https://doi.org/10.26599/IJCS.2023.9100012 International Journal of Crowd Science

Crowd-Based Traffic Control Model and Simulation

Dingding Wu[1], Hongbo Sun[1] ✉, and Zhihui Li[1]

ABSTRACT

With the development of modern science and economy, congestions and accidents are brought by increasing traffics. And to improve efficiency, traffic signal based control is usually used as an effective model to alleviate congestions and to reduce accidents. However, the fixed mode of existing phase and cycle time restrains the ability to satisfy ever complex environments, which lead to a low level of efficiency. To further improve traffic efficiency, this paper proposes a crowd-based control model to adapt complex traffic environments. In this model, subjects are deemed as digital selves who can perform actions in complex traffic environments, such as vehicles and traffic lights. These digital selves have their own control processing mechanisms, properties, and behaviors. And each digital self is continuously optimizing its behaviors according to its learning ability, road conditions, and information interactions from connections with the others. Without a fixed structure, the connections are diverse and random to form a more complex traffic environment, which may be connected or disappeared at any time with continues movements. Finally, feasibility and effectiveness of the crowd-based traffic control model is demonstrated by comparison with fixed traffic signal control model, indicating that the model can alleviate traffic congestion effectively.

KEYWORDS

crowd science; traffic control model; digital self; simulation

With the development of living standards, vehicles are increasing rapidly. Although vehicles have undoubtedly brought convenience to our lives, they have also introduced traffic congestions and frequent accidents. The environment of traffic control is more complex than ever.

Existing traffic control methods usually use traffic lights at intersections. And each intersection is equipped with a fixed duration of traffic lights at alternating cycles. Although this approach can be simply implemented, it may lead to wasted time and increased traffic congestions. At the same time, heuristic traffic signal control enabled by wireless communication and sensing technology can effectively address these issues in local scope or separated intersections. However, the problem of traffic control is a global problem which needs cooperations among several related intersections in a relative large area. In this sense, the adaptive signal control emerges as an alternative solution, which has stronger adaptability and can alleviate traffic congestion through real-time dynamic coordination of traffic signal duration and cycle times at each intersection. This paper proposes a novel adaptive signal control model, crowd-based traffic control model, to further improve traffic control efficiency.

In this model, subjects are deemed as digital selves who can perform actions in complex traffic environments, such as vehicles and traffic lights. These digital selves have their own control processing mechanisms, properties, and behaviors. And each digital self is continuously optimizing its behaviors according to its learning ability, road conditions, and information interactions from connections with the others. Without a fixed structure, the connections are diverse and random to form a more complex traffic environment, which may be connected or disappeared at any time with continues movements.

This paper is organized as follows. First, this paper constructs individual components in traffic lights and vehicles as affecter, decider, executor, monitor, connector, and their respective operating mechanisms. The relationships among various members are described, mechanisms of mutual influence are introduced, and a simulation advance algorithm is designed. Then, the overall design of the crowd-based traffic control model is presented, including the meta-model of various members and the description of the crowd-based network. Finally, the simulation results demonstrate the efficiency of the proposed model.

1 Related Work

Generally speaking, adaptive signal control models usually adjust signal timing according to vehicle detections. Some researchers study traffic signal control by allowing traffic lights to extend or shorten the current phase based on the accurate position information of arriving vehicles, or to use additional phases to improve signal timing[1,2]. Beak et al.[3] proposed a two-stage optimizing control method towards arterial signals, in which with considering coordination constraints, a dynamic programming approach assigns optimal green times to each signal phase of individual intersections. Zhou et al.[4] proposed a hybrid intersection cooperative control framework to achieve unsignalized intersection cooperative control based on virtual queuing and traffic flow regulation. However, the information obtained by these methods are not always accurate for the dynamic essence of traffic flows.

An improvement of adaptive signal control is the Internet of Vehicles, which makes full use of information from networked vehicles. The concept of the Internet of Vehicles appears at the first Association for Computing Machinery (ACM) International Workshop on Vehicle Ad Hoc Networks[5]. Rakha and Kamalanathsharma[6] proposed an economical driving strategy based on signal control in the context of the Internet of Vehicles,

1 School of Computer and Control Engineering, Yantai University, Yantai 264005, China
Address correspondence to Hongbo Sun, hsun@ytu.edu.cn

which uses an emission model to describe fuel consumption during driving. The model takes vehicle speed as a decision variable to minimize the fuel consumption. Ala et al.[7] and Wan et al.[8] established an intersection vehicle speed control model to optimize vehicle trajectories in the Internet of Vehicles environments, which ensures economical fuel consumption for networked vehicles. Cao[9] proposed a segmented numerical intelligent optimization algorithm of traffic green wave, which can control continuous intersections with a stable traffic flow but a changing one. Song et al.[10] built a signal collaborative optimization model to improve the utilization of space-time resources at intersections. Xu et al.[11] and Touhbi et al.[12] collected road data, and quantified complex traffic scenes into states by dividing intersections into grids. Feng et al.[13] proposed a real-time adaptive signal phase allocation method and established a two-layer optimization model with minimal delay time and queue length on the Internet of Vehicles environment. This two-layer model optimizes phase sequence of one intersection, but cannot be applied to multi-intersections. Zhou[14] built a simulation based on TransModeler, and proposed a single intersection adaptive control algorithm. Simulation results show that this algorithm can effectively reduce the delay time and queue length of vehicle. In a word, existing adaptive traffic control models in the Internet of Vehicles environment pay more attention to homogeneous collaborations among vehicles than heterogeneous collaborations among vehicles and traffic lights.

The crowd-based traffic control model proposed in this paper combines adaptive traffic control methods with data-driven approaches. In this model, heterogeneous subjects are all deemed as digital selves who can perform actions in complex traffic environments, such as vehicles and traffic lights. These digital selves have their own control processing mechanisms, properties, and behaviors. And each digital self is continuously optimizing its behaviors according to its learning ability, road conditions, and information interactions from connections with the others.

2 Implementation

2.1 Traffic light model

(1) Pattern

As shown in Fig. 1, the traffic light model follows a single-step binomial pattern, which represents the behavior choices of traffic lights. Nodes represent the state of traffic lights, including red or green light states. When a traffic light is red, no vehicles can go straight or turn left. When a traffic light is green, vehicles can choose to go straight, turn right, or turn left according to their decisions. Arcs represent the behavior of a traffic light changing its state.

(2) Affecter

In this traffic light model, traffic light members record the location information of vehicles in adjacent sections in real-time and count the number of vehicles in those sections.

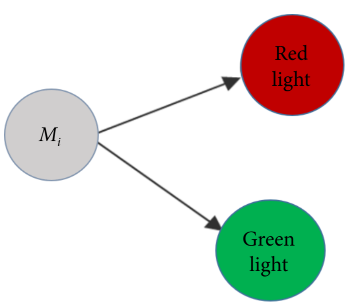

Fig. 1 Traffic light pattern diagram.

If there is a traffic accident on the current road, traffic police can intervene directly on the affecter and temporarily take control of the traffic command system. The direction of traffic flow is determined subjectively by the traffic police based on current road conditions. The adviser's suggestion information obtained by the affecter is the command information of the traffic police, which is executed by the affecter on the executor.

(3) Decider

As shown in Fig. 2, a signal node represents a set of traffic lights, specifically four traffic lights in four directions. For example, at a four-way intersection, the traffic light system at each intersection has four different roads: W, E, S, and N. In this paper, these four sections represent only entrance lanes, while the exit lanes are represented by entrance lanes at the next intersection.

The decision of the decider aims at maximizing the traffic capacity of the intersection. The calculation formula for traffic capacity is as follows:

$$Q_i = \sum_{j=1}^{M_i}\left[\frac{1}{T_i}\left(W_{j,i}\sum_{k=1}^{N_i}\psi_{k,j,i}\pounds_{k,i}\right)\right] \tag{1}$$

where Q_i is the capacity of intersection i; M_i is the number of lanes; N_i is the signal phase of intersection i; $\psi_{k,j,i}$ is the coefficient, when the number of lanes has the right of way at phase N in intersection i, $\psi_{k,j,i}=1$, otherwise, $\psi_{k,j,i}=0$; $\pounds_{k,i}$ is the effective time of phase N in intersection i; $W_{j,i}$ is the saturation flow rate of lane group M in intersection i; and $T_i=\sum_{f=1}^{N_i}\pounds_{i,f}+Y_f+R_f$ is the cycle time of intersection i, where Y_f is the duration of the yellow light and R_f is the duration of the red light.

(4) Executor

The executor executes commands from the decider, such as determining the duration of traffic lights for each phase and setting the length of yellow light steps. In the traffic light model, the executor does not exhibit self-degradation or mutation behavior.

(5) Monitor

Since the executor does not exhibit self-degradation, the monitor of traffic light members does not work.

(6) Connector

As shown in Fig. 3, each member of the traffic light model is connected not only to its adjacent members but also to other non-adjacent members. By interacting with other members, this model can obtain information about road conditions of other traffic

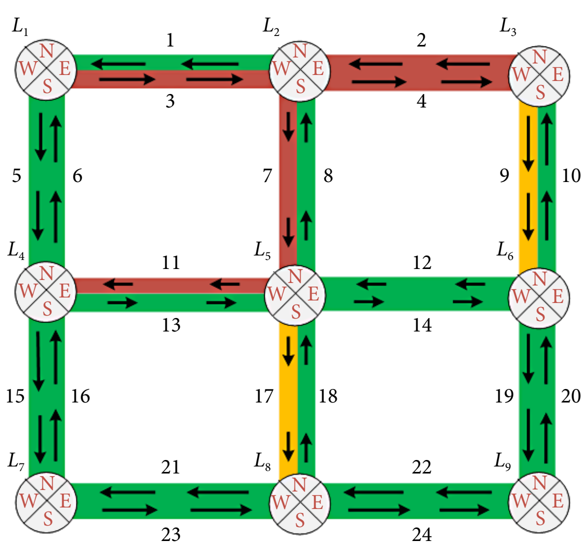

Fig. 2 Traffic light pattern diagram.

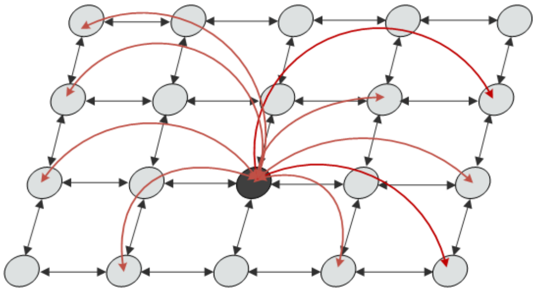

Fig. 3 Schematic diagram of traffic light connector.

lights and integrate this information to allocate the phase duration of traffic lights at the current location. The information obtained by the connector is fed back to the decision of the next round of traffic lights as an important reference. The final decision is made by the decider based on the self-inclination, ability, and resource condition.

2.2 Vehicle model

(1) Pattern

In this paper, road traffic information is represented as a grid pattern. This pattern is a directed graph arranged based on road information, which represents all possible behaviors when vehicles make decisions. As shown in Fig. 4, each node represents the state of the member (the current location of the vehicle), and arcs among nodes indicate the behavior of members (the direction chosen by the vehicle).

(2) Affecter

As shown in Fig. 5, vehicle members in the network are connected to each other and share real-time location information within their immediate area. Additionally, the adviser members (navigation systems) provide guidance for vehicle members. Vehicle members also have the ability to subjectively choose which adviser to use.

(3) Decider

The decider makes decisions based on their own reasons and resource situation. The higher the self-confidence level of the decider, the more inclined to their own decision behavior. Specifically, the decider makes decisions based on the current traffic light indications and the status of the road ahead. First, the decision result follows the decider's own opinion, the larger the self-inclination value, the more inclined to their own decision behavior. Second, the decider tends to choose a decision that avoids congested roads ahead. The self-inclination value is determined as follows:

$$\text{Inclination} = \frac{f_i \cos \alpha_z \cos |\alpha_e - \alpha_f|}{e_i} \tag{2}$$

where f_i represents the information vector strength, α_z represents the correlation between the information vector and the vector area, α_e represents the preference range of simulation members, and α_f represents the preference range of information.

As shown in Fig. 6, $f_i \cos \alpha_z$ is used to calculate the projection of the information vector onto the current decision domain. $f_i \cos \alpha_z \cos |\alpha_e - \alpha_f|$ calculates the projection of the above projection perpendicular to the inclination vector e. e_i represents inclination intensity. If the inclination is greater than zero, it means that the self-inclination value is large and follows the member's own decision behavior.

When the decider makes a decision, it is influenced by the advice from the adviser and the historical optimal decisions of other members, which are obtained through the connector. The decider compares self-inclination, influence coefficient, learning ability, and self-confidence level to determine which option to choose.

(4) Executor

The executor executes the decision result of the decider and chooses a behavior route based on the decision. The executor has the self-degradation phenomenon, which always tends to the route with the lowest cost. At the same time, there is also a mutation phenomenon during the execution of the executor, and the direction of the mutation is uncertain.

(5) Monitor

The monitor monitors the execution results of the executor, which is a self-correcting process. For the execution behavior that deviates from the decider, the monitor will try to pull back the

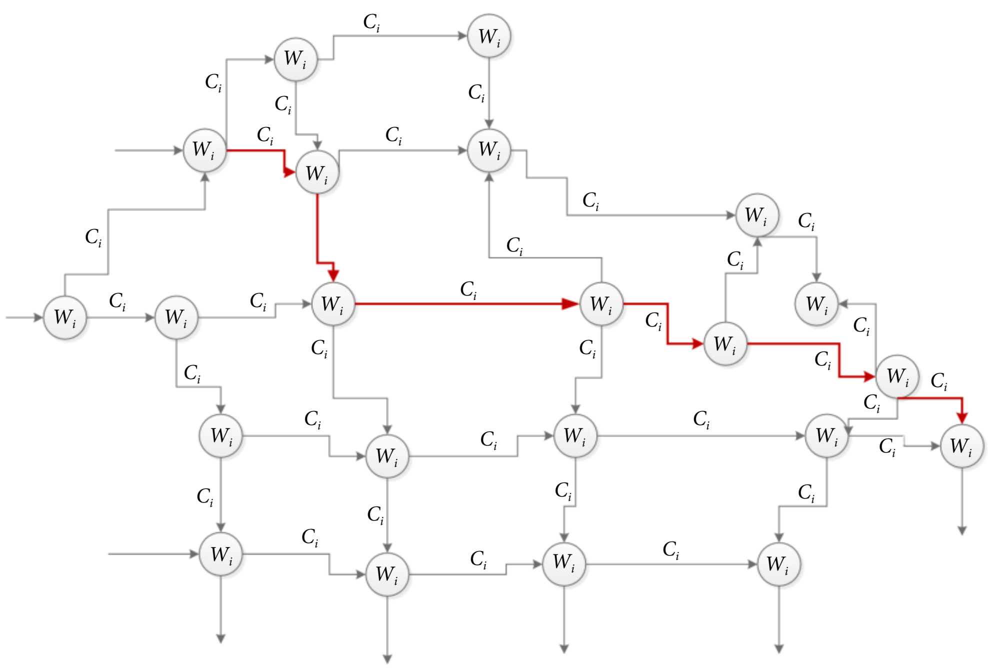

Fig. 4 Schematic diagram of the vehicle pattern.

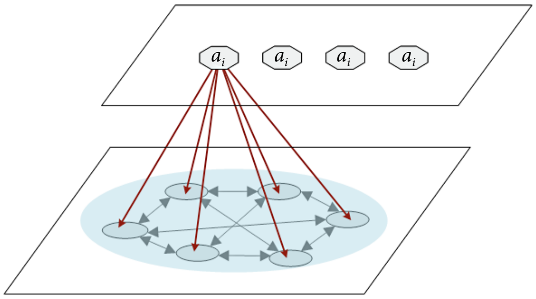

Fig. 5 Schematic diagram of the vehicle member affecter.

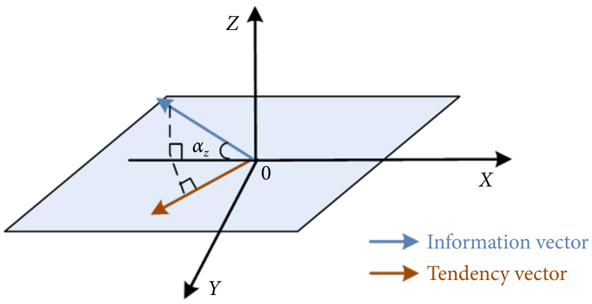

Fig. 6 Propensity vector and information vector relationship representation diagram.

decision of the decider.

(6) Connector

As shown in Fig. 7, the shaded area represents connections among members within a region. The central node represents the current vehicle member model, which is connected to other vehicles and obtains position information from each other. This position information is used to determine the basic conditions of the current roadway and to learn about the historical optimal decisions of other members, which provide a reference for the decider.

2.3 Simulation advancement model

2.3.1 Simulation advancement

During the entire simulation process, members such as traffic lights and vehicles continuously make judgments and decisions based on their own behavioral algorithms. Traffic lights adjust the cycle of signal steps and step length according to current road congestion. At the same time, they also optimize their signal steps cycle by referring to the status and change period of traffic lights at adjacent intersections. Vehicles have a self-confidence level and can learn from the decisions of other vehicle members to determine whether to choose the fastest route through the current intersection or the shortest route to their destination. The simulation process is described as follows:

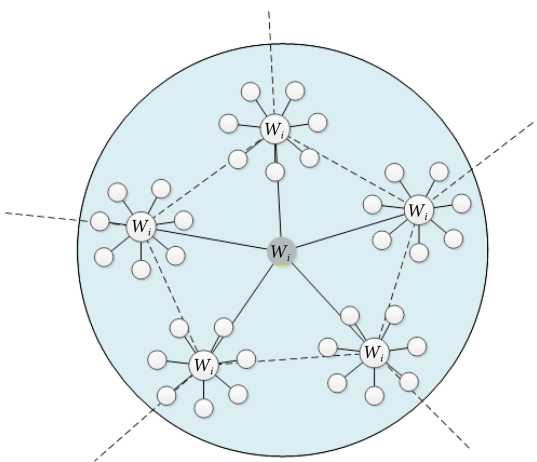

Fig. 7 Schematic diagram of the vehicle member connector.

First, w vehicle member models and n traffic light member models should be generated. Second, during the simulation advancement, when vehicle models reach an intersection, they determine whether to go straight, turn left, or turn right based on their self-confidence level, affect intensity, and learning ability. Vehicle models must update their location information every time they take a step, and their decisions to go straight, turn left, or turn right at the next intersection should be modified based on their current position information. The initial state location information and initial state destination information of vehicles entering the road network are both randomly distributed.

(1) Based on self-confidence level: First, determine whether the maximum throughput has been reached in the intersection at this time. If it has not been reached, vehicles can pass; otherwise, they must wait.

Second, if the self-inclination value is greater than zero, the decision of inclination will be implemented directly. Otherwise, vehicles will tend towards smoother road.

Third, according to the road direction select in the second step, comprehensively judge the state of traffic lights and the deviations of the destination, and make the final choice.

(2) Based on the suggestion of the adviser: Select a route according to the adviser's instructions. If the vehicle deviates from the indicated route, the adviser will replan the route based on the vehicle's current location.

(3) Based on the optimal decision learned by the connector: Each vehicle has location information, establishes contact with other vehicles within the same or adjacent road, and learns their decisions.

(4) Arrive at destination and update data: The complex traffic light system is connected through the network to adjust overall traffic lights from a macro perspective, which can improve road traffic efficiency more scientifically and efficiently.

2.3.2 Advance algorithm

Using the previously designed member meta-model, this section presents algorithms for the advancement model, as shown in Algorithms 1–8.

3 Crowd-Based Traffic Control Model

3.1 General digital selves

3.1.1 Digital selves

In this paper, subjects are considered as digital selves that can perform actions in complex traffic environments, such as vehicles and traffic lights. All of the members' behavior and decisions may be described as the pattern. As shown in Fig. 8, the member model consists of the affecter, decider, executor, monitor, and connector.

The affecter collects suggestions from multiple advisers to influence the decision process. The affecter of each member can realize wireless communication to exchange information and decisions.

The decider takes into current resource conditions, capabilities, and tendencies to make decisions.

The executor performs actions based on decisions made by the

Algorithm 1 Pattern

Input: number of vehicle members num_c
number of traffic light members num_t
start node
end node
output: pattern, {CL}
Begin
  foreach (NUM, begin node, end node)
  Start at starting node and end at termination of the node, num_c, and num_t nodes are generated
  Set the ID for each node
  Assign weights to each node, weight_edge
  Records the edges between adjacent nodes and assign weights to the edges, weight_edge
  Generates a list of node adjacencies, {CL}
  End foreach
End

Algorithm 2 Vehicle-affecter

Input: simulation members ID
the adviser list {SL}
Output: suggestion
Begin
  select SL in {SL}
  select mode in SL
  mode = shortest_time/shortest_distance/shortest_spend
  suggestion ← mode
return suggestion
End

decider and the advice provided by the affecter.

The monitor corrects deviations according to specific goals, which have a self-discipline level to represent the self-correction ability of crowd members.

The connector connects with other related members, learns from their behavior, and provides reference opinions for the decider. The connector takes the current decision as a feedback result and acts on the next decision.

3.1.2 Crowd network model

As shown in Fig. 9, the crowd network relationship of simulation members is represented as upper and lower layers.

The lower layer represents connections among vehicle model members. In Fig. 9, vehicle members within the shaded area are connected to each other. Shaded overlapping areas in Fig. 9 indicate that these members are connected to both other vehicle members in this area and to other vehicle members in another area. In addition, some advisers influence members' decisions, and members subjectively choose which advisers to connect with.

The upper layer represents connections among traffic light models. Traffic lights within the area are connected to each other through a complex network, which can collect road condition information of adjacent or other roads, and provide feedback to the decider to make more reasonable traffic light instructions. Traffic light and vehicle models have a many-to-many relationship.

Algorithm 3 Vehicle-decider

Input: self-confidence level
inclination
traffic lights ID
influence
learn ability
pattern
Output: decision order of the decider OD
Begin
  Judge the current intersection situation (traffic jams/congestion/unblocked)
  if condition == unblocked **then**
    order = go;
  else if condition == congestion **then**
    order = go;
  else if condition == unblocked **then**
    order = no;
  end if;
  if remote **then**
    order = other road;
  end if
  OD ← max (self-confidence level, influence, learn ability)
  if inclination > 0
    OD = inclination;
return OD
End

Algorithm 4 Vehicle-executor

Input: decision commands generated by decider algorithms OD
mutation probability m
monitoring intensity E_m
self-degradation level s
Output: none
Begin
  execute ← OD
  execute = $m \times s \times E_m$
  Update vehicle.direction and trafficLight.condition
End

Algorithm 5 Vehicle-monitor

Input: monitor collection list {ML}
Output: monitoring intensity E_m
Begin
  foreach ML in {ML} **then**
  E_m += ML ()
  end foreach
  return E_m := random({E_m });
End

Algorithm 6 Vehicle-connector

Input: list of members within the local area {CL}

Output: learnDecision

```
Begin
    foreach CL in {CL} then optimal decision of selecting member in the local area;
    learnDecision ← optimal decision
    end foreach
return learnDecision
End
```

Algorithm 7 Decider for traffic light

Input: traffic lights ID

adjacent member list {CL}

pattern

Output: decider's decision order OD

```
Begin
    foreach road in (trafficLight.e, trafficLight.s, trafficLight.w, trafficLight.n) then
        if sum_vehicle > maxThroughput then
            road.condition = trafficJams;
        else if 0.8 × maxThroughput < sum_vehicle < maxThroughput then
            road.condition = congestion;
        else if sum_vehicle < 0.8 × maxThroughput then
            road.condition = unblocked;
        end if
        setLightTime({CL}, sum_vehicle, road.condition)
        redLight.time = newRedTime;
        greenlight.time = newGreenTime;
    end foreach
return OD
End
```

Algorithm 8 Connector for traffic light

Input: list of members within the local area {CL}

Output: adjacent member information set {IL}

```
Begin
    foreach CL in {CL} then
        IL.ID ← traffic Light.ID
        IL.condition ← trafficLight.road.condition
    end foreach
return {IL}
End
```

3.1.3 Adviser model

In this crowd-based traffic control model, traffic light members do not receive advice from advisers because the connector can directly obtain the status information of other adjacent members. This information provides a basis for making reasonable decisions. For vehicle members, the adviser is the vehicle navigation system.

Vehicle members choose different navigation schemes according to their needs (the shortest distance, the shortest time, and the lowest charge). Specifically, after the adviser accepts the member's self-inclination and starting or current location, it uses these conditions to provide the most optimal path planning for members.

As shown in Fig. 10, vehicle members choose different solutions, and the adviser will provide different suggestions accordingly. In Fig. 10, the red path represents the globally optimal route, the yellow path represents the nearest route, the green path represents the shortest time route, and the blue path represents the route with the lowest charging cost.

4 Case Study

4.1 Simulation process

Based on the above simulation design, a simulation example is run to verify the efficiency of the crowd-based traffic control model.

As shown in Fig. 11, the simulation begins by inputting initial data such as the total number of simulation steps, the number of vehicle members, and the number of traffic lights. Next, generate the initial values of various members and their attributes, construct the road network, and establish connections among members. During the simulation, all traffic lights dynamically update road conditions and communicate with adjacent traffic lights to monitor the layout of nearby vehicles. According to the maximum number of vehicles, judge whether allow vehicles to pass. When a vehicle updates its location information in the simulation, which means that it has passed a road section, and the traffic light passing count on that section is increased by one. When all vehicle members arrive their destination, simulation data and experimental results are recorded, and the simulation is ended.

4.2 Simulation result

In the following section, we use three indicators to compare the performance of the crowd-based traffic control model with an existing traffic control model: average number of queues at intersections, average throughput at intersections, and average delay time of vehicles. In order to show the comparison results clearly, this paper set up a simulation comparison chart with 60 time slices as a simulation step. The orange curves in Figs. 12–14 represent the control algorithm of the existing traffic control model, which has a fixed cycle time of 100 s. The green light duration for the first to fourth phases is 35 s, 15 s, 35 s, and 15 s, respectively, and the yellow light duration for each phase is set to 2 s. The blue curve represents the control algorithm of the crowd-based traffic control model. The maximum phase cut-off time is 60 s, and the minimum phase maintenance time is 10 s.

(1) Average number of queues at intersections

As shown in Fig. 12, the orange curve represents the performance of the existing traffic control model, which uses fixed traffic signal cycles and fixed green signal ratios. The experimental results show that, with the simulation progresses, the number of vehicle members queues increases rapidly, which aggravates road congestion. When congestion reaches its limit, vehicles are unable to continue passing without the intervention of traffic police. As a result, the average number of queues remains at a very high level and fluctuates slowly, unable to self-clear.

In contrast, the blue curve represents the crowd-based traffic control model, which the number of vehicle members queue grows slowly. Over time, through the self-adjustment of the traffic

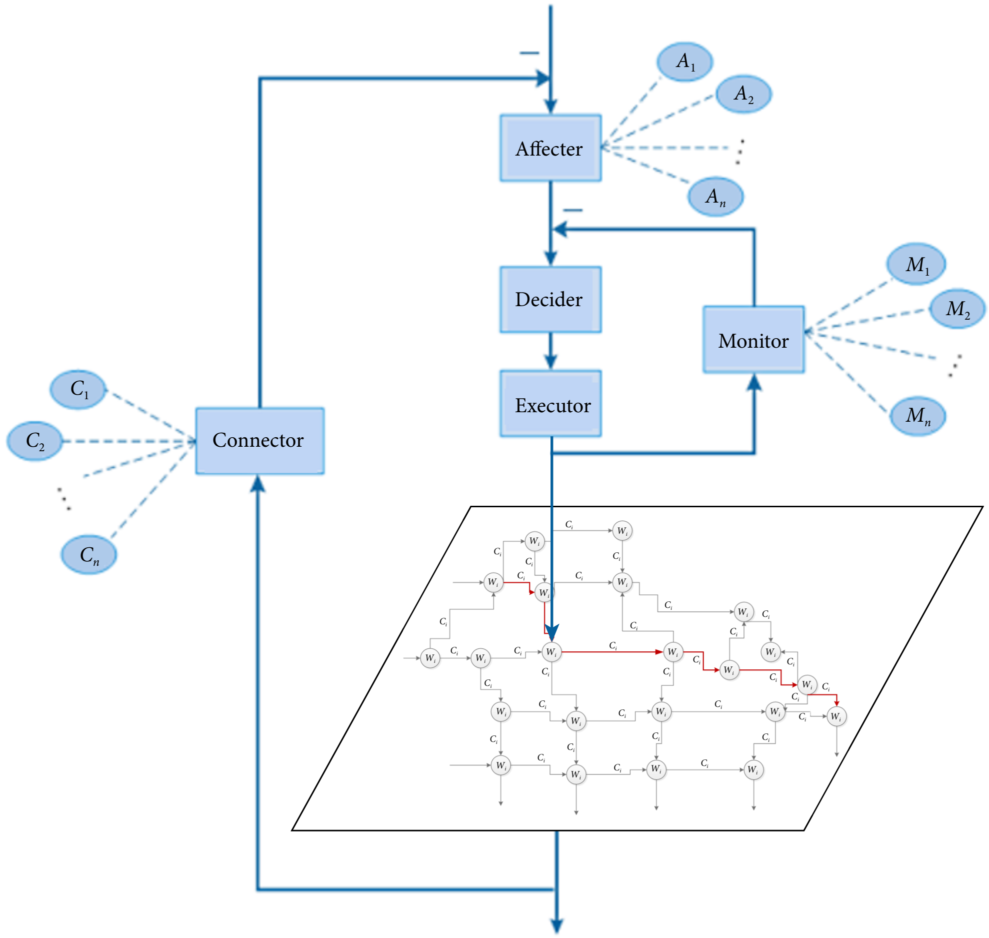

Fig. 8 Crowd intelligence member meta model.

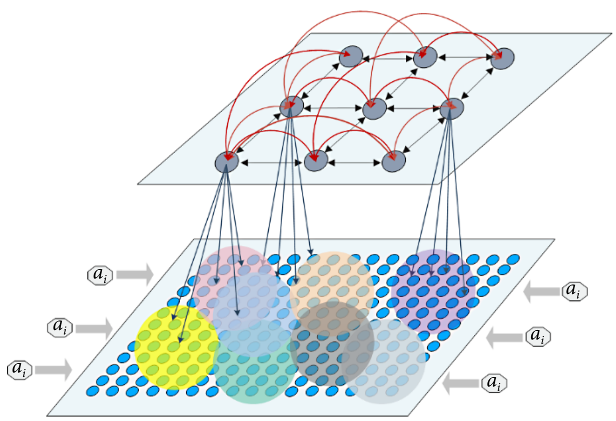

Fig. 9 Crowd network model.

light member model and the optimal selection of the vehicle model, traffic conditions are finally improved.

(2) Average throughput at intersections

As shown in Fig. 13, the average throughput at intersections for both modes increase rapidly and soon reaches a peak, which is accompanied by traffic congestion. As congestion increases, the throughput at intersections begins to decline rapidly. The key difference is that members of the crowd-based traffic control model coordinate and self-adjust with each other. Traffic light members share information with adjacent traffic lights through connectors, monitor road conditions in real-time, adjust their phase length, and guide vehicles to avoid congestion as much as possible. As a result, traffic flow in the crowd-based traffic control model remains stable at a high level, while traffic flow in the existing fixed-cycle model is significantly lower.

(3) Average delay time of vehicles

As shown in Fig. 14, with the experiment progresses, the existing fixed phase and periodic traffic control model cause the average vehicle delay time increases rapidly at the beginning, and soon reaches a high state. In contrast, although there is a rapid growth trend in the crowd-based traffic control model, the average delay time of vehicles is reduced under its adjustment, which demonstrates that traffic congestion has been effectively improved.

5 Conclusion

Although vehicles have brought convenience to our lives, they have also introduced traffic congestions and frequent accidents. The environment of traffic control is more complex than ever. This paper proposes a crowd-based traffic control model to alleviate traffic congestion and improve traffic efficiency. Compared with existing adaptive traffic control models in the Internet of Vehicles environment, the crowd-based traffic control model pays more attention to heterogeneous collaborations among vehicle and traffic light members. In this model, heterogeneous subjects are all deemed as digital selves who can perform actions in complex traffic environments, such as vehicles and traffic lights. These digital selves have their own control processing mechanisms, properties, and behaviors. And each digital self is continuously optimizing its behaviors according to its learning ability, road conditions, and information interactions from connections with the others. Finally, the simulation results demonstrate the efficiency of the proposed model.

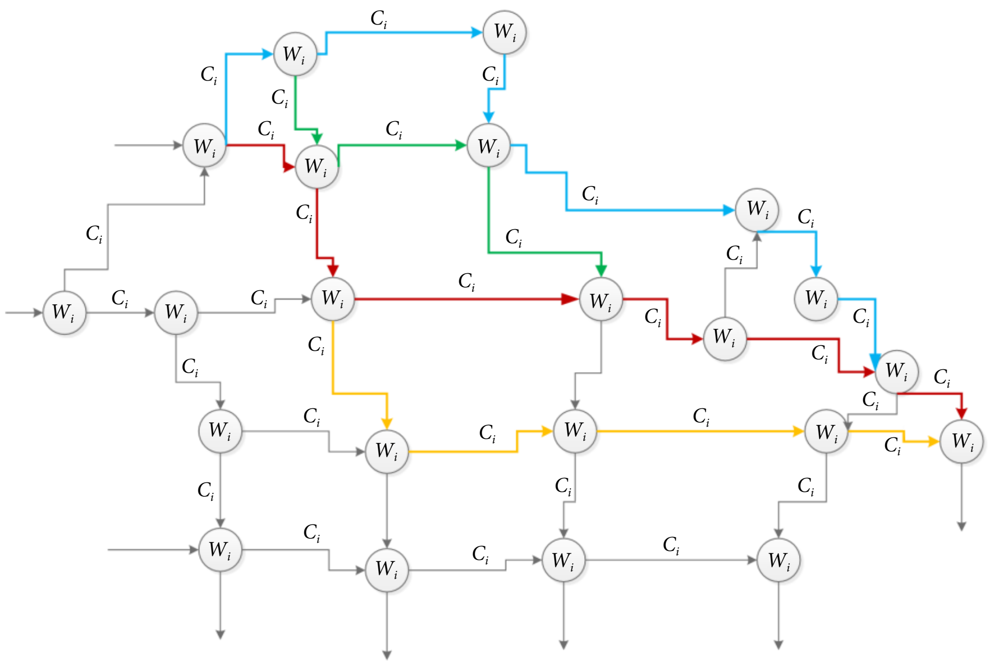

Fig. 10 Diagram of the route suggested by the vehicle member proponent.

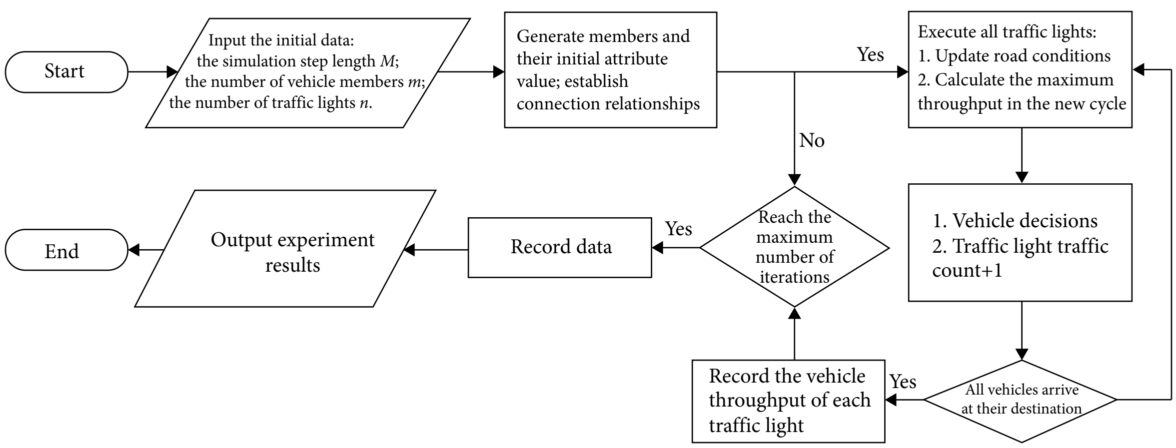

Fig. 11 Crowd intelligence traffic simulation flowchart.

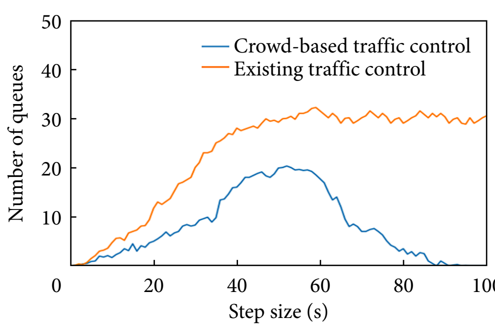

Fig. 12 Average number of queues at intersections in each step.

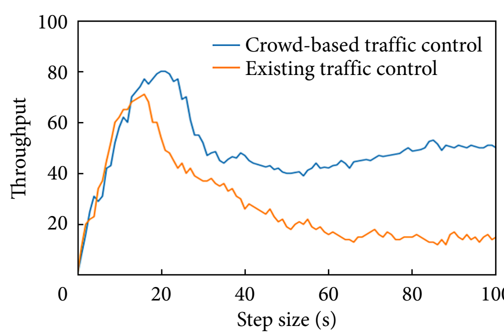

Fig. 13 Average throughput of each step at intersections.

The research in this paper only considers the relationship among vehicles and traffic lights, without considering the impact of pedestrians and non-motorized vehicles on traffic. The next step is to consider adding pedestrians and non-motorized vehicles to this model and simulation.

Dates

Received: 25 December 2022; Revised: 8 June 2023; Accepted: 14 June 2023

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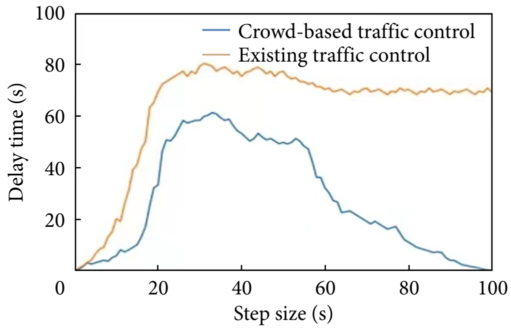

Fig. 14 Average vehicles' delay time of each step.

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