A GENERATED ROAD-NETWORK

The second group of simulation experiments examines how our model using adaptive weight-based two-objective optimization algorithm reduces the road-network congestion on a generated road-network topology. To compare the simulation results, we set three agent groups with different composition of two types of agents as shown in Table 4.3. All agents are generated with random departure and destination nodes, and added into the road-network at different time stamps. We choose *ALCD*, *ALCT* and *ALCI* of those congested links and *ANCD* of congested nodes as the evaluation criteria to measure the simulation results. The experiment sets the values of parameter *K* to 1.4, and the simulation will be stopped after executing 1000 steps.

4.5.3.1 COMPARISON AND ANALYSIS ON SIMULATED RESULTS

Fig 4.10, Fig 4.11 and Fig 4.12 present the results of *ALCD*, *ALCT* and *ALCI* of all congested links in the generated network under three groups of agents. The results show our model effect on those seriously congested links such as (19, 16), (16, 19), (25, 28), (26, 22), (33, 31), (35, 34), (37, 33) and (38, 34).

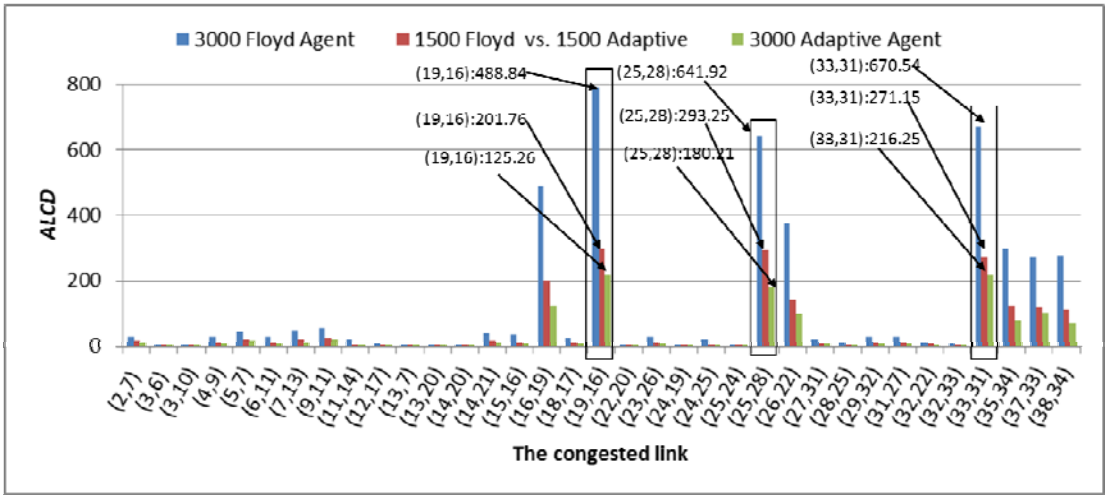


Fig 4.10 *ALCD* of congested links under different setup of agents

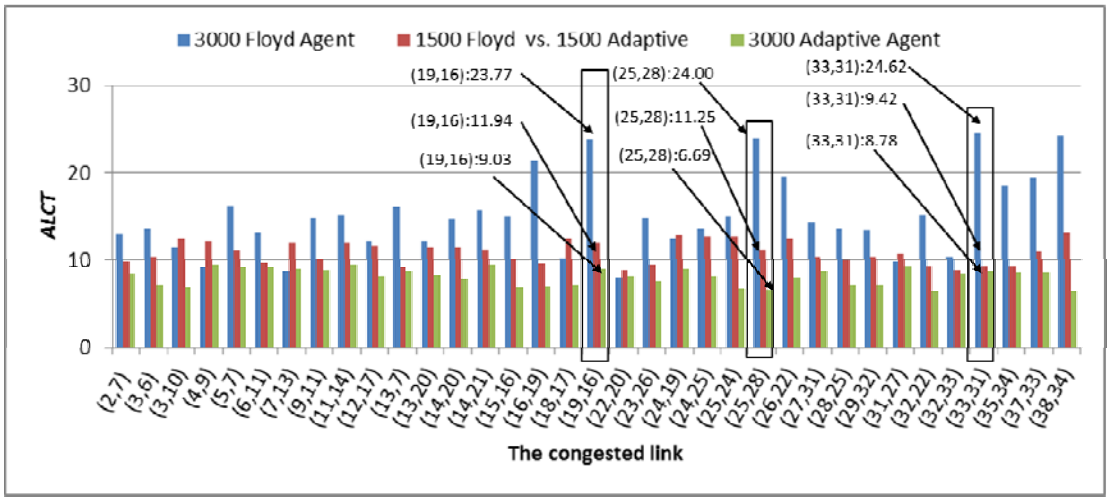


Fig 4.11 *ALCT* of congested links under different setup of agents

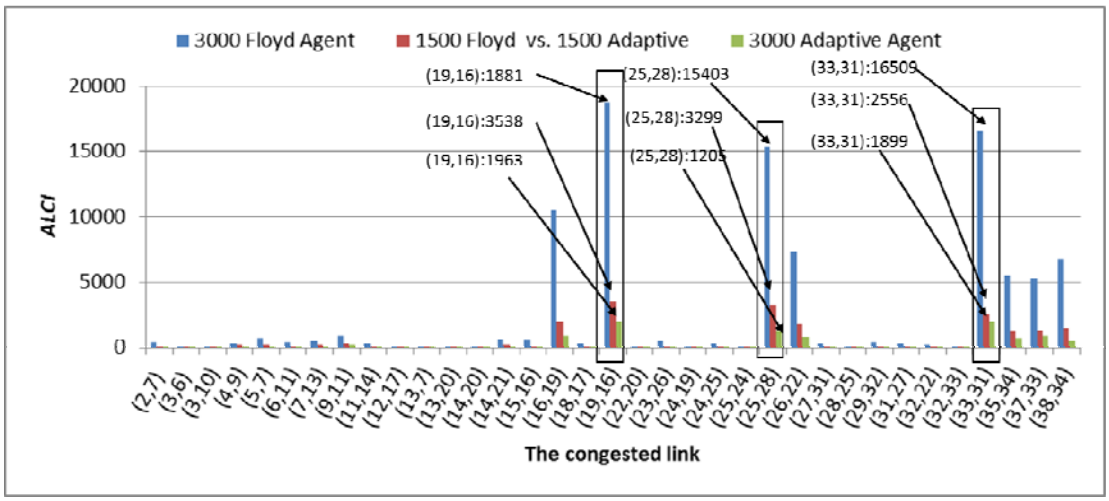


Fig 4.12 *ALCI* of congested links under different setup of agents

Further, Fig 4.13 presents the results of *ANCD* of all congested nodes in the generated network under three different agent groups. The simulation results show obvious effectiveness of our proposed model in reducing the road-network congestion. Meanwhile, it is interesting that the resulted congested nodes such as 16, 19, 25, 28, 31 and 33 are corresponding to the end nodes of those seriously congested links obtained in Fig 4.10, Fig 4.11 and Fig 4.12.

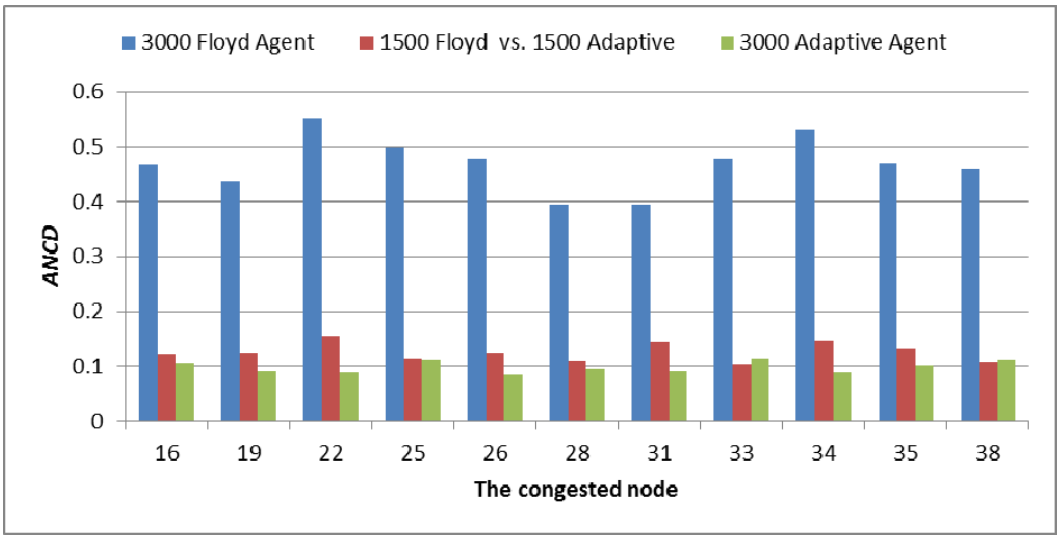


Fig 4.13 *ANCD* of congested nodes under different groups of agents

We further compare the number of occurrences of congestion feedback nodes. Fig 4.14 presents the emerged frequency of congestion feedback nodes under three agent groups of the generated road-network.

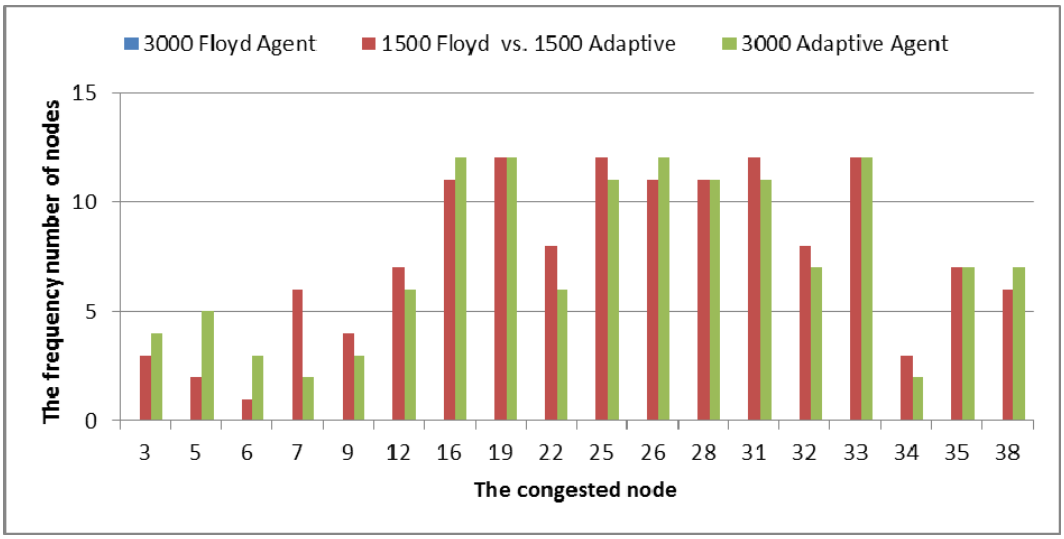


Fig4.14 The number of occurrences of congestion feedback nodes of the generated network under deferent agent groups.

As shown in Fig 4.14, the congestion feedback nodes are also located on some specific nodes 16, 19, 25, 26, 28, 31and 33. These nodes appeared 11 or 12 times as congestion feedback nodes during the simulation. Such results indicate that the congested links or nodes may have some common geographical distributed features of the road-network.

4.5.3.2 THE IMPACT OF AGENT NUMBER ON CONGESTION IMPROVEMENT

Next, we conduct experiments with mixed agent group to examine how the number of agents influences the road-network congestion on the generated road-network. The number of agents ranges in the collection of {1000, 2000, 3000, 4000, 5000}. Fig 4.15 records the number of occurrences of congestion feedback nodes after simulation under each case. The results in Fig 4.15 show that the congestion feedback nodes are also located on some specific nodes 16, 19, 25, 26, 28, 31and 33. These nodes appeared over 8 times as congestion feedback nodes during the simulation under each case. Such results also suggest that the congested nodes may have some common geographical distributed features of the road-network. Furthermore, the

congestions become more serious with an increasing number of agents, indicating that bigger travel requirements would cause worse congestion condition.

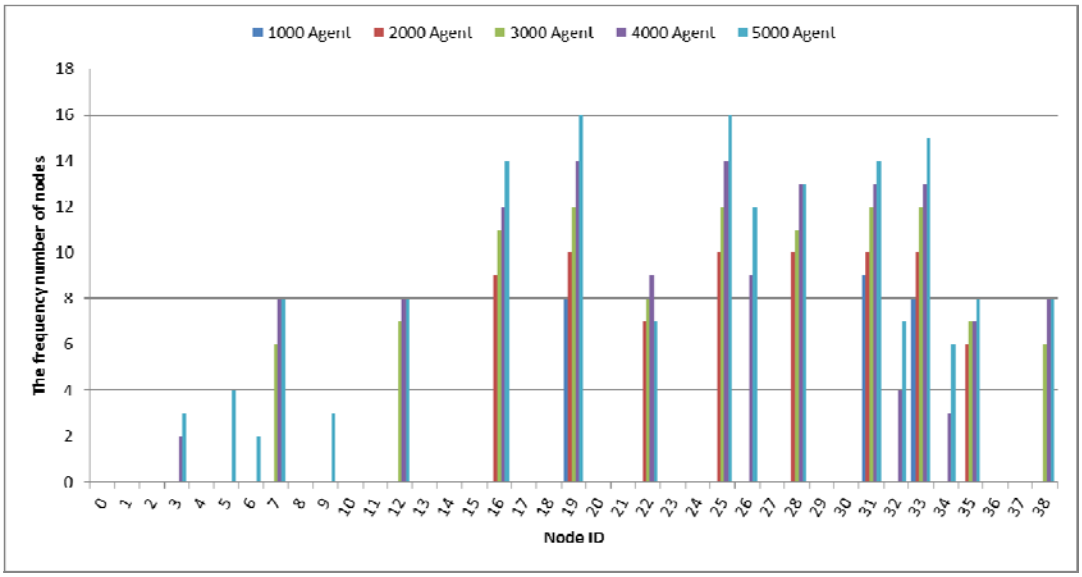


Fig 4.15 The number of congestion feedback nodes under different number of agents.

4.5.4 EXPERIMENT-3: VALIDATION OF THE MODEL ON A REAL ROAD MAP

Finally, the third group of simulation experiments runs to validate the applicability and effectiveness of our agent model on a real road map. The road-network consists of 514 nodes and 791 links, with its topology defined in Fig 3.5. First, we examine the effectiveness of the model under different traffic flows by increasing the number of agents. The experiment sets the mixed agent group under each simulation case. Table 4.4 gives the resulted number of congestion feedback nodes under a growing number of agents.

The results in Table 4.4 show that the number of congestion feedback nodes increases from 12 to 106, with the number of agents changing from 3000 to 10000. Since the number of congestion feedback nodes reflects an ability of the model in improving congestion, therefore, such results also has

confirmed the efficiency of our model on congestion control.

Table 4.4 The number of congestion feedback nodes with different number of agents

The number of Agents	*N_CFN*
3000	12
6000	38
8000	73
10000	106

Next, we fix the number of agents to 6000, and sort the links by their *ALCD* values in a descending order and the top ten links are found and summarized in Table 4.5.

Table 4.5 The list of the top ten links sorted by *ALCD*

Link Id	6000 Floyd Agent	3000 Floyd and 3000 Adaptive	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 4.5, nine of the top ten congested links have improved their *ALCD* values more than 17%. The most seriously congested link (385, 386) has its *ALCD* value been improved 9%, and the congestion in link (244, 243) disappears. Next, we fix the number of agents to 6000, and sort the links by their *ALCT* values in a descending order. Table 4.6 lists the

top ten links with larger *ALCT* values.

Table 4.6 The list of the top ten links sorted by *ALCT*

Link Id	6000 Floyd Agent	3000 Floyd 3000 Adaptive	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 4.6, most links with bigger values of *ALCT* decrease greatly, such as link (379,380) (380,110), (56, 57), (57, 58) and (396,395). The improvement rates of these links are over 50%. Especially, the congestion no longer occurs on link (58, 59).

Further, Fig 4.16 gives the weight distribution (NW) of end nodes corresponding to those seriously congested links in Table 4.5 and 4.6, where the red line represents the average weight of all congestion feedback nodes of the road-network, which was 0.36. According to the results in Fig 4.16, most nodes have 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 modified to 0.08 and 0.12 after the model effect.

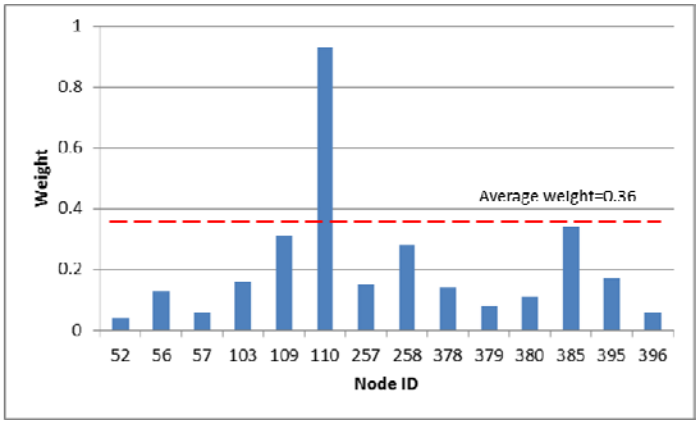
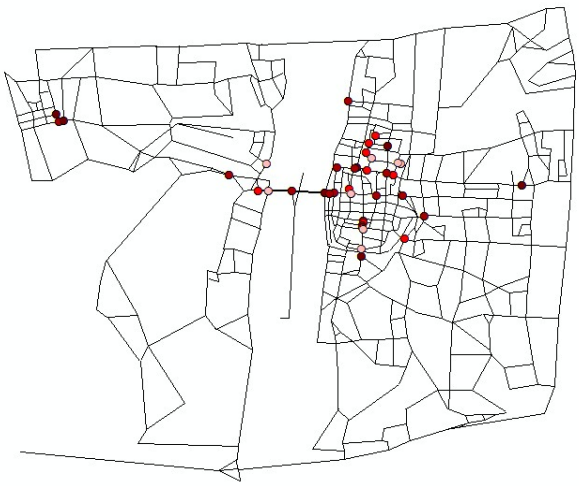
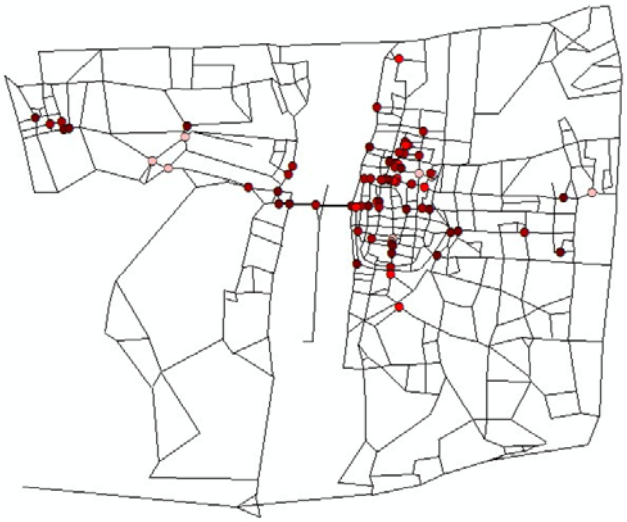


Fig 4.16 The weight distribution of those seriously congested links.

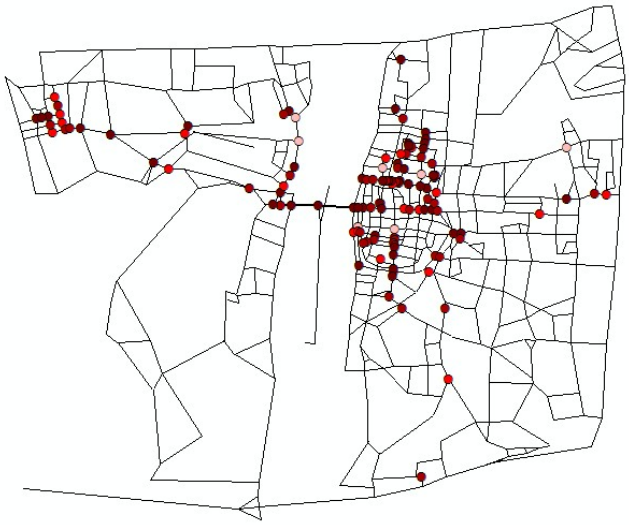
For a more intuitive display with congestion feedback nodes to describe the distribution of congestion, we mark the locations of the congestion feedback nodes on the real road map in Fig 4.17. We compare the resulted congested location with 6000, 8000 and 10000 agents respectively. In this figure, the nodes with darker red color represent smaller values of the weight, which actually indicates more severe congestion of connected roads. According to the results on Fig 4.17, it is obvious that the congestion becomes worse when the number of agents increase. We also find that those seriously congested nodes have some common features, such as end nodes of major traffic arteries or road junctions.



(a) 6000 agents



(b) 8000 agents



(c) 10000 agents

Fig 4.17 The distribution of congestion feedback nodes on the real road map under different number of agents.

4.6 Further Extension and Experiments of the agent-based models on Congestion management

We future extends our agent-based model based on the principles of proportional and the integral Regulator (*PI* Regulator) of automatic control

field [Pavlis, 1999]. The main idea of *PI* regulator is also to balance the travel time of different ways that connects the same start and destination. Suppose that the road-network has one node *a* connecting a link *r*, the node weight at simulation step *t* would be updated by the following equation (4-4) and (4-5):

$$NW(a,t) = NW(a,t-1) - K_i \Delta T(r,t) - K_p(\Delta T(r,t) - \Delta T(r,t-1)), \quad NW_a \in (0,1] \qquad (4\text{-}4)$$

$$\Delta T(r,t) = \frac{T(r,t) - T(r,t-1)}{T(r,t)}, \qquad \Delta T(r,t-1) = \frac{T(r,t-1) - T(r,t-2)}{T(r,t-1)} \qquad (4\text{-}5)$$

where $NW(a, t)$ and $NW(a, t-1)$ are the weight of node *a* at time step *t* and *t-1* respectively, $T(r, t)$, $T(r, t-1)$ and $T(r, t-2)$ are the expected travel time of a vehicle on link *r* at time step *t*, *t-1* and *t-2* respectively, K_i and K_p are the model parameters. According to the equations, the node weight is adjusted iteratively according to the difference between vehicle's passage times on the target link in three consecutive time steps. As $NW(a, t)$ gets smaller in magnitude, the more seriously congested degree of the node becomes.

In this experiment, we set three agent groups: the first group is composed of 3000 Floyd agents using shortest path strategy, the second group consists of 1500 Floyd agents using shortest path strategy and 1500 adaptive agents using hybrid strategy, and the third group includes 3000 adaptive agents using hybrid strategy. We choose *ALCD*, *ALCT* and *ALCI* of all links and *ANCD* of all nodes as the evaluation criteria to measure the simulation results. The experiment sets the values of parameter K_i and K_p are 0.9 and 0.05 by preliminary sensitivity test, and the simulation step is set to 1000.

Below, Fig 4.18, Fig 4.19, Fig 4.20 and Fig 4.21 present the results of the *ALCD*, *ALCT*, *ALCI* and *ANCD* after simulation. The results also show better effect of this model on congestion improvement.

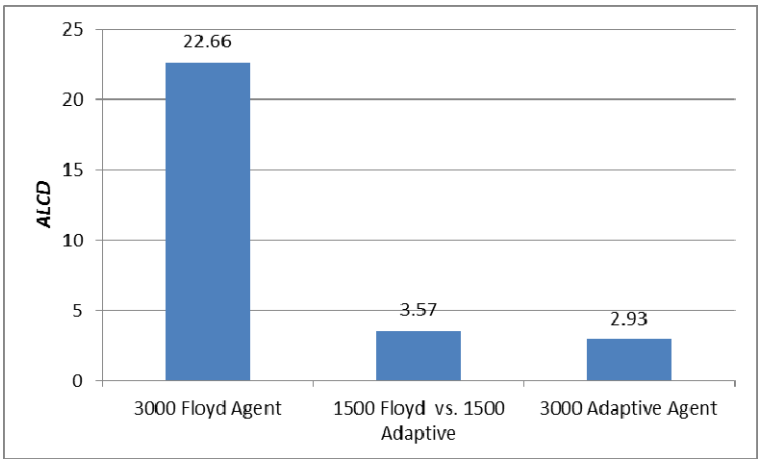


Fig 4.18 Variation of *ALCD* under three agent groups

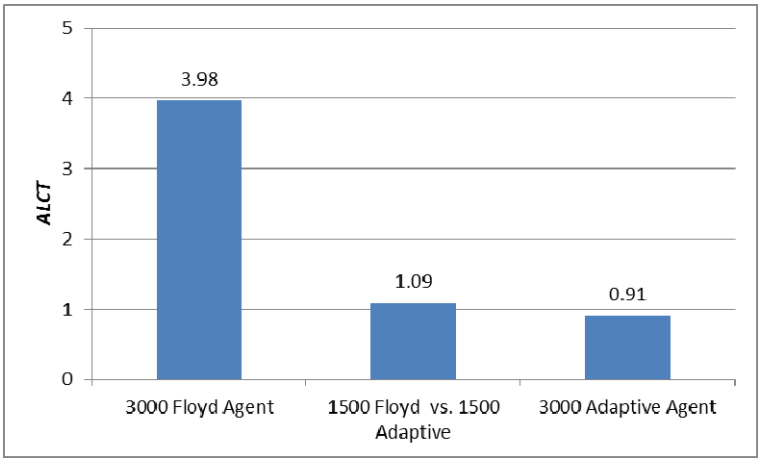


Fig 4.19 Variation of *ALCT* under three agent groups

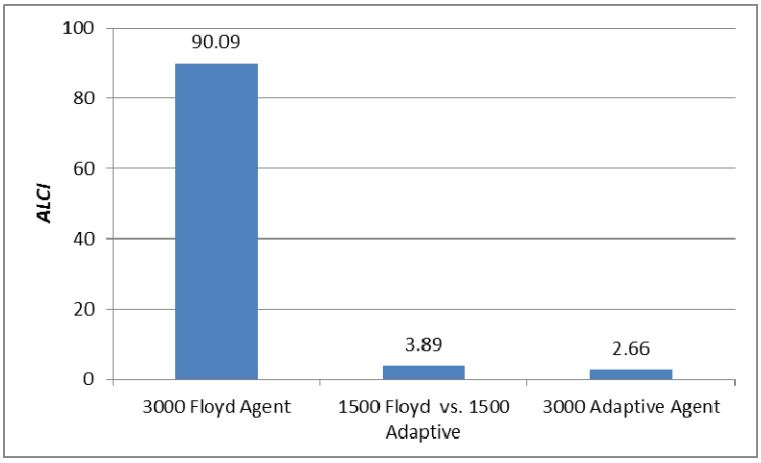


Fig 4.20 Variation of *ALCI* under three agent groups

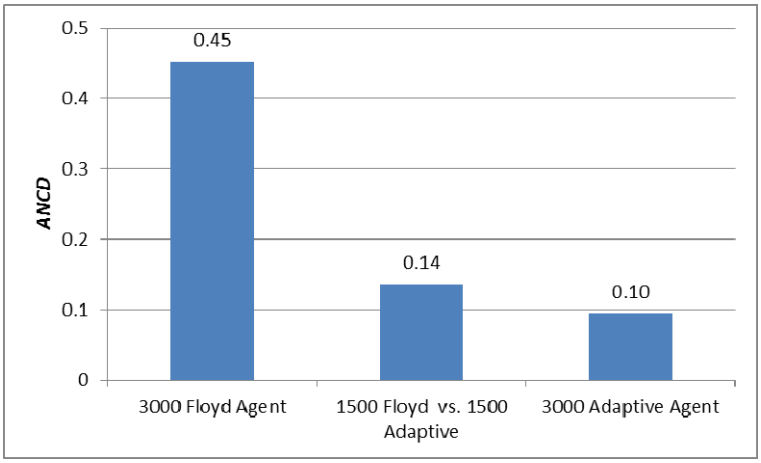


Fig 4.21 Variation of *ANCD* under three agent groups

4.7 DISCUSSION

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

(1) The results in the first group of simulation experiments show that the performance of our proposed approach is affected by the values of parameter K and the number of agents. The sensitivity test finds that the number of congestion feedback nodes decreased with a growing value of parameter K. Such results indicate that the congested nodes and related links are also decreased and the network congestion is greatly improved. And, the simulation results achieve best performance when K equal to 1.4. On the contrary, the result that no more congestion feedback nodes appear when K is bigger than 2 indicates 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 is unable to accurately measure the congestion distribution of the road-network. Furthermore, the simulation results show that the congestion feedback nodes are mainly located on some specific nodes, such as end nodes of major traffic arteries or road junctions. The results also show that the number of congestion feedback nodes increased with a growing number of agents, which indicates that bigger

traffic flow would cause more serious congestion status. This shows that the node weight is affected by the agent quantity to a certain degree. Further, the distribution of congestion feedback nodes under different amounts of agent again shows that the congestion nodes mainly depended on the network topology.

(2) In the second group of simulation experiments, the results of *ALCD*, *ALCT* and *ALCD* show that our proposed model helps to decrease the congested degree of those congested links. This exactly explains the model effect on vehicle shunting and congestion equilibration. Additionally, the achieved adaptive weight sequence confirms 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 adaptive agent using hybrid strategy travel along the shortest routing according to equation (4-3). When the simulation proceeds, some roads become congested, and the connected nodes would adjust their weights based on equation (4-1) and implement vehicle shunt via the two-objective optimization by equation (4-3). During the simulation process, the extremely small weight of nodes mean a seriously congested situation with those connected links while the nodes with higher values of weight approximating to or more than one denote less congestion or never congestion. Therefore, the results show that our model successfully constructs a new quantitative index of nodes which could achieve the congestion evaluation and congestion management simultaneously.

(3) The results obtained from the third group of simulation experiments show that the agent model with adaptive weight-based two-objective optimization algorithm successfully reduces the traffic congestion on the real road map. The increased amount of congestion feedback nodes denotes that

the performance of the agent model is affected by the different traffic scales, and also indicates the effect of different traffic scales on the nodes weights. The improvement rate of those seriously congested links with higher values of *ALCD*, *ALCT* and *ALCD* confirm the shunting effect of our proposed model on congestion control. The node weights exactly provide 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 road map, we find most nodes located at the road junction or near the unique road connecting the east and west urban area. Because these nodes connect traffic arteries, most agents of the simulated traffic system have to pass such nodes to go through the regions and finally reached their destinations. Although we do not set agents according to the real traffic flow in the city map, the simulation results reflect the same congested node with the real map in actual life. Also, the improvement made by our model on those seriously congested links provide a dynamic balancing diversion idea from the vehicles perspective, which has its significant potentials for guiding actual operation of the congestion control. Therefore, the simulation results verify an applicability and effectiveness of our proposed model on the real road map.

Further experiments of the agent model with adaptive-weight based multi-objective algorithm by using PI regulator also show obvious effect of our model in reduction of congestion, we will discuss this extension in the future work.

4.8 SUMMARY

In this chapter, following our previous work, we have proposed an agent model with adaptive weight-based algorithm for studying the road-network congestion problem with a hybrid perspective.

We have constructed a quantitative index series which is employed to measure the real-time congestion distribution of the road-network and as weights in the two-objective functions to shunt vehicles on those congested links simultaneously. Accordingly, an adaptive node weight algorithm has been presented based on the proportional regulator of automatic control field. In this way, our proposed 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.

The simulation results show that the model has realized a timely control on road-network congestion, through which it reduces the road congestion and promots traffic capacity of the road-network. Especially, the validation of the model with a real traffic map of a Medium-sized city in China has turned out that our proposed model could balance and reduce the congestion in the road-network. The simulation results also has 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 with adaptive weight-based multi-objective optimization algorithm will have its significant potentials for actual traffic congestion control by considering the global congestion distribution and the local vehicle routing preference at the same time.

5 CONCLUSION AND FUTURE WORK

In this thesis, we study the road-network congestion management issue based on vehicle route guidance of intelligent transportation system. As agent-based framework with bottom-up perspective is natural and suitable for capturing the dynamic and geographically distributed features of transportation systems, we design and implement agent-based models with weighted multi-objective optimization algorithm to implement vehicle route guidance.

First, a multi-agent system is built, where each agent stands for a vehicle that would adapt its route to a dynamic road-network congestion condition 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 status, thus we can observe the formation and evolution of road-network congestion through agent-based simulations. Next, a series of quantitative indexes is constructed to describe the congested degree of road nodes, and such indexes are used as weights in the two-objective function employed by the agents for routing decision in a changing traffic environment. In this way, our proposed agent models with adaptive weight-based multi-objective optimization algorithm could achieve congestion distribution evaluation and congestion management at the same time. Besides, we define a set of evaluation criteria to measure the effect of our proposed agent models on road-network congestion improvement.

Intensive experiments on a generated road-network topology and a real road map have both shown an applicability and effectiveness of our proposed agent model on reducing congestion. We further examine the agent model

effect with adaptive weight-based two-objective optimization algorithm. The simulation results have also confirmed an applicability and effectiveness of the node weights as a new quantitative index sequences which describe the road-network congestion distribution, and shunt vehicles on seriously congested roads based on that index simultaneously. By comparing the distribution of those congested links or nodes on the real road map, we find that most congested locations are the unique road connecting two regions or road junction. The reason is that these locations always connect traffic arteries, thus most agents of the simulated traffic system have to pass such links or nodes to go through the regions and finally reach their destinations. Although we have not set agents according to the real traffic flow in the city map, the simulation results have reflected the same congested node with the real road map in actual life. Also, the improvement made by our model on those seriously congested links has provided a dynamic balancing diversion idea from the vehicles perspective, which has its significant potentials for guiding actual operation of the congestion control.

The contributions of our study in the field of congestion management are mainly: (1) a hybrid route guidance strategy which quantifies the influence of congestion avoidance and implements a two-objective function which considers both shortest path and congestion avoidance for the routing optimization; (2) agent-based models with weighted two-objective algorithm for understanding the formation and reduction of road-network congestion by capturing the nonlinear feedback between agent routing behaviors and road-network congestion conditions; (3) a quantitative index sequence which measures the real-time congestion distribution and also is used as weights of the two-objective function simultaneously for implementing agent routing selection function, it could achieve a good tradeoff between user satisfaction and effective utility of road-network.

With the help of GPS devices, the proposed model and method will have their theoretical value and practical significance for both vehicle navigation and route guidance 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.

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