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QoS Aware Multi-Convergence Node Coordination Mechanism Based on Cellular Automata in Vehicular Sensor Networks

LUJIE ZHONG[1], SHUJIE YANG[2] AND JIEWEI CHEN[2]
[1]*Information Engineering College*
Capital Normal University
Beijing, 100048 P.R. China
[2]*State Key Laboratory of Networking and Switching Technology*
Beijing University of Posts and Telecommunications
Beijing, 100876 P.R. China

In recent years, wireless sensor networks have gradually expanded in the field of transportation. Among them, in-vehicle sensor networks, as a new generation of network technologies that have received much attention, have broad application prospects in urban road condition detection and traffic anomaly detection. In particular, vehicles with wireless communication capabilities and roadside access points (APs) are interconnected to form a new application system, the Vehicular Ad-hoc NETwork (VANET), which provides information distribution between vehicles. Services such as querying, sharing and downloading multimedia materials continue to improve the user's harsh driving environment and enrich the driving life of network users.

However, with the popularization of intelligent transportation, the Internet of Vehicles also brings some problems. For example, the high-speed movement of vehicle nodes leads to highly dynamic changes in the network topology, and the energy, storage, transmission distance and processing capability of the nodes make QoS insufficient. Aiming at these problems, we propose a multi-convergence node coordination mechanism based on cellular automata, which improves the network's perception ability by simulating the state of vehicle sensor movement in traffic flow, and adopts a heuristic algorithm considering multi-convergence nodes' capability. This method effectively solves the problems of network coverage life and QoS. Finally, we verify the effectiveness of the method through simulation.

Keywords: vehicular sensor network, QoS, cellular automaton, energy consumption, multi-convergence

1. INTRODUCTION

It is obvious that the transportation system has become an important part of human activities. With the continuous development of science and technology, especially in urban areas, the number of cars has increased year by year. However, the lack of land resources and the lag caused by the long period of infrastructure construction make the rapid growth of people's demand for automobiles and the slow construction of transportation infrastructure an inevitable contradiction. In cities, people need to move quickly from one location to another, and a variety of transportation-related problems have erupted. The common problems are the intensification of urban road traffic congestion and the frequent occurrence of traffic accidents. Traffic jams not only increase car fuel consumption, but also

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increase the risk of a heart attack for drivers [1-4]. In addition, traffic congestion delays people's time and seriously affects human activities, which can reduce a country's productivity, competitiveness and overall growth rate. The frequent occurrence of traffic accidents has greatly threatened the property and safety of the people. The emergence of intelligent transportation systems (ITS) has effectively alleviated this traffic pressure, and the accident rate has dropped significantly. ITS can predict traffic flow, reduce traffic flow delays, and further improve the advantages of traffic efficiency at intersections, thereby bringing safety and convenience to people's lives [5-10].

Since the intelligent transportation is realized based on the in-vehicle wireless sensor network, it mainly realizes the control and control of the entire traffic through the cooperation of the in-vehicle sensor and the road-based sensor. However, wireless sensors are mostly characterized by small storage, low energy consumption, and strong mobility, which form some limitations of the in-vehicle sensor network:

Discontinuities in network connections. In the actual deployment of wireless sensor networks, the high-speed movement of vehicle nodes and the existence of communication obstacles such as urban buildings and trees will cause the network topology to change frequently. At the same time, the sensor nodes that make up the network topology will increase or decrease at any time, which makes the network topology more complex and changeable. As a result, the network connection lasts for a short time and is often disconnected, and the network connectivity is poor [11, 12].

Insufficient node transmission and processing capabilities. The nodes in a wireless sensor network are generally battery-powered, and the effective power is very limited. Due to the application environment, it also makes it more difficult to replace the battery. Therefore, the storage space, transmission distance and processing capacity of nodes in WSN will be limited, which will affect the effectiveness of sensor network functions [13, 14].

Unbalanced network topology. Affected by the road topology and traffic conditions, the nodes are not balanced and have large differences at different times of the same section and between different colleagues, so that the node density frequently switches between sparse and dense states. Furthermore, there will be a large number of networks in the network, and there may be an "information island effect" in a certain period of time [15, 16].

These features greatly reduce the QoS of intelligent transportation networks, so how to effectively solve these problems is an urgent problem to be solved.

In recent years, researchers have done a lot of research on the above issues. In terms of perception, some classical algorithms have been proposed, such as TORA [17], QSDN-WISE [18], RARE [19]. Most of these algorithms or models retain the "sleep wake-up" mechanism, that is, some nodes are in working mode. Other nodes are in sleep state, saving energy. In literature [20], in order to maintain a long network life and a sufficient sensing area, the method is to turn off the excess sensor, which is one of the most widely used methods. K. Wu *et al.* also advanced a lightweight deployment-aware scheduling (LDAS) algorithm that provides new insight into network perception, which is able to shut down redundant sensors without using accurate location information. In terms of information transfer, some algorithms based on QoS transmission are proposed, for example, the suggested QoS aware Multi-Constrained Node Disjoint Multipath Routing (QMCNDMR) protocol [21] is devoted from Triangle link quality metric Multipath Routing (TIGMR) protocol. This work generates fresh insights into eliminating path interference, that is to say, it is possible to avoid path interference between paths by calculating the triangle mass, the distance remaining, and the energy, and then searching for a route through the forwarding node, and ensuring that the route is not intersected by multiple nodes.

In addition, the literature [22] proposed a CODA congestion control scheme, which takes into account both the link load and the buffer, thus enabling more effective congestion control. Furthermore, the literature [23] elaborates on the MM SPEED protocol, which optimizes both the network layer and the MAC layer, and proposes a multi-path and multi-speed routing mechanism for reliability and real-time. However, most of these studies are optimized based on a single performance. The combination of mobility and energy consumption of sensor nodes including QoS as an optimization indicator is not considered.

In response to the above problems, we propose a Dynamic-Aggregation Node Collaboration (DANC) Algorithm based on the cooperation between cellular automata and multi-convergence nodes. This method is mainly solved by the following steps:

Firstly, we use BowTie analysis method to establish a cellular automaton system based on Markov process, and simulate the position of the car sensor moving in the traffic flow, also get the speed of the mobile sensor, which lay the foundation for the synergy of the aggregation nodes that advanced later. Secondly, we use K-means cluster analysis to determine the aggregation node, then the aggregation node is abstracted as the second layer. For the node of the “second abstraction layer”, we introduce the concept of “force”, so that the data packets in the node will adaptively select the next hop node according to the attraction of “force”. Finally, the simulation results show that in the new algorithm, the data packet will bypass the load-bearing area and select the path with smaller load for data transmission. Compared with the traditional algorithm, the new algorithm makes the network consume less energy.

2. SENSOR-MOVEMENT MODEL BASED ON CELLULAR AUTOMATON

Assume that each car is equipped with a Mobile-Vehicle Sensor, and Road Sensors (ordinary nodes) are installed on each road. Data can be transferred between them via a wireless network. In this study, we did not update the network’s maximum life cycle rules by optimizing the size of the data packet. Instead, we focused our attention on the sensor itself and studied the trends of dynamic sensor node movement, such as frequency, displacement, speed, direction and *etc.* by which is expected to improve the performance of the entire network.

Cellular automata is widely used. Its advantage is that even in complex systems, discrete individuals can effectively simulate the linear evolution process through computers. In this model, we will extend the standard cellular automaton (CA). In real life, we can easily observe that the change in vehicle density on the road will not change much in the short term, but when the time dimension is expanded to the number of days, the trend of the number of cars will be more obvious, such as single and double The number limit policy, repair bridges, *etc.*, will lead to an increase in the number of cars over time; in some cases, the number of cars will decrease over time, such as the concept of energy saving and emission reduction.

In this study, we believe that the study of short-term mobile changes in wireless sensor networks is more valuable, and that at some point, vehicle changes are only affected by its previous state. Assume that the number of vehicles on the road at the time t is x, then the number of cars at the time $t+1$ is only affected by the condition of the vehicle on the road at the previous moment t. We can see the car's moving state satisfies the homogeneity. We can simulate the car movement on the road by establishing a cellular automaton model based on the weighted Markov chain. The principle is to use the Markov chain to improve the vehicle speed change mechanism, and to use the spatial and temporal parallelism of the cellular automaton to see the changes of the dynamic sensor nodes of the entire network. Meanwhile, we have considered the impact of a variety of factors as well as the cell conversion rule are more comprehensive.

2.1 Structure of the Cellular Automaton System

The whole urban transportation system is regarded as a cellular automaton system A, we take the unit floor area in the road as a cell in the system, and their collection constitutes a two-dimensional quadrilateral cell space L. Then the state set of the cell $S = \{with\ car, no\ car\}$, the elements of S are limited and discrete. Let the set of all vehicles in the neighborhood of the vehicle be N, with F being the local mapping. Then the cellular automaton system can be expressed as

$A = (L, d, S, N, F)$ where $d = 2$.

- Cell Space

The whole urban space is abstracted into an $n \times m$ square mesh structure, and each grid is divided into smaller grids according to the length of the road. Each small grid represents a cell.

- Cell State

The vehicle movement status is $\{with\ car, no\ car\}$. The letter S_c^t expresses the state of the vehicle at time t:

$S_c^t = \{1, 2\}$.

Where 1 indicates that there is a vehicle on the road, and 2 means the road is accessible.

- Cell Neighborhood

The cell neighbor relationship is the type of Moore with $r = 2$ [24].

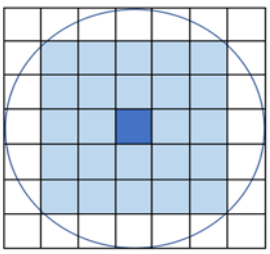

Fig. 1. Type of Moore ($r = 2$).

• Status Update Rule

The state update rule is the core part of the cellular automaton. The cell state at the next moment is affected by the state of the cell at the previous time and the set of cell states in the neighborhood. The mobile vehicle sensor can transmit data through neighbor sharing, reducing errors. Here, we combine the Markov chain to determine the state update rules, replacing the traditional probability distribution. Expressed as a mathematical formula as:

$$S_i^{t+1} = f(S_i^t, S_N^t).$$

Where S_N^t is the set of cell neighborhood states at time t, and is also the local mapping of cellular automata. Here, local mapping of two indicators needs to be determined: (1) vehicle speed update; (2) vehicle position update.

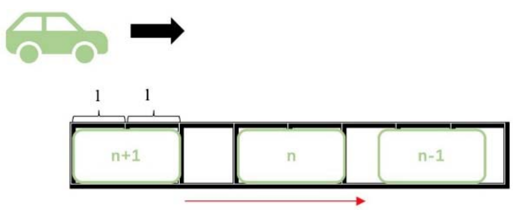

Fig. 2. Vehicle cellular automaton.

2.2 Parameter Determination

When the initial state of the cell is a car, its next state is related to the acceleration of the car

$$a = \{a > 0, a < 0\}.$$

In a short time, the acceleration of the car cannot be zero.

When the initial state of the cell is "no car", it is related to the traffic flow and the car density of the road section to determine whether there is a car near the cell.

Set in the unit time t, the average speed of the nth car v_n^t, the distance traveled by the nth car is x_n^t, h_n^t is the distance from the rear of the nth car to the rear of the previous ($n-1$)th car. The vehicle flow rate q is the number of vehicles passing through the road surface sensor per unit time T, the vehicle density ρ is the number of vehicles per unit area, and ρ_N^t indicates the density of the neighborhood of the cell at time t. From time t to time $t+1$, there are four cases of changes in the state of the cell i:

(1) As for $s_i^t = 1$,

Having a car $\rightarrow$ still having a car: The speed of the car n is so slow that it has not left the cell i; or the $n+1$ car is followed by the pace of n to occupy the cell i immediately at time t, which is expressed by the formula

$$\begin{aligned}&\text{if } x_n^t = v_n^t t \le 2r, s_i^{t+1} = 1,\\ &\text{if } h_n^t < v_{n+1}^t t, \quad s_i^{t+1} = 1.\end{aligned}$$

Having a car → with no car: the car n is away from the cell i, and the following vehicles have not been able to reach i.

$$\text{if } x_n^t = v_n^t t > 2r \ \ \& \ \ h_n^t > v_{n+1}^t t, \ s_i^{t+1} = 0$$

(2) As for $s_i^t = 0$,

No car → with a car: there is a car near the cell.

$$\text{if } \rho_N^t > c, \quad s_i^{t+1} = 1$$

Where c is a fixed value.

No car → still no car: there is no car near the cell.

$$\text{if } \rho_N^t < c, \quad s_i^{t+1} = 0$$

Suppose $P(K)_{decelerate}$ is the probability that K factor causes the car to decelerate, while $P(K)_{decelerate}$ is the probability that the K factor causes the car to accelerate. Since each impact factor is not in the same dimension, it is finally necessary to normalize to establish the state transition matrices N_{dece} and N_{acce}.

Below we stand in the driver's perspective, specifically analyze the factors that will cause changes in the speed of the car on the traffic road, and finally figure out the mapping between it and the speed of the car.

Table 1. Factors of state change.

Why the car would decelerate?	Why the car would accelerate?
Brake light up of front vehicle F_{BL}.	The road ahead is empty F_{RE}.
Meet the traffic light or intersection F_{TL}.	The vehicle ahead is accelerating F_{VA}.
Obstructions ahead F_{OB}.	Overtake F_{OV}.

We mathematically see the change in car speed as a change in acceleration:

$$a = \frac{dv}{dt}.$$

Traditional models often use V2R communication to estimate car speed and road traffic. However, we found that the speed of a normal car is also affected by the brake lights on the front, road conditions, and so on. Therefore, this model can obtain some basic data values by using V2V communication: whether the brake light of the preceding vehicle is turned on O_{light}, the distance h from the preceding vehicle, and whether there is a changeable lane C_{lane}. The values that can be obtained by V2R communication are: the flow rate q of the road in a certain period of time, and the vehicle density ρ_{car} of the road at a certain time.

When the acceleration $a > 0$, the car accelerates, and when $a < 0$, the car decelerates. Then the current road is empty, that is, when the distance between the two vehicles is greater than the safety distance h_{safe}, the car accelerates, and the farther the distance is, the greater the acceleration:

$$\text{if } h > h_{safe} > s, \qquad a = k_1 h.$$

Where s is a fixed value and k_1 is a coefficient.

When there is a vehicle in front of the car, that is $h \leq s$, we discuss the situation separately. We have assumed that the driving state of the car is “good driving conditions”, so the abnormal road conditions such as bad weather, geological conditions, and traffic accidents are not considered here. Here is the effect of the rear brake light $L = \{0, 1\}$ on the acceleration of the rear car:

$$\begin{aligned}
&\text{if } O_{light} = 0 \;\&\; h > h_{safe} < s, && a = k_2 h\\
&\text{if } O_{light} = 0 \;\&\; h > h_{safe}, && a = k_3 h\\
&\text{if } O_{light} = 1 \;\&\; h > h_{safe} < s, && a = k_4 h\\
&\text{if } O_{light} = 1 \;\&\; h > h_{safe}, && a = k_5 h
\end{aligned}$$

According to the data analysis, the current brake light will give the rear vehicle driver more reaction time. If the brake light does not indicate that the two vehicles are less than the safe distance, the driver will slam on the brake, which is a very large deceleration acceleration. According to this mechanism, the following relationship can be obtained:

$$k_1 > 0 > k_4 > k_2 > k_5 > k_3.$$

2.3 Markov Weight Optimization

After obtaining the changes in speed, the cellular automaton model can be used to predict the position of the sensor node. Before the cellular automaton was run, in order to improve the accuracy and optimize the state update rules, we introduce the principle of the Markov process. The two states are divided into two state spaces R_τ, where i is the initial state of the cell, j is the state after the state transition, p_{ij} is the probability of transitioning from state i to state j when the car is decelerating, and q_{ij} is the state of the car from acceleration. The probability that i will transition to state j. Therefore, the state transition matrix of the cell in the acceleration and deceleration states at time t is

$$N_{dece}(t) = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix},$$

$$N_{aece}(t) = \begin{pmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{pmatrix}.$$

Here we use the BowTie analysis commonly used in risk assessment to determine the values of p_{ij} and q_{ij}.

$$p_{ij} \bowtie \{\mathrm{F}_{BL}, \mathrm{F}_{TL}, \mathrm{F}_{OB}\}$$
$$q_{ij} \bowtie \{\mathrm{F}_{RE}, \mathrm{F}_{VA}, \mathrm{F}_{OV}\}$$

In summary, by (i) *BowTie Analysis method*, combined with (ii) *Markov process*, and finally using (iii) *cellular automaton system*, the number of sensor nodes in each autonomous region, that is, the amount of data of the aggregation node can be calculated. This is beneficial for wireless sensor networks to transmit data at an appropriate rate to prevent congestion from affecting the quality of the entire network.

3. COLLABORATIVE MULTI-CONVERGENCE NODE MODEL

Due to the large amount of data in the entire network, especially when the number of cars is large and the traffic volume is large, effective data transmission cannot be performed in a large-scale WSN. Therefore, the network needs to be divided into autonomous regions. However, most of the traditional algorithms only consider the data transmission of a certain autonomous region, so as to the other autonomous regions, so as to carry out data transmission of the entire network. In this section, the author will propose a collaborative computer system that guarantees the lowest energy consumption of the sensor when considering QoS. The quality of service here is mainly designed for algorithms that reduce latency and ensure data integrity.

3.1 *K*-means Clustering Method to Determines the Aggregation Nodes

The network is divided into K autonomous regions, and then all sensor nodes are clustered and analyzed by K-means clustering method to determine the mobile aggregation node. The algorithm steps are as follows:

(1) First enter the value of k, that is, obtain k packets by clustering;
(2) randomly selecting k data points from the sensor set as the initial centroid;
(3) For each sensor node in the network, calculate the distance from each centroid, which centroid distance is close, and which centroid collection is placed. Here the "degree of difference" is embodied in a wide range of Euclidean distances:
(4) At this time, a collection of data points is gathered under each centroid collection, and then a new centroid is selected by the algorithm under this set.
(5) Set a certain threshold. If the distance between the new centroid and the old centroid is less than a certain threshold, it can be considered that the position of the recalculated centroid has reached the convergence effect, that is, the clustering we have performed has reached the desired result and the algorithm is terminated.
(6) If the distance between the new centroid and the old centroid is significantly different, the algorithm continues with iterations (3) to (5).

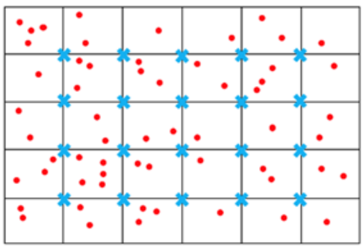

Fig. 3. Floor plan of WSN (simple ver.).

The entire wireless sensor network can be abstracted as shown in the figure, wherein a red dot represents a common node, and a lower right corner of each autonomous region represents a sink node of the region, that is, a blue cross indicates a sink node. (Note: the nodes on the graph are not complete)

Abstract all the aggregation nodes (centroids) into a new layer:

Fig. 4. Abstract second layer.

Then, the ordinary node may go through multiple hops when it reaches the data center via the aggregation node, and the QoS problem is involved here.

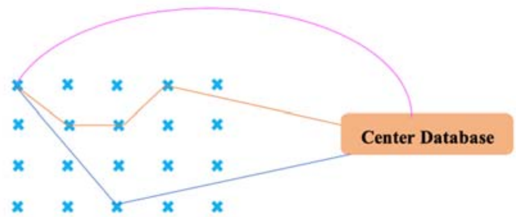

Fig. 5. Path types.

In order to avoid the long queue time in the process of data transmission, we need to increase the data transmission efficiency under the condition of maximizing the network coverage life, so that the data transmission reaches the best QoS, which is represented by

$$\begin{cases} \min E_{charge} \\ \max Q_{service} \end{cases}$$

$$\begin{cases} E_{charge} = f(S_{doment}, S_{work}) \\ Q_{service} = g(T_{delay}, P_{loss}) \end{cases}$$

(A) Minimum Energy Consumption Module

For a typical wireless sensor network, there is a long enough time between network reassembly cycles. This means that in all scenarios, network maintenance values are at least an order of magnitude lower than data transmission values, so path discovery and maintenance operations consume only a fraction of the total energy budget (less than 1.0% [1]). So even if this paper ignores the energy overhead of network maintenance, it will not lead to a significant underestimation of the total energy budget.

We consider two types of sensors below that consume power.

The first one is that the sensor actively senses the traffic flow, which is denoted by E_1. In this case, the more common nodes in the coverage of the sensor, the greater the power consumption; if there is no data transmission in the network for a long time, the sleep time is set. However, it must be guaranteed to cover every in-vehicle sensor node in the network.

When a specific sensor node uploads data to a central database, data transmission and communication between the sensors (prepared for collaboration), that is, E_2. In this case, it is necessary to consider the necessity of coordination, and not every information needs to be communicated between each aggregation node. Since the position and speed of the car are dynamically changing, the aggregation node is also dynamic and changeable. At this time, the multi-aggregation node uploads the data to the central database, and the routing determines the energy consumption.

The basic rule is that when the node has no packet transmission for a long time, it will sleep during this time period, so that the coverage life of the entire network is maximized. When a packet arrives, it wakes up again, reducing the latency of the entire network. Thus, we need to set up a dynamic sleep schedule. The wake-up state time is t_{wake}, which is predictable by the cellular automaton model.

$$E_{sleep} = P_{idle}t_{wake} + P_{sleep}t_{sleep}$$

Where P_{idle} indicates the power when the node is in the idle listening state, and P_{sleep} is the power in the sleep state.

As a result of that, the optimal energy consumption model ensures that every common node is covered and consumes the least amount of energy required within a certain time delay. Energy consumption includes the power required for operation and the power during sleep. Expressed as a mathematical formula as:

$$\min E_{charge} = E_1 + E_2 + E_{sleep}$$
$$s.t \begin{cases} \forall n_{sen} \in N_{agg} \\ t_{delay} < t_{deadline} \end{cases}$$

(B) Algorithm of Attractive-Force Transmission

Congestion awareness requires the network to predict the dynamic changes of the entire network at the next moment in order to make corresponding routing decisions and prevent a large number of congestion conditions in the network. In this model, the most important thing is to determine the weight, which is the decision of priority. The concept of gravitational domains is introduced here. The end-to-end data transmission is seen as a process similar to the flow of rivers from high to low and finally to the sea, and the direction and speed of the water are related to the force acting on the water. The factor that affects the efficiency of packet transmission is abstracted as the "force" here, which is a vector unit.

Define a Depth Gravitational Domain (DGD) $R_i^d(t) = D_i(t)$. The depth indicates the distance that the ordinary node passes the data packet to the sink node, which can be understood as the length of the path to be taken. $D_i(t)$ is the depth of node i in the network at time t, so the expression of the force acting on the data packet from node i to node B is:

$$F_{i \to b}^d(t) = D_i(t) - D_b(t).$$

Similarly, define a Queue Gravitational Domain (QGD) $R_i^q(t) = Q_i(t)$. A queue refers to a queue of packets that are aggregated in a node buffer. The longer the queue, the easier it is to be congested at that node. $Q_i(t)$ is the length of the queue of node i at time t, so the expression of the force acting on the data packet from node i to node B is:

$$F^{q}_{i\to b}(t) = Q_i(t) - Q_b(t).$$

By synthesizing two gravitational domains, we can get the expression formula of the mixed gravitational field of node A at time t:

$$R^{m}_{i}(t) = \alpha R^{q}_{i}(t) + \beta R^{q}_{i}(t) + C.$$

Where C is a constant domain.

So the mixed force from node i to node B is:

$$F^{m}_{i\to b}(t) = \alpha(D_i(t) - D_b(t)) - \beta(Q_i(t) - Q_b(t)) + c.$$

Where c is a constant.

In order to determine the values of α and β, the dynamic results of Model A can be used. The depth gravitational domain weight can be expressed as:

$$\alpha = \frac{l_{i\to aggr}}{v_o t} \times 100\%.$$

Where v_o represents the transmission speed of the data packet per unit time, $l_{i\to aggr}$ represents the distance from the i node to the sink node, and the larger α, indicating that the data packet is difficult to be kicked out of the pre-selected optimal path.

Use the buffer occupancy to estimate the congestion in the network, so that the weight of the impression queue gravitational domain:

$$\beta = \frac{buff_i + buff_{neighbor}}{buff_{i\max} + buff_{neighbor\max}} \times 100\%.$$

Among them, $buff_i$, $buff_{neighbor}$ respectively indicate the buffer size of the normal queue and the neighbor queue. Also, $buff_{i\max}$, $buff_{neighbor\max}$ respectively indicate the total capacity of its buffer. The larger the β, the more the path will be looking for a smaller load path for transmission.

The following describes the Dynamic-Aggregation Node Collaboration (DANC) Algorithm steps. As for the packet queue in node i at time t:

(1) $\alpha = \frac{l_{i\to aggr}}{v_o t} \times 100\%, \beta = \frac{buff_i + buff_{neighbor}}{buff_{i\max} + buff_{neighbor\max}} \times 100\%.$

(2) Calculate the force acting on the data packet P by the formula:

$$F^{m}_{i\to b}(t) = \alpha(D_i(t) - D_b(t)) - \beta(Q_i(t) - Q_b(t)) + c.$$

(3) Select $\{W_{i\to b}\}_{\max}$, the force acting on the maximum value on P, the neighbor node pointed to by the force is the next hop route, where

$$W_{i\to b} = \{F^{m}_{i\to b}(t)\},\ b \geq 1.$$

(4) Send the packet P from node i.
(5) Loop this way until reaching the sink node.

Since the aggregation nodes are dynamically changing, the data packets of the respective aggregation nodes are cooperatively transmitted to more accurately perform network sensing.

In summary, the collaborative mechanism of the entire network can be expressed as:

$$\min E_{charge} = E_1 + E_2 - E_{sleep}$$
$$s.t \begin{cases} \forall n_{sen} \in N_{aggr} \\ t_{delay} < t_{deadline} \\ t_{response} \leq k \\ P_{loss} \leq n \end{cases}.$$

Where P_{loss} indicates the percentage of packets successfully delivered.

$$P_{loss} = \frac{N_{success}}{N}$$

The step of the algorithm that we designed as below:

Dynamic-Aggregation Node Collaboration (DANC) Algorithm

1: Initialization
2: calculate the value of α and β
$$\alpha = \frac{l_{i\to aggr}}{v_o t} \times 100\%, \beta = \frac{buff_i + buff_{neighbor}}{buff_{i\max} + buff_{neighbor\max}} \times 100\%.$$
3: do (4,5) until reaching the sink node.
4: Calculate the force acting on the data packet P by the formula:
$$F^{m}_{i\to b}(t) = \alpha(D_i(t) - D_b(t)) - \beta(Q_i(t) - Q_b(t)) + c.$$
5: Send the packet P from node i.

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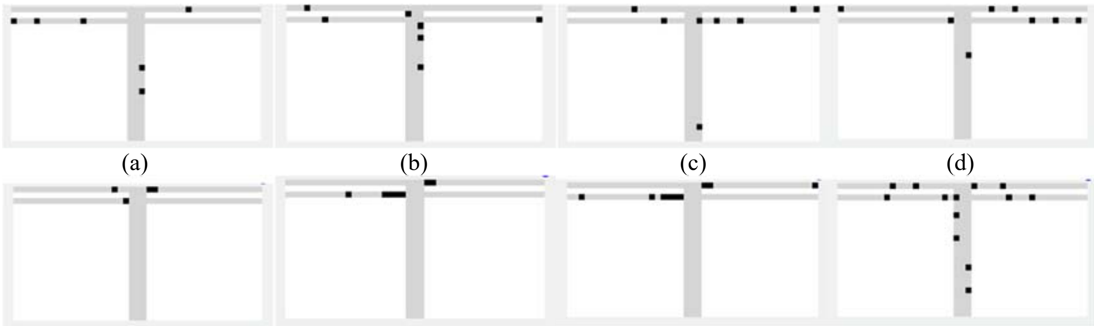
4. SIMULATION

In this section, the simulation results of the model are shown. We use MATLAB to add a new state update rule to the original traffic model, and simulate the movement state of the on-board sensor with a typical T-shaped traffic intersection, so that the traffic flow condition of the road at different times can be obtained [25]. As shown in Fig. 6, it is the location information of the car we intercepted at different times. (black dots represent the position of the car sensor)

Compared with the traditional probability-based cellular automaton model [25-27], the model in this study is more real-time, can predict the behavior of the car more accurately in a short time, and better detect the traffic flow of the entire traffic.



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 6. Cellular-automaton to sensor-movement modeling.

We performed simulation experiments in NS-2 [4] using the Dynamic-Aggregation Node Collaboration (DANC) Algorithm. Scene setting: 500 sensor nodes are randomly deployed in a square area of $500 \times 500\text{m}^2$. Table 2 shows the experimental simulation parameters set by the algorithm, which provided a general example of parameters setting.

Table 2. Simulation parameters set.

Parameters	Definition	Numerical Values
N	Number of sensor nodes.	500
E_0	Initial energy.	2kJ
P_{idle}	The power when the node is in idle listening state.	15nJ/bit/s
P_{sleep}	The power of the node in the sleep state.	10nJ/bit/s
P_{is}	The power by which the node actively senses the traffic flow.	25nJ/bit/s
E_{sc}	The energy consumed by a node to transfer data to data center.	50nJ/bit
ε_{fs}	Transmission expansion factor in free space.	10pJ/bit/m^2
ε_{mm}	Transmission expansion factor under multipath model.	0.0014pJ/bit/m^4

The parameter α and β are important factors in determining the next hop node of the data packet. A series of simulation experiments were performed by setting different initial values, *i.e.* different sensor speeds and sensor positions, to generate different parameter values. Fig. 7 compares the network differences between two different algorithms in the application scenario, observing how much energy is left in the same round when the initial energy is the same.

It can be seen from Fig. 7 that the DANC algorithm exhibits stronger sensing ability than the traditional LDAS algorithm. This is because in the entire wireless sensor network, the new algorithm uses the weight of the buffer queue and the distance of the path to weight, so that the network has a faster response speed, and thereby cooperate with multiple aggregation nodes in the network.

In order to better analyze the role of the parameter α and the parameter β in the algorithm, we respectively remove one of the parameters to perform simulation and comparison, so as to verify the robustness of the analytical model.

As shown in Fig. 8, the DANC algorithm that removes one of the weights will cause the network to consume more energy. After the 70th round, the algorithm for removing the parameter α shows a tendency for the energy to drop rapidly. This is because the data flow in the later network will become more and more complicated and complicated. If the long

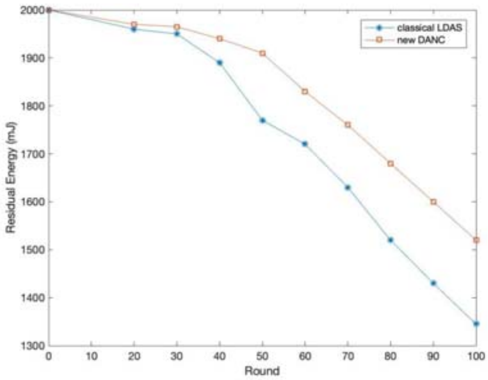


Fig. 7. Compare the relationship between residual energy and rounds under two algorithms.

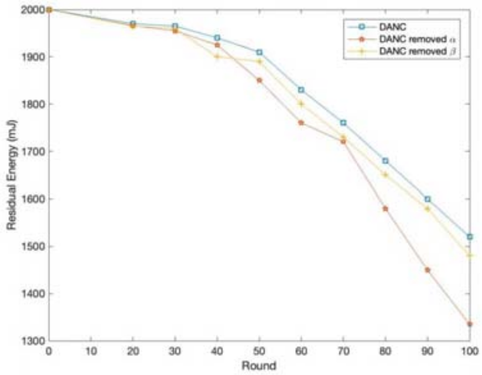


Fig. 8. Sensitivity analysis.

nodes of the buffer queue are not bypassed, the path congestion will easily occur, which is not conducive to the extended coverage life of the entire network.

In summary, we have implemented the process of the DANC algorithm and compared the effect with the classic LDAS algorithm. Numerical simulation experiments have proved that our algorithm has a good effect. At the same time, in order to further analyze the sensitivity of the algorithm, we separated two important parameters in the algorithm, eliminated the α, β parameters, and observed the degree of influence of these two parameters on the algorithm's effect. From the simulation results, these two parameters have an impact on the results, and the α parameter has a greater impact.

5. CONCLUSION

In this study, we propose a cellular automaton model based on Markov process and a multi-convergence node coordination mechanism based on classical algorithm for the traffic system under real conditions, so as to jointly optimize the transmission of wireless sensor networks.

We not only pay attention to the harsh conditions of the road driving environment (for example, intersection turns, obstacles in front, *etc.*), but also pay special attention to practical aspects, such as the relationship between the normal queue and the neighbor queue, setting weights, and so on.

Finally, we test the superiority of the algorithm through simulation experiments, and carry out sensitivity analysis on important parameters, which proves that the model has strong stability.

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Lujie Zhong (衷璐洁) received the Ph.D. degree from the Institute of Computing Technology, Chinese Academy of Sciences, Beijing, China, in 2013. She is an Associate Professor with the Information Engineering College, Capital Normal University, Beijing. Her research interests include communication networks, computer system and architecture, mobile Internet technology, Internet of things, and vehicular networks.

Shujie Yang (杨树杰) received the Ph.D. degree from Institute of Network Technology, Beijing University of Posts and Telecommunications, Beijing, China, in 2017. He is a Lecture with Institute of Network Technology, Beijing University of Posts and Telecommunications, Beijing, China. His current research interests are in the areas of high-speed railway networks, wireless communications, and wireless networking.

Jiewei Chen (陈洁蔚) is a master candidate in Institute of Network Technology, Beijing University of Posts and Telecommunications, Beijing, China. Her current research interests are in the area of wireless network, wireless communications and federated machine learning.