Solving Road-Network Congestion Problems by a Multi-objective Optimization Algorithm with Brownian Agent Model

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Abstract. The past decades witnessed a big effort in solving road-network congestion problem through routing optimization approaches. With a multi-objective optimization perspective, this paper proposed a new method which solved the road-network congestion problem by combining two objectives of shortest routing and congestion avoidance. Especially, we applied the approach of Brownian agents to find the next intersection of road network to avoid congestion. Vehicles were simulated as Brownian agents with automatic movements in the road-network, and the entire network congestion distribution were optimized at the same time. We tried to find out the relationship between the moving strategies of the vehicles and the network congestion. By means of computer simulation, we implemented our proposed method with a predefined road-network topological structure. We tested the parameters sensitivity by scaling the proportion of agent with two moving strategies: the shortest path strategy and a mix strategy combining two objectives of shortest routing and congestion avoidance. Furthermore, we analyzed the various network congestions under a mix strategy by changing the weights to represent different focus on two moving strategies. The simulation results proved the applicability and efficiency of our proposed method for alleviating the network congestion distribution, and the intersections within a higher vehicle density were observed decreased.

Keywords: road-network congestion, multi-objective optimization, Brownian agent.

1 Introduction

Road-network congestion becomes a more and more serious problem in our daily life. Facing the traffic problems, ITS (intelligent transportation system) was proposed to handle it. There lots of agent-based traffic applications and systems among the ITS. In the early year, Nagel introduce a stochastic discrete automaton model to simulate

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freeway traffic [1], and lots of traffic application using CA (Cellular Automata) in the later years were proposed [2][3][4]. Wang also summarized the multi-agent system used for traffic management systems, and rethink control systems and reinvestigate the use of simple task-oriented agents for traffic control and management of transportation systems in 2005[5]. Later, more and more researchers focus on this area. Du proposed an urban traffic coordination control system based on Multi-Agent-Game, the system uses the coordination control of each agent to coordinate the urban traffic signal for elimination the congestion of traffic network [6]. Chin introduced a Q-Learning algorithm acts as the learning mechanism for traffic light intersections to release itself from traffic congestions situation in 2012[7].

Based on the above mentioned works, the conventional traffic applications using agents were focus on one or intersections or traffic signals. Although these methods improved the road network congestion in some degree, it is difficult to find deep level optimization objectives in the practical application problems and research focus.

In our research, we mainly focused on the road-network congestion problems by using Brownian agent motion model. At the early stage of application of agent models, agents was defined either complex or minimalistic ways. A complex agent can be regarded as an autonomous entity with either knowledge or behavior based rules, performing complex actions such as learning and building its own strategy with multiple attributes [8]. The conceptual design of complex agent is ideal but impractical. The alternative is the minimalistic agent, which has the simplest rule set to guide its decision, without referring the internal attributes. But due to oversimplification, the practical application of such agent is also very limited. To avoid both extremes, Brownian agent approach is proposed [9][10]. A Brownian agent is a minimalistic agent with internal degrees of freedom. Through specific action, Brownian agents are able to generate a self-consistent field which in turn influences their further movement and behavior [9]. The non-linear feedback between the agents and the field generated by themselves results in an interactive structure formation process on the macroscopic level.

The applications with Brownian agent model mostly simulated the agent's own activities and analyzed their macro-emergence. Schweitzer and his colleges began their research on the BA in the early years; they defined a potential attribute which described a two-dimensional plane, the attribute would influent the agent movement decision, and the agents' movements would cause changes of the potential attribute and result in the aggregation phenomenon [11]. Schweitzer also optimized the network topology by using a mix Brownian Agent-based strategy which combined the Boltzmann and Darwin hybrid genetic strategy [12]. Another interesting work was done by Espitia in 2011. He proposed a complex Brownian particle swarm model for solving the routing planning problems [13]. Minazuki focused on the optimization of traffic flow and traffic management, the extent of the traffic congestion can be predicted using a model based on the Brownian motion process [14]. Li and Dan proposed a conflict detection algorithm based on Brownian motion, their algorithm had better results for practical application of automated air traffic control systems [15].

Compared to the previous agent application, the characteristic of Brownian Agent was more macroscopic, their whole behaviors and merging characters are more suitable for global optimization. In our work, the design of intelligent transportation system should at least achieve two objectives. One is the shortest routing length to the destination, and the other is the avoidance of the adjacent high-density congestion area. With a multi-objective optimization perspective, this paper proposed a new method which solved the road-network congestion problem by combining two objectives of shortest routing and congestion avoidance. Especially, we applied the approach of Brownian agent to find the next intersection of road network to avoid congestion. Vehicles spontaneously move to the destination, and the entire network congestion distribution would be optimized at the same time. By means of computer simulation, we proved the efficiency and applicable of our model in solving road-network congestion problem.

The rest of the paper is organized as follows: Section 2 describes the model through ODD protocol. Section 3 gives experimental settings and discusses the results of computer simulations. Section 4 analyzes the simulation results. Finally, Section 5 gives concluding remarks and an outlook of future work.

2 Model Description with ODD Protocol

The model description follows the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models [16].

2.1 Purpose

The Multi-Objective Optimization Algorithm with Brownian Agent Model is designed to solve the road-network congestion problem. We also focus on the methodology: a multi-objective optimization with Brownian agent model. Vehicles are regarded as Brownian agents, they spontaneously move to the destination, and the entire network congestion distribution would be optimized at the same time. We analyze the various network congestions under a mix strategy by changing the weights to represent different focus on two moving strategies: the shortest path strategy and a mix strategy combining two objectives of shortest routing and congestion avoidance. We repeated the optimization processes of model parameters through agent strategies, in order to reduce the degree of congestion of the whole network, and provide a new model for the road-network congestion and traffic control methods.

2.2 Entities, State Variables, and Scales

Table 1. Entities and Descriptions

Entities	Description	Entities name in the model
Vehicle	mobile nodes of the road-network	Id(integers from 1 to 500)
Intersection	immobile nodes of the road-network where vehicle passed or located	Id(integers from 1 to 39)

Table 2. State Variable and Descriptions

State variables	Descriptions	Variables name in the model
Links between Interactions	The connection between intersection nodes	adjMatrix
Density of Intersection	The number of vehicles at each intersection node	locationDensity
Source Node Set	The list of intersection nodes where vehicle departures	start
Destination Node Set	The list of intersection nodes where vehicle moves to	end
Vehicle Path	The list of intersection nodes where vehicles passed by	pathMap
Waiting Vehicles	The vehicles of waiting queue at each intersection node	waitQueue
Vehicle State	The states of vehicles at present intersection, either mobile or immobile	vehicleState

2.3 Process Overview and Scheduling

In the simulation model, each vehicle would choose one of its neighbor intersections with the minimum value as next moving target at each simulation step. The minimum value is addressed as an attribute of intersection nodes, estimated by a fitness value of

```
At each simulation cycle
start
          for i = 0 to 500
            Initialize the vehicles in the network
          end for
          for i = 0 to 39
            Initialize the intersection nodes in the network
          end for
          for Simulation Step = 0 to the end of simulation step
            for i = 0 to 500
              if (Simulation Step == the time step a vehicel should be added)
                add vehicle to the network
              end if
            end for
            update the information of intersection nodes in the network;
            for i = 0 to 500
              if (vehicle in the network)
                calculate its next jump and update it
              end if
              if (vehicle arrived its destination)
                remove this vehicle
              end if
            end for
          end for
End
```

Fig. 1. Pseudo-Code of the Agent Simulation Model

a multi-objective function. At each simulation step, a vehicle in the first position of the waiting queue at present intersection node would move to the next neighbor intersection with minimum attribute value. When a vehicle arrived at its destination, it would be moved out from the road-network. A simulation cycle is defined as one execution of vehicles movement and nodes update. The following pseudo-code describes the process and scheduling of the simulation.

2.4 Design Concepts

Basic principles. The general concepts underlying the models' design is Brownian Agents and Active Particles, which is addressed systematically by Frank Schweitzer [10]. Brownian particles were observed in 1826 by the British botanist Brown (1773-1858). According to the concept of Brownian Agents that Schweitzer mentioned, Brownian Agents can be described by external variables and internal degrees of freedom. The external variables can be observed from the outside, and internal degrees of freedom can be indirectly concluded only from observable actions. During the motion, the internal degrees of freedom can be described as indirect influence of the environment condition. In our model, vehicle agents will leave those intersection nodes with a high density in order to avoid congestion. With a multi-objectives optimization perspective, we used two objectives of shortest routing and congestion avoidance. The internal degree of freedom can be reflected by dynamics of vehicle agents' decisions on next movement. For the entire network, vehicle agents clustered in one intersection node would lead to a density increasing, causing other vehicle agents to skip this intersection to find another path, through which to alleviate the network congestion.

Emergence. Different moving strategies would lead to a different congestion distribution. Even with the same strategy, the distribution would show some features.

Adaptation. Vehicle agents would make their moving decisions based on the attributes (a combination influence of shortest path and congestion avoidance) of location nodes. Vehicle agents behaviors would lead to the network congestion changed. Such a feedback between vehicle agents and the network state generates agent's adaption.

Objectives. The objective of the model is to alleviate the entire network congestion. The congestion of each intersection node is measured by the density of vehicle agents. And, the congestion of the entire network is estimated by the density distribution of the whole network.

Stochasticity. When vehicle agents moves in the road-network, its source and destination intersection node, and the time step when the vehicle agent put into the network are randomly generated. For the calculation of next jump, a Gaussian random number is employed to simulate the stochastic behaviors during such process.

Observation. The data collected from the agent-based model are the time consumption when a vehicle arrives at the destination intersection and the dynamics of vehicles density at each location node during the entire simulation.

Road-Network description. We define the attributes U_x of a intersection node in the following:

$$U_x = preA(r,t)desiG(r,t) \tag{1}$$

Where *preA(r, t)* represents the constant influence on intersection node *r* with time *t*, *desiG(r, t)* denotes the influence of local vehicle density of the intersection node. At an initial stage, we set the value of *preA(r, t)* as 1 to simplify the experiments.

According to the statistical data from the internet, the numbers of vehicles through an intersection varied in time, average numbers were 28 or 29 cars per one minute. Therefore, we define the vehicle density as follows: if the number of vehicle agents is greater than or equal to 28, the density is set to 1; otherwise the density is computed as the vehicle number plus one divided by 28.

2.5 Initialization

At the initial stage, The road-network topology is show in Fig.2, the nodes distribution were same with the network in [12].

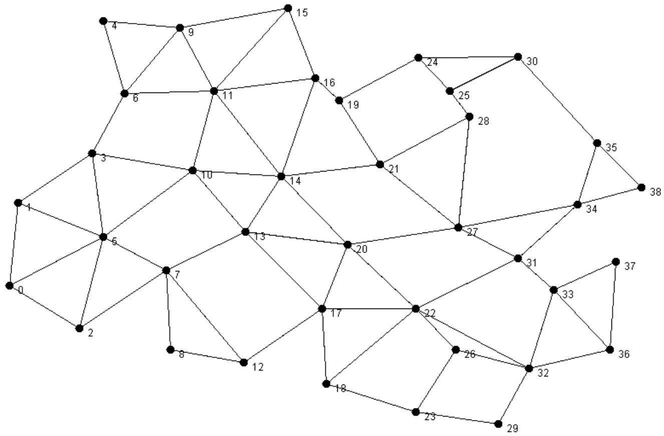

Fig. 2. The Road-Network Topology of the Simulation

2.6 Sub Models

The sub model is agent mobile model, introduced by equation (2):

$$\frac{dx_i}{dt} = v_i, \quad m\frac{dv_i}{dt} = -\gamma_0 v_i - \frac{\partial U(x)}{\partial x}\Big|_{x_i} + \sqrt{2k_B T\gamma_0}\,\xi_i(t) \tag{2}$$

Equation (2) was another type of Langevin equation within external potential. In our model, we did not consider the friction factor γ_0. $\frac{\partial U(x)}{\partial x}$ was regarded as the environment factor at location. $\sqrt{2k_B T\gamma_0}\,\xi_i(t)$ was the Gaussian random disturbance. We set a fitness function involves two objectives as in Equation (3). Where Λ represents a utility value of adjacent intersection node. Vehicle agents would choose the intersection node with minimum value as next jump. The first term $f\ (U_x)$ of Equation (3) denotes the attributes of the adjacent node. The second term $g(x)$ represents the restraint of the agent, that is, agents should always move towards destination mode. The parameter λ is used to balance the two objectives (shortest path and congestion avoidance). In order to retain certain randomness of the motion, we add Gaussian random number into the utility function and obtained equation (3).

$$\Lambda(U_x, \lambda) = (1-\lambda) f(U_x) + \lambda g(x) + Gaussian \tag{3}$$

3 Experimental Setup and Result Discussion

3.1 Experimental Setup

Given the network topology in Fig.2, the simulation model randomly generated 500 vehicle agents, which were put into the network during the first 50 simulation steps. Each vehicle agent is assigned its source and destination random. For a robust result, each simulation was executed 50 times and the average value was obtained as the final result.

There are two types of vehicle agents defined in our model:

1. In the first type, agents directly used the shortest path of travel in the network. At each simulation step, agents select the intersection node with the shortest path to the destination. We use Floyd Shortest Path algorithm to calculate the shortest path, so we give the name of this type as Floyd Agent.
2. Of the second type, agents move or choose the next movement intersection mode based on the multi-objective utility function (3). We define such type as Mix Agent.

To simplify the experiments, we made the following additional restrictions: each intersection node only allowed one vehicle agent to go through at one simulation step. When vehicles lined up at one intersection node, the simulation model would select the vehicle node at the top of the waiting queue.

3.2 Experimental Result and Discussion

In order to examine the efficiency of our proposed model and algorithms, we summarized the methods of simulation experiments in Table (3).

Table 3. Experimental Descriptions

Group No.	Description	Measurements
Group 1	The effect of λ on network congestion with fixed agent occupation	The average arrival time of agents
		The average vehicle density of 39 intersection nodes
		The density distribution at one simulation step
Group 2	The effect of agent occupation on network congestion with fixed λ	The average time cost and average node density of road-network

The first group of experiments was executed to examine the effect of λ on network congestion with fixed agent occupation. We measured the system performance based on the average arrival time of agents, the average vehicle density of 39 intersections nodes, and the density distribution a one simulation step. In this series of simulations, we set two groups of vehicle agents: the first group has all agents with Shortest Path Strategy, while in the second group the agents with Floyd Strategy or Mix Strategy occupied a 50% rate, respectively.

In the first step of group 1, we tried to find out the effects of different strategies on the agents. Figure 3-5 showed the results of average arrival time under different experimental settings of experiments group 1 in Table (3). Figure 3 gave the average arrival time of Floyd agents with effect of Mix agents, figure 4 showed the average arrival time of Mix agents with the effect of weight(λ), Fig.5 showed the relationship between arrival time cost of Mix agents and the weight.

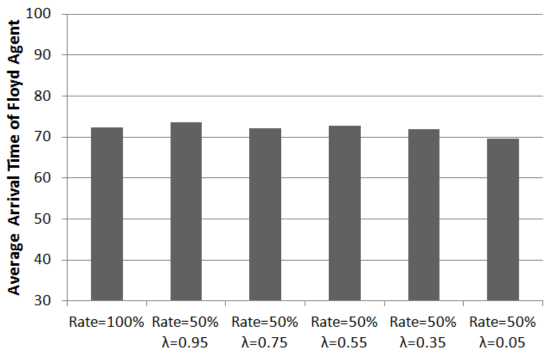

Fig. 3. The Effects of Mix Agents with Different Weight on Floyd Agents

In Fig.3, the *x*-axis represented a set of situations distinguished by agent proportion (rate) and weights (λ) of the agents with the shortest path strategy; the y-axis denoted the average arrival time of the Floyd agents, described by simulation steps. The first column of the figure showed the average time step when all the agents were Floyd agents and they arrived the destination. The second column gave the average time step when Floyd agents and Mix agents respectively occupied a half rate, the weight (λ) was assigned value 0.95. The rest columns of Figure 3 ranged the weight from 0.75 to 0.05. Based on the results, we found that the average time steps of Floyd agents were in the scale of (60, 80), no matter the various weight of Mix agents. The results indicated that the changes of Mix agents had little effect on the average arrival time of Floyd agent.

In Fig.4, the *x*-axis represented 50 simluation trials by three different weight of Mix agent, the y-axis denoted the average arrival time of agents, described by simulation steps. Compared the simulation results with the results of Floyd agents in Fig.3, we found that the average arrival time of Mix Agent is longer than Floyd Agent; and the value would be longer when the weight (λ) decreased. Based on the description of equation (3), we found these agents tended to avoid congestion. This tendency became more apparent when the weight was getting smaller.

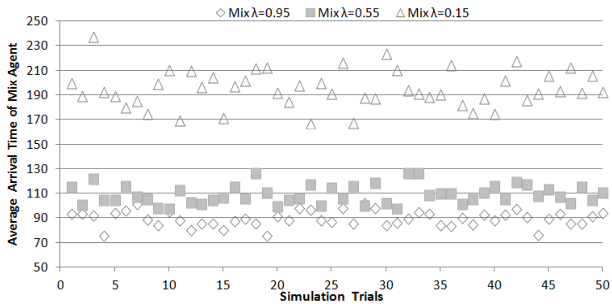

Fig. 4. Average Arrival Time of the 50% Mix Agents in the Network with Different Weight

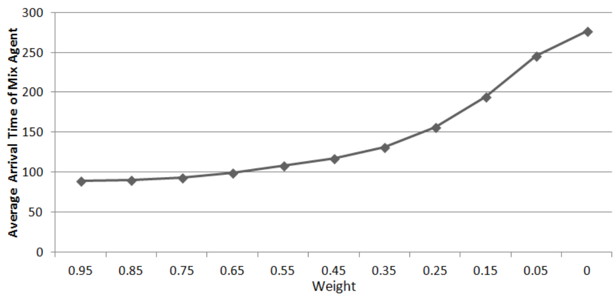

Fig. 5. Average Arrival Time of Mix Agent with Different Weight

In Fig.5, the *x*-axis represented the different weights, the y-axis denoted the average arrival time of the Mix Agents, described by simulation steps. The results indicated that the average arrival time of the Mix Agent would be longer when the weight was smaller. This increasing tendency represented in Fig.5 became greater when the weight was set below 0.35.

In the second step of group 1, we studied the effect of Mix Agent to the network congestion. We analyzed the feasibility of improving the network congestion by multi-objective algorithm with Brownian Agent. Fig.6-7 showed the results of congestion improvements under different experimental settings of experiments group 1 in Table (3).

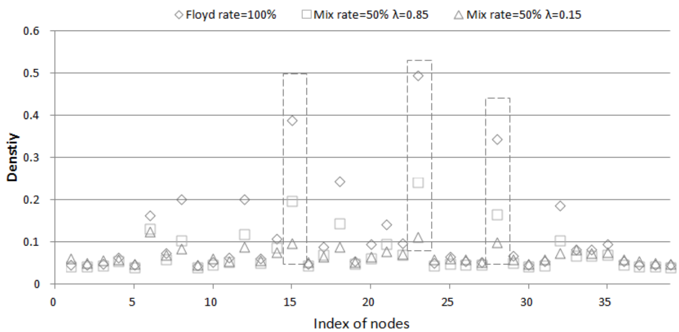

Fig. 6. Density of 39 nodes of the Network

In Fig.6, x-axis represented the index of 39 nodes, and y-axis represented the average density of the 39 nodes. The calculation of density was defined in Section 2. The three kinds of splashes denoted the density of agents in the network with three types of moving strategies as the complete shortest path strategy, the Floyd and Mix agent occupied a 50% rate respectively with different weight values as 0.85, 0.15. From the results, we found that the entire network congestion decreased obviously when the weight of Mix Agent decreased. The results could be observed distinguished among those nodes selected by the rectangles. Because Mix Agent were more inclined to avoid congestion node when the weights decreased according to equation (3), thus the average density of the network nodes was significantly decreased.

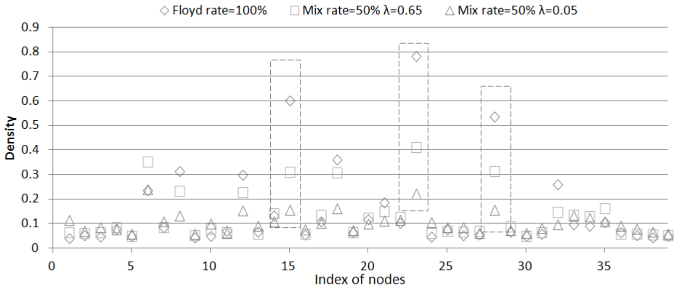

Fig. 7. Density of 39 Intersection Nodes at Time Step 49

Fig.7 gave the density distribution of the network node at one selected simulation step. By sorting the density distribution of 100% Floyd Agents, we found that the time step 49 held the most serious congestion during the whole simulation process. Therefore, we picked up this single time step to verify the feasibility of Mix Agent to improve the congestion of the entire network. Based on the results shown in Fig.7, we found that the congestion of the intersection nodes selected by the rectangles had been notably improved.

According to the results of experiments described in Table (3), we could conclude that the Mix Agents using the multi-objective algorithm would greatly alleviate the congestion of the special intersession nodes and the entire network. Meanwhile because of the shunt in the congestion intersection node, Mix Agents arrival time may be increased.

In the second group of experiments described in Table (3), we tried to found the effects of agents' proportions on the simulation results. The parameters were set as follows: the weight of Mix Agents was 0.35, the occupation rates of two types of agents were set to 25%: 75%, 75%: 25%. Fig.7-8 showed the simulation results changed when modifying the occupation rate.

From the results of Fig.8-9, we found that the greater the occupation rate of Mix Agent was, the smaller the network congestion became. On the other hand, the more the number of Mix Agent was, their average time steps became longer with fixed weights.

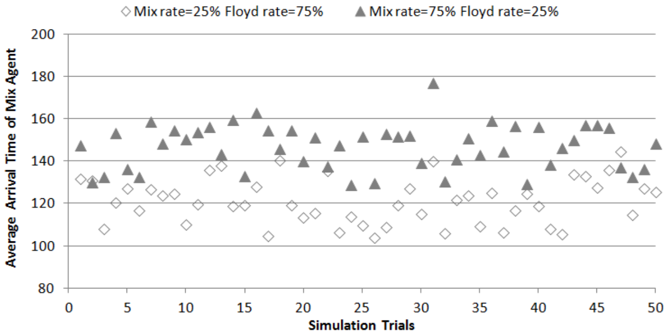

Fig. 8. Average arrival time of Mix Agent with different occupation rate

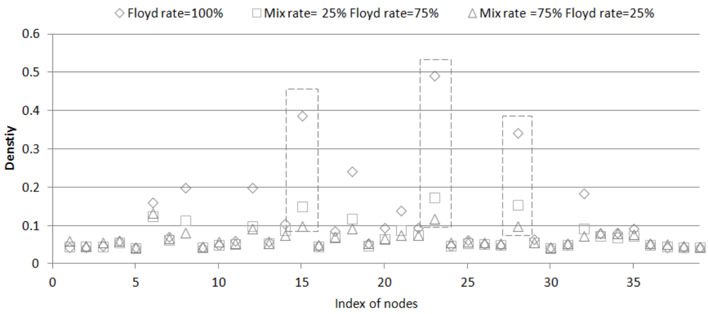

Fig. 9. Density of nodes with different Agent occupation rate

Compared with other congestion control model or algorithm, just like Chiu introduced vehicle navigation systems, which were equipped with Dynamic Route Guidance System, providing shortest distance path of given target location with a multi-objective algorithm [17]. Yoshikawa et al. proposed a hybrid genetic algorithm to solve path optimization [18]. The traditional road-network congestion optimization was focus on the route optimization. Our experiment was based on the entire network, the individual can sense the surrounding environment, from the macro point of view, improved the network congestion, the method herein used is of creativeness.

4 Conclusion

This paper proposed a new method which solved the road-network congestion problem by combining two objectives of shortest routing and congestion avoidance. By means of computer simulation, we implemented our proposed method with a predefined road-network topological structure. We tested the parameters sensitivity by scaling the proportion of agent with different moving strategies and the weights of Mix agent. The simulation results proved the applicability and efficiency of our proposed method for alleviating the network congestion distribution, and the intersections within a higher vehicle density were observed decreased.

The bigger average time consumption with Mix agent, which indicated a mix strategy by considering both effects of shortest path and congestion avoidance might result more time cost than the shortest path strategy. But the actual traffic situation is far more complicated, and the intersection waiting time consumption seems bigger than the cost of detours. Therefore, our model made its sense in its applicability and efficiency of solving road-network congestion problem by a multi-objective optimization algorithm with Brownian agent model.

5 Future Works

In the present version, our model only simulated agent movement via network nodes, while in the real transportation system, the vehicles mobile continuously and could not jump to the next intersection. In the future work, we will change agent motion in line with the actual road condition. Furthermore, other traffic effects, such as some nature impact from the intersection node itself (such as *preA* we mentioned in our equation and model in section 2) should be far more designed and implemented.

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