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Article

Container-Based Internet of Vehicles Edge Application Migration Mechanism

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Abstract: Internet of Vehicles (IoV) applications integrating with edge computing will significantly drive the growth of IoV. However, the contradiction between the high-speed mobility of vehicles, the delay sensitivity of corresponding IoV applications and the limited coverage and resource capacity of distributed edge servers will pose challenges to the service continuity and stability of IoV applications. IoV application migration is a promising solution that can be supported by application containerization, a technology for seamless cross-edge-server application migration without user perception. Therefore, this paper proposes the container-based IoV edge application migration mechanism, consisting of three parts. The first is the migration trigger determination algorithm for cross-border migration and service degradation migration, respectively, based on trajectory prediction and traffic awareness to improve the determination accuracy. The second is the migration target decision calculation model for minimizing the average migration time and maximizing the average service time to reduce migration times and improve the stability and adaptability of migration decisions. The third is the migration decision algorithm based on the improved artificial bee colony algorithm to avoid local optimal migration decisions. Simulation results show that the proposed migration mechanism can reduce migration times, reduce average migration time, improve average service time and enhance the stability and adaptability of IoV application services.

Keywords: Application migration; container; internet of vehicles; edge computing

1 Introduction

The Internet of Vehicles (IoV) is widely regarded as a key component of the future intelligent transportation system. It supports a variety of application services (broadcasting, navigation, road condition warning, etc.), which can greatly enhance the urban transportation intelligence, relieve traffic pressure and reduce potential traffic safety risks. With growing vehicle users and massive access to new IoV apps, there is a dramatic rise in demand for the abilities of data communication and computation in IoV. As most IoV apps are delay-sensitive, a large number of decisions need to be made in real-time, and users need to access and utilize closer computing and storage resources [1,2]. Edge computing has gotten a lot of attention in delay-sensitive IoV apps as it saves processing time and improves efficiency by running apps or performing partial computations close to the service terminals [3]. However, the limited communication coverage of the distributed and fixed located edge servers makes it hard to provide continuous services from a single edge server for the low-delay IoV apps carried by high-speed vehicles. Furthermore, the limited resource capacity of each edge server makes it hard to guarantee high concurrent application services for multiple vehicles at the same time. Therefore, edge computing-based IoV apps encounter the service continuity and stability challenges.

IoV application migration, enabling IoV apps to migrate from one edge server to the next within the low delay constraints, will be a feasible and inevitable solution to address the above challenges. The hosting application components [4], commonly including virtual machines (VMs), containers and agents, are mainly utilized to implement edge-side application migration. High migration efficiency is necessary since the migration process involves frequent data caches and resource interactions between different edge servers. A ready-made agent framework is yet to be available as the agent is still in the early development stage. Moreover, VMs must adapt to the operating system, which will increase the switching delay while transmitting a large amount of data in the migration process. The excellent features of the container, such as application resource encapsulation, heterogeneous edge server resource shielding and agile start/stop operations, exactly support rapid seamless application migration without user perception in the case of interacting with a small amount of data.

Container-based IoV application migration is to stop the app running in the container of the source server, then save the application context data, and transmit it to a container with the equal capability of the migration target server to continue running this app. The limited coverage of the edge server makes it necessary to stop running and request a migration before the vehicle leaves the coverage area. In addition, the limited resource of the edge server makes it necessary to weigh the application load on candidate target servers to determine whether there are enough container resources to restart the app within the tolerance time range under user no-perception. In essence, container-based IoV application migration needs to solve the issues of when to migrate (migration trigger determination) and where to migrate (migration target decision), that is, how to migrate (migration mechanism).

There are two main migration trigger types involved in current research: Cross-Border Migration (CBM) [3–10] triggered by the vehicle moving out of the edge server coverage, and Service Degradation Migration (SDM) [5], [11–15] triggered by the edge server application support capability degradation.

Fig. 1 shows a container-based IoV edge application migration scenario. Containers are utilized to host apps on edge servers (ES), connected vehicles obtain application services by accessing nearby edge servers, and the service domain coverage and resource capacity of each edge server are limited. The scenarios for these two migration trigger types are described as follows.

CBM: when the connected vehicle A is about to leave the service domain of the edge server ES_1, the communication with ES_1 will be cut off, at this time the corresponding IoV app should be migrated from ES_1 to a suitable candidate target edge server such as ES_2. In this regard, this paper proposes a CBM-type migration trigger determination algorithm based on trajectory prediction, which can avoid unnecessary migration decisions at intersections, parking and deceleration situations, and improve the accuracy of migration trigger determination by predicting the vehicle driving direction.

SDM: when the vehicle A is driving in the service domain of ES_2, while application service support capability degradation suddenly happens on ES_2 (service interruption caused by traffic surge or service response delay caused by traffic congestion), the vehicle A can seldom obtain application services in real-time. At this time, the corresponding IoV apps should be migrated from ES_2 to a suitable candidate target edge server such as ES_3. In this regard, this paper proposes a SDM-type migration trigger determination algorithm based on traffic awareness, which can improve the timeliness of migration trigger determination by measuring the traffic status and the service priority on the edge server.

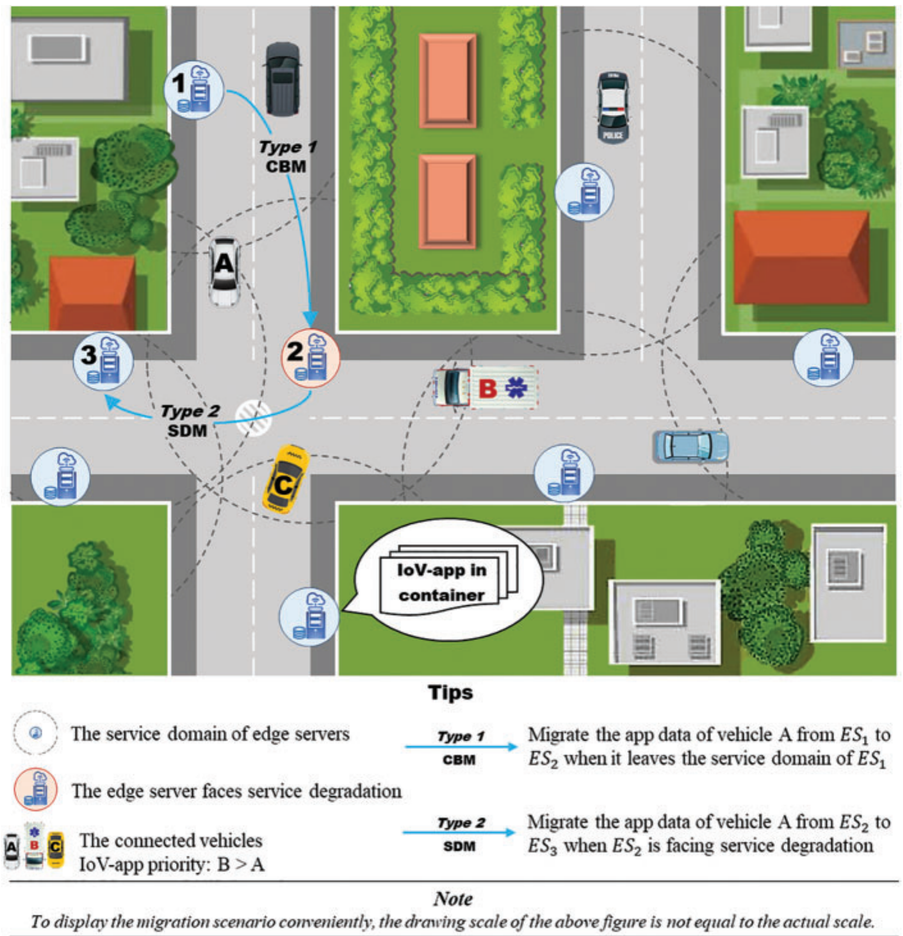


Figure 1: Container-based IoV edge application migration scenario

When the migration is triggered, a new edge server needs to be decided as the migration target, and then the vehicle will obtain services again by accessing the target edge server. Current solutions to the IoV edge application migration decision problem are relatively few and simple. Reference [3] proposed that application data can be cached to all edge nodes that may be reached to ensure the service continuity, but leading to high implementation cost and low resource utilization. Reference [5,16] only considered the distance factor in migration decisions but ignored other influencing factors such as the resource status, typically resulting in more additional migrations. Reference [17] proposed to optimize the migration cost through the greedy algorithm, but it tends to fall into the local optimum and has poor overall performance in the long term. Reference [18] proposed a mobility-aware pre-migration strategy based on Lyapunov, it considered migration accuracy, load balance and migration efficiency from factors such as vehicle trajectory prediction and nearby edge server resource constraints, thus striking a good balance between minimizing the migration cost and losing the service continuity, but it lacks consideration of the stability and adaptability of migration decisions in various migration scenarios. Therefore, it is necessary to study a more accurate, efficient, highly-adaptive, and globally-optimal migration decision strategy.

To this end, this paper adopts the "When-Where-How" 3-step decision mindset to study the container-based IoV edge application migration mechanism. The main contributions are as follows:

1) Migration trigger determination algorithm based on trajectory prediction and traffic awareness is designed respectively for CBM and SDM to improve the accuracy of the trigger determination.
2) Migration target decision calculation model oriented to minimize the average migration time and maximize the average service time is constructed, which optimizes the accuracy of migration target decisions while reducing migration times and improving the stability and adaptability of migration decisions.
3) Migration decision algorithm based on the improved artificial bee colony algorithm is proposed, where the fitness function and search update method are modified to reduce the possibility of optimal local decisions. Simulation results show that the algorithm can reduce the average migration time and migration times, improve the average service time, and enhance the stability and adaptability of IoV application services.

The rest of this paper is organized as follows. Section 2 reviews the related works. Section 3 presents the migration trigger determination algorithm. Section 4 constructs the migration target decision calculation model. Section 5 proposes the migration decision algorithm. Section 6 shows the simulation results and analysis. Section 7 draws the conclusion.

2 Related Works

This section introduces the research backgrounds, existing solutions in the field and the overall research process of this paper.

2.1 Backgrounds

Edge Computing in IoV: With the dramatic increase in demand for massive real-time decisions and strong process abilities in urban vehicle networks nowadays, some studies [3,5] suggest it is more beneficial to process the computation at the edge of networks owing to the cooperability, proximity to terminals and dense distribution of edge devices, where the network edge components are typically located on cellular base transceiver stations (BTSs) or roadside units (RSUs) [19]. Edge computing helps to overcome the contradiction between limited resources and heavy computing tasks of some terminals (e.g., Global Positioning System (GPS) devices) [20], thus helping to reduce the data transmission cost and improve the process efficiency in distributed vehicle task processing scenarios [21]. Recently, several countries [22–24] have already deployed their joint projects of edge computing and IoV in practical field tests.

Container in Edge IoV: Hosting applications via VMs or containers is a common means to improve the efficiency of task execution and switching for edge computing nodes [25]. VM is the most common way in the early years, but it will lead to higher deployment delays and resource consumption relatively when hosting edge-side services, and most IoV terminal devices still lack the resource ability to support efficient downloads and startups of heavy VMs [26]. Recently, some studies [9,27–29] suggest that the container is more suitable to deploy on edge platforms than the VM due to the features of lightweight, isolation and agility, and it has more potential to enable seamless service migration across edge servers without user perception. Many institutions have successfully designed and deployed their containerized edge computing platforms for IoV, such as the CUTE from Shenzhen University [30] and the Connected Vehicle Platform from Google [31], and verified the benefits of containers applied to edge IoV.

2.2 Solutions to IoV Edge Application Migration

When applying edge computing to IoV, the contradiction between the high-speed vehicles carrying delay-sensitive IoV apps and the distributed edge servers with limited communication coverage and limited resource capacity triggers the demand for IoV edge application migration. This migration issue should be divided into 3 sub-issues: migration trigger determination, migration target decision, and migration optimization mechanism.

For the first sub-issue, the movement of the vehicle [32] and the service density of the current server [33] are generally considered to be the key trigger conditions.

For the second sub-issue, the suitability of the candidate target servers should be comprehensively weighed by some factors such as the vehicle moving direction, migration cost, user Quality of Service (QoS), reliability, migration frequency, and resource status [7,32,34–36]. For example, the source server should negotiate with target servers before migrations to determine whether there is enough processing power and storage space, if not, other running containers may be paused or stopped depending on priority to make room [35]. Reference [37] selects target servers based on the user's moving speed and the delay requirements of the offloading tasks.

For the third sub-issue, the reliable optimization goal is generally to reduce the average total cost. For example, Reference [38] proposes a migration scheme based on the local dynamic optimal algorithm, aiming to optimize the average delay of multiple services with different QoS. Reference [39] proposes a load-balancing optimization scheme to reduce the total response time of IoV apps. Reference [34] evaluates three service migration schemes in terms of the end-to-end delay, reliability, migration time and frequency: no service migration, service migration triggered by VM handover, and QoS-aware service migration. Reference [36] proposes a four-stage loop migration framework: monitor-analyze-plan-execute. Reference [6] models the container migration strategy as a multi-dimensional Markov decision process (MDP) space and utilizes the deep learning algorithm to make decisions rapidly, aiming to reduce the delay, computation consumption and migration cost.

The above research reveals the challenges in the IoV edge application migration scenario and proposes corresponding solutions. However, some studies are not comprehensive and detailed enough to describe their migration mechanisms. Therefore, it is necessary to further study the migration mechanism in the IoV edge application migration scenario.

2.3 Contribution

The main contribution and overall research process of this paper is shown in Fig. 2.

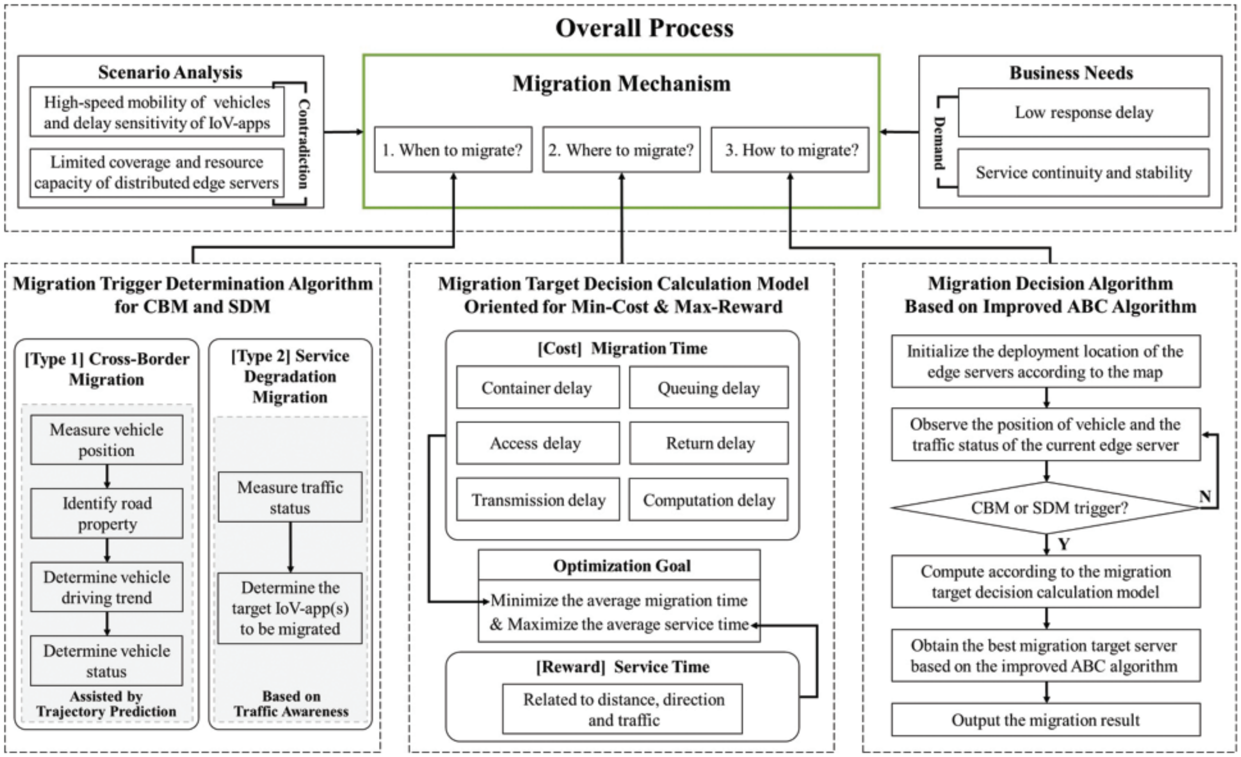


Figure 2: The overall research process

3 Migration Trigger Determination Algorithm

In this section, this paper proposes the migration trigger determination algorithm to answer when to migrate. To describe trigger conditions conveniently, this paper sets all models to be based on the two-dimensional plane road scenes, covered densely and seamlessly by edge servers, then defines the following variables.

d_t denotes the distance between the vehicle position and the current service domain center at time t. d_{pre}, d_{thr} denote the pre-judgment trigger radius and the coverage radius of edge servers, respectively, and $d_{pre} < d_{thr}$.

$\vec{O}_t$ denotes the unit vector from the vehicle position to the current service domain center at time t, called the centripetal vector. The vector direction of $\vec{O}_t$ changes over time but always keeps pointing from the vehicle position to the current service domain center.

$\vec{m}_t, \vec{m}_{t+1}$ respectively denote the moving direction vector of the vehicle at the current time t and the next time $t+1$.

β_t denotes the angle between the moving direction vector $\vec{m}_t$ and $\vec{m}_{t+1}$ of the vehicle at two adjacent moments.

α_t denotes the angle between the moving direction vector $\vec{m}_t$ and the centripetal vector $\vec{O}_t$ at the current time t.

v_t denotes the vehicle speed at the current time t. The minimum speed limit for normal driving is v_{min}, usually set $v_{min} = 30$ km/h in urban road scenes.

$Q_{i,t}$ denotes the traffic carried on ES_i at time t. On the premise of meeting application service response delay requirements, the upper traffic limit that each edge server can handle is Q_{max}. In addition, a small part of the capacity space Q_{hold} should be reserved for buffer adjustment.

$pri_{i,t}$ denotes the priorities of all accessed services on ES_i at time t, where the priority of the IoV app A is pri_A, for example.

3.1 CBM Trigger Determination Algorithm Assisted by Trajectory Prediction

This section discusses a trajectory prediction method first and then brings out the CBM trigger determination process based on that.

3.1.1 Trajectory Prediction

The moving directions of vehicles on urban roads are variable, especially at crossroads, there are four possible directions: straight ahead, left turn, right turn and U-turn. The vehicle trajectory is a key condition in the CBM trigger determination process. However, the possible measurement errors and determination delays for trigger distance, driving trend and direction change in the driving process may cause higher risks of misjudgments or redundant migrations. To improve the accuracy and timeliness of determinations and reduce error or unnecessary migrations, this paper utilizes trajectory prediction results trained by the long short-term memory (LSTM) model [40] to help CBM trigger determination.

In the LSTM model, the input data is historical trajectories of the object vehicle in the past few seconds, and the output data is predicted trajectories in the next few seconds. As the future trajectory of the object vehicle V_s is easily affected by the movements of its nearby vehicles V_i in the two adjacent lanes, set that V_i can only have an effective effect on the future trajectory of V_s when the distance projection along the lane between V_s and V_i is less than 80 m. The model only focuses on the nearest vehicles from six directions around the object vehicle, which are front left, front, front right, rear right, rear and rear left, denoted as $V_1 \sim V_6$ separately.

$\boldsymbol{x}_s^t$ and $\boldsymbol{x}_i^t$ $(i = 1, 2, \ldots, 6)$ respectively denote the historical trajectory of the object vehicle V_s and its nearby vehicles $V_1 \sim V_6$. $\boldsymbol{x}^t = \left[\boldsymbol{x}_s^t, \boldsymbol{x}_1^t, \boldsymbol{x}_2^t, \ldots, \boldsymbol{x}_6^t\right]$ denotes the input historical trajectory dataset of V_s and $V_1 \sim V_6$. $\boldsymbol{y}_s^t$ denotes the output predicted trajectory result of V_s.

- Step 1: Preliminarily predict trajectories of V_i and V_s, and obtain the preliminary prediction results $\boldsymbol{h}_i^t$ and $\boldsymbol{h}_s^t$.
- Step 2: Evaluate impacts of the spatial interaction between V_i and V_s on the future trajectory of V_s, and adjust preliminary prediction results to obtain the trajectory correction sequence $\boldsymbol{h}_{i,s}^t$.
- Step 3: Weighted correct the above predicted trajectories $\boldsymbol{h}_s^t$ and $\boldsymbol{h}_{i,s}^t$ through the weight coefficient w_i, and output the final predicted trajectory result $\boldsymbol{y}_s^t$.

3.1.2 CBM Trigger Determination Process

The CBM trigger determination process is shown in Fig. 3. The steps of Algorithm 1 (CBM trigger determination algorithm) are as follows:

- Step 1: Determine whether the vehicle has arrived near the current service domain border.

If $\alpha_t > 90^\circ$ and $d_t \geq d_{pre}$ at current time t, go to Step 2; otherwise, the migration is not triggered.

- Step 2: Identify the road property.

If $\beta_t < 45^\circ$, it is regarded as a straight road, go to Step 4; otherwise, if $\beta_t > 45^\circ$, it is regarded as a cross or fork road, then go to Step 3.

Note: the road property is only for model analysis and sometimes may differ from actual roads. For example, if the vehicle drives straight on a cross or fork road, it can be analyzed as a straight road; similarly, if the vehicle turns around on a straight road, it can be analyzed as a cross or fork road.

Significantly, the direction change behaviors that occur near the current service domain border, which may cause a mutation in α_{t+1}, is closely related to whether the migration is triggered or not.

- Step 3: Determine whether the vehicle maintains leaving the current service domain.

If $\alpha_{t+1} > 90^\circ$ at the next time $t + 1$, go to Step 4; otherwise, the migration is not triggered.

- Step 4: Determine whether the vehicle maintains a normal driving status.

If $v_t \geq v_{min}$, the migration is triggered; otherwise, emergencies such as parking or breakdowns may occur, uniformly determined as not triggered.

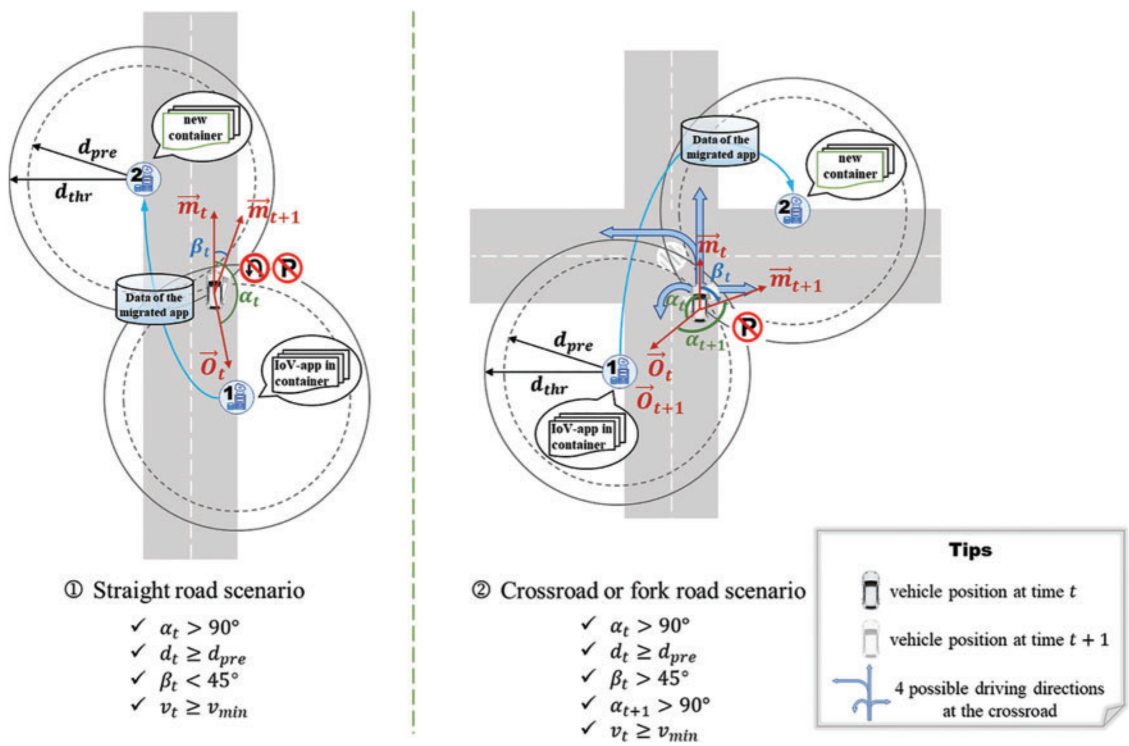


Figure 3: CBM trigger determination process

Algorithm 1: CBM trigger determination algorithm

Input: α_t, d_t, β_t, v_t, α_{t+1}
Output: bool $trigger_A$
1: **if** $\alpha_t > 90^\circ$ && $d_t \geq d_{pre}$ **then**
2: **if** $\beta_t < 45°$ **then**
3: skip to Line 11
4: **else if** $\beta_t > 45°$ **then**

(Continued)

Algorithm 1: Continued

```
5:          if α_{t+1} > 90° then
6:            skip to Line 11
7:          else
8:            return false
9:          end if
10:       end if
11:       if v_t ≥ v_min then
12:         return true
13:       else
14:         return false
15:     end if
16: else
17:   return false
18: end if
```

3.2 *SDM Trigger Determination Algorithm Based on Traffic Awareness*

This section discusses a traffic awareness method first and then brings out the SDM trigger determination process.

3.2.1 Traffic Awareness

The traffic of each edge server on urban roads is variable, especially around the commonly congested roads with heavy traffic flow where high traffic concurrency is prone to occur on edge servers, thus easily leading to traffic surged or crowded. The real-time traffic status on edge servers is a key condition in the SDM trigger determination process. However, along with the fast traffic in-out flows, the possible measurement errors and determination delays for real-time traffics may cause higher risks of misjudged migrations or service degradation. To improve the accuracy and timeliness of determinations, this paper introduces a traffic-aware method [41] to help SDM trigger determination.

First, define the traffic status factor as CF to model traffic flows in IoV, which reflects traffic status in the specific period through the weighted combination of a series of parameters $E_1 \sim E_n$ (vehicular dynamic parameters such as speed, acceleration, driving direction, etc., and road historical inferred parameters such as congestion level, accident frequency, etc.). The traffic status factor $CF_{i,t}$ for ES_i at time t is expressed as $CF_{i,t} = \dfrac{1}{t - t_0}\sum_{t_0}^{t} \varepsilon_1 E_1 + \varepsilon_2 E_2 + \cdots + \varepsilon_n E_n$. Each edge server is responsible for computing and updating the weight coefficients $\varepsilon_1 \sim \varepsilon_n$ in its service domain, and deciding whether to authorize sharing or querying relevant weight coefficients to nearby edge servers depending on app types.

3.2.2 SDM Trigger Determination Process

The SDM trigger determination process is shown in Fig. 4. The steps of Algorithm 2 (SDM trigger determination algorithm) are as follows:

- Step 1: Determine whether the traffic on ES_i reaches the critical trigger value.

If $Q_{i,t} > Q_{max}$ at the current time t, the migration is triggered (note that app A may not be migrated), go to Step 2; otherwise, the migration is not triggered.

- Step 2: Determine the scope of target applications to be migrated according to the traffic load.

If $Q_{i,t} > Q_{max} + Q_{hold}$, the traffic surges and overflows, then the breakdown of ES_i will cause service interruption, and all apps originally connected must be migrated.

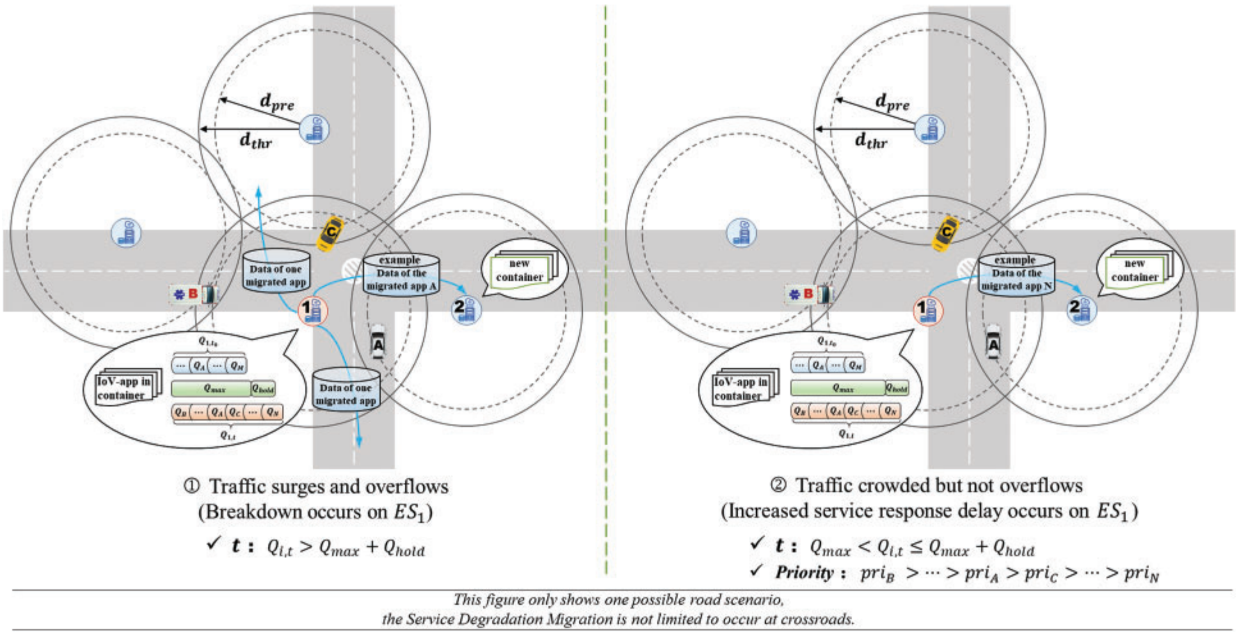


Figure 4: SDM trigger determination process

If $Q_{max} < Q_{i,t} \le Q_{max} + Q_{hold}$, traffic congestion occurs but not overflow, the service response delay of ES_i increases, and at least one low-priority application service needs to be migrated to balance the load. Then low-priority apps will be migrated first according to the priority order to free up some resource space, while high-priority apps may not need to be migrated.

Algorithm 2: SDM trigger determination algorithm

Input: $Q_{i,t}$, $pri_{i,t}$
Output: bool $trigger_A$
if $Q_{i,t} > Q_{max}$ **then**
  if $Q_{i,t} > Q_{max} + Q_{hold}$ **then**
    all apps on ES_i must be migrated
    return true
  else if $Q_{max} < Q_{i,t} \le Q_{max} + Q_{hold}$ **then**
    update $pri_{i,t}$ and sort them
    repeat
      migrate app N if pri_N is the lowest in $pri_{i,t}$
      if $N == A$ **then**
        return true
      end if
      update $pri_{i,t}$ and $Q_{i,t}$
    until $Q_{i,t} \le Q_{max}$

(Continued)

Algorithm 2: Continued

```
        if A is still on ES_i then
            return false
        end if
    end if
else
    return false
end if
```

4 Migration Target Decision Calculation Model

In this section, this paper constructs the migration target calculation model to answer where to migrate. The key is to clarify decision factors and optimization goals. As mentioned in Section 2, current research regards migration time and energy consumption as major decision factors involved in the application migration problem. Since it is relatively easy to replenish energy in IoV edge computing scenarios, this paper focuses more on reducing time than saving energy during designing decision factors and optimization goals. Of course, it's not enough to only rely on migration time.

Suppose the edge server quantities in the map area to be SN, and number them from 1 to SN. Then, when a vehicle triggers migration in the service domain of source server ES_i, there should exist other edge servers, called the valid migration range, whose service domains can cover the vehicle position at this moment. Store the server IDs in this range to a 0–1 matrix of $SN \times SN$, denoted as *valid*, where $valid\,(i,j) = 1$ indicates that ES_j is a candidate target server in the valid migration range of ES_i, otherwise, it is not. Let the distance from the vehicle position to the deployment position of the candidate target server ES_j be d_{v2j} at the migration trigger moment, where satisfies $d_{v2j} \leq d_{thr}$.

Since the source server usually has more than one candidate target server, and the small gap between migration time from the source server to each candidate target server is typically at the millisecond level, moreover, where different candidate target servers may even have equal migration time. Therefore, this paper can't distinguish the pros and cons degree of different migration targets just depending on migration time alone.

Migration time can be regarded as a cost metric to measure the consumption level of different migration target decisions, while the consumption level is almost equal, there is a need for a reward metric such as service time in each candidate target server for an additional evaluation to measure the sustainability level of different migration target decisions. That means the evaluation criteria should be composed of two decision factors (migration time and service time) and a two-objective optimization problem should be formed to achieve the Pareto optimal solution.

4.1 Decision Factors: Migration Time and Service Time

This section discusses respectively how to measure the two decision factors: migration time as a cost metric and service time as a reward metric.

4.1.1 Cost: Migration Time

This paper summarizes the migration time components and their calculation equations by splitting and analyzing the migration process, then determines the impact of each part on migration decisions. As shown in Fig. 5, the container-based IoV edge application migration process will go through 8 steps, which are: ① Freeze the container and hold the state on the source server; ② Create a new container on the target server; ③ Queuing for transmission on the source server; ④ Transmit data from the source server to the target server; ⑤ Queuing for computation on the target server; ⑥ Compute and process the data of this application; ⑦ Connect the vehicle to the target server; ⑧ Return the relevant application data back to the vehicle from the target server.

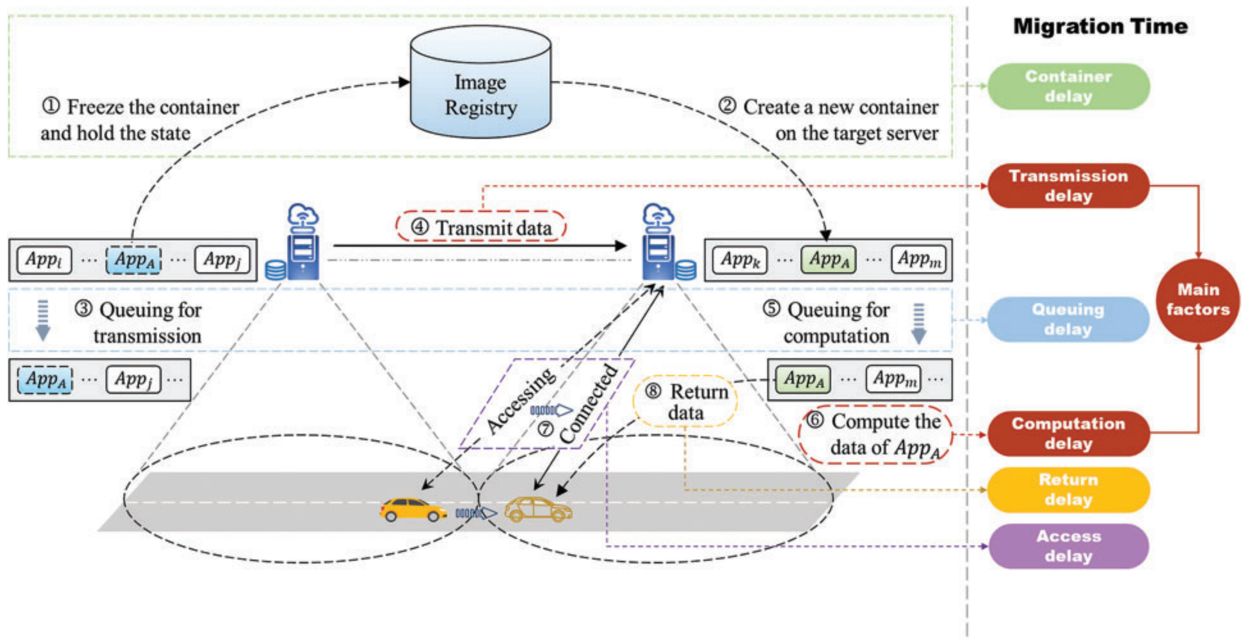


Figure 5: Container-based IoV edge application migration process

Steps ① and ② generate container delay; steps ③ and ⑤ generate queuing delay; step ④ generates transmission delay; step ⑥ generates computation delay; step ⑦ generates access delay; step ⑧ generates return delay. These six parts together constitute the migration time, analyzed respectively as follows.

1) Container delay

Container migration is the process of migrating its hosted app by freezing, saving, rebuilding and restoring containers from source to target servers without service interruptions. Container delay includes two major parts: holding state delay and creating container delay, denoted as T_{hold} and T_{create}, respectively. Container delay is the sum of the above two parts.

$$T_{container} = T_{hold} + T_{create} \tag{1}$$

The rapid process of container migration [42] is almost no gap between container delays of different migration processes. Therefore, container delay is not a major factor in optimizing migration time, so set $T_{container}$ constant in later simulations for calculation convenience.

2) Queuing delay

The total migration data amount includes the app data, container resource status, etc., that is required to re-run the migrated app on the target server. There are queuing processes on both source and target servers before transmitting and computing data, thus queuing delay includes two parts:

transmission queuing delay on the source server and computation queuing delay on the target server, denoted as T_{queue}^{trans} and T_{queue}^{comp}, respectively. Queuing delay is the sum of the above two parts.

$$T_{queue} = T_{queue}^{trans} + T_{queue}^{comp} \tag{2}$$

The strong computing and load capacity of edge servers make a rapid queuing process of transmission and computation, which accounts for a small proportion of overall migration time, and there is almost no gap between the queuing delays of different migration processes. Therefore, queuing delay is not a major factor in optimizing migration time, so set T_{queue} constant for calculation convenience.

3) Transmission delay

The consuming time of transmitting data from the source to the target server is the transmission delay, denoted as T_{trans},

$$T_{trans} = \frac{D_{i,j}^{A}}{\eta_{i,j}(t)} \tag{3}$$

where $D_{i,j}^{A}$ denotes the total migration data amount of app A sent from ES_i to ES_j; $\eta_{i,j}(t)$ denotes the average data transmit rate between ES_i and ES_j at time t.

$\eta_{i,j}(t)$ usually varies in different migration processes, causing larger gaps between transmission delays. Therefore, transmission delay is a major factor in optimizing migration time.

4) Computation delay

The received total migration data will be computed and processed by the target server. The consuming time is the computation delay, denoted as T_{comp},

$$T_{comp} = \frac{C_{i,j}^{A}}{p_j} \tag{4}$$

where $C_{i,j}^{A}$ denotes the computation amount of the total migration data of app A. $C_{i,j}^{A} = \omega D_{i,j}^{A}$ ($\omega \in [0, 1]$, called the computation demand coefficient, whose exact value varies according to app types); p_j denotes the computation bit rate of the target server ES_j, regarded as independent of time due to the strong and stable computation capacity of edge servers, whose value only varies depending on server IDs.

p_j usually varies on different target servers, causing larger gaps between computation delays. Therefore, computation delay is also a major factor in optimizing migration time.

5) Access delay

During migrating apps, the connected vehicle should request access to the target server once it obtains the target server ID before leaving the source service domain, and ensure the successful connection to the target server while driving into the target service domain. The consuming time is the access delay, denoted as T_{access}.

The tiny gaps between access delays of different migration processes make it not a major factor in optimizing migration time, so set T_{access} constant in later simulations.

6) Return delay

The target server will return the required information to the connected vehicle after processing the total migration data of app A. The consuming time is the return delay, denoted as T_{return}.

The tiny gaps between return delays of different migration processes make it not a major factor in optimizing migration time, so set T_{return} constant in later simulations.

Overall, migration time includes six parts: container delay, queuing delay, transmission delay, computation delay, access delay and return delay. The symbol $\mathcal{M}_{i,j}$ denotes the migration time consumed from ES_i to ES_j,

$$\mathcal{M}_{i,j} = T_{container} + T_{queue} + T_{trans} + T_{comp} + T_{access} + T_{return} \tag{5}$$

4.1.2 Reward: Service Time

The time interval between the vehicle accessed and disconnected to the candidate target server ES_j is the service time obtained on ES_j, denoted as $\mathcal{S}_j$. $\mathcal{S}_j$ is approximately equal to the migration trigger interval of the vehicle on ES_j.

$$\mathcal{S}_j \approx {t_{trig_j}}^n - {t_{trig_i}}^{n-1},\ \text{s.t. } valid\,(i,j) = 1\ \ (i \neq j,\ n \geq 1) \tag{6}$$

where n denotes the migration number experienced in time order, ${t_{trig_j}}^n$ denotes the moment when migration n is triggered on ES_j, ${t_{trig_i}}^{n-1}$ denotes the moment when migration $n-1$ is triggered on ES_i.

However, at the migration trigger moment in the source server ES_i, it is hard to accurately calculate the service time $\mathcal{S}_j$ provided by the candidate target server ES_j because SDMs can occur at later any time in ES_j. But this paper focuses on 3 parameters that can be measured relatively accurately: the distance d_{v2j} from the vehicle position to the deployment position of the candidate target server ES_j, the azimuth deviation angle $\langle \vec{V}, \overrightarrow{O_{v2j}} \rangle$ between the vehle driving direction and the direction from the vehicle position to ES_j deployment position, and the service traffic capacity Q_j^{offer} available from ES_j, which are positively or negatively related to the service time $\mathcal{S}_j$, denoted by symbols cr^+ and cr^- respectively.

$$\begin{cases} cr^+ \left(\mathcal{S}_j, d_{v2j}\right) \\ cr^- \left(\mathcal{S}_j, \langle \vec{V}, \overrightarrow{O_{v2j}} \rangle\right) \\ cr^+ \left(\mathcal{S}_j, Q_j^{offer}\right) \end{cases} \tag{7}$$

The above 3 parameters can reflect the size of service time $\mathcal{S}_j$ obtained on ES_j.

4.2 Optimization Goal: Minimize the Average Migration Time and Maximize the Average Service Time

Current studies for IoV edge application migration decision problems typically focus on the single migration decision, actually a kind of optimal local decision, which only guarantees the immediate reward of individual migration decisions but ignores the long-term reward of overall migration decisions, thus easily leading to the case where the loss outweighs the gain. To optimize the long-term average performance of overall migration decisions, this paper regards that as a series of migration target optimization problems oriented for all edge servers involved in the vehicle journey from the current vehicle position. Then this paper designs the optimization goal (OG) from the long-term average perspective based on the decision factors in subsection 4.1 as follows.

4.2.1 Min-Cost: Minimize the Average Migration Time

$$OG_1:\ \min \overline{\sum\nolimits_t^{\infty} \mathcal{M}_{i,j}^n} \tag{8}$$

where t denotes the current migration trigger moment; n denotes the migration number experienced in time order; i and j respectively denote the source server ID and the target server ID corresponding to each migration.

To minimize the long-term average migration time, it is necessary to make the migration time of each migration as small as possible. However, different migration target path schemes may also cost equal average migration time. Therefore, OG_1 is not enough to guarantee the optimization effects, this paper still needs other indicators to evaluate the superiority of schemes.

As the service interruption risk is closely related to the trigger frequency of migrations and the service support capacity of edge servers, except for optimizing the average migration time, it is necessary to minimize migration times and improve the stability and adaptability of migration decisions.

4.2.2 Max-Reward: Maximize the Average Service Time

$$OG_2: \ \max \overline{\sum\nolimits_t^{\infty} \mathcal{S}_j^n} \tag{9}$$

The longer the service time on ES_j, the longer the break since the last migration trigger. The maximum of $\mathcal{S}_j$ is equal to the time interval between the vehicle connected to ES_j and moved out ES_j, which means the connection between the vehicle and ES_j has never been cut off due to SDMs during the whole serving process in ES_j. Therefore, the longer the average service time, the lower migration times and the SDM frequency, finally the higher the stability and adaptability of the migration decision.

In summary, the optimal global solution refers to the next edge server that minimizes the long-term average migration time and maximizes the long-term average service time, which is the best migration target server at the current migration trigger moment. However, since the condition *long-term* is infinite in the time dimension, it is hard to verify in practice whether the obtained solution is globally optimal. Therefore, this paper limits a time interval as the observation period to express *long-term*.

Thus, the approximate global optimal solution, actually a Pareto optimal solution, refers to the next edge server that minimizes the average migration time and maximizes the average service time within the observation period, namely the best migration target server denoted as dst^*,

$$dst^* = \arg\min_{dst_{path}} \frac{1}{n_{sum}} \sum\nolimits_t^{t_{end}} \mathcal{M}_{i,j}^n \cap \arg\max_{dst_{path}} \frac{1}{n_{sum}} \sum\nolimits_t^{t_{end}} \mathcal{S}_j^n \tag{10}$$

where t_{end} denotes the end moment of the observation period; n_{sum} denotes the entire migration times occurred within the observation period; dst_{path} denotes the migration target path scheme.

5 Migration Decision Algorithm

In this section, this paper designs the migration decision algorithm to answer how to migrate. This paper modifies the artificial bee colony algorithm to design the IoV edge application migration decision algorithm. The artificial bee colony algorithm can find the optimal solution by iterating the behaviors of individual bees, the key elements are the nectar source and the bee colony. The details of the migration decision algorithm Algs. 3 and 4 based on the improved artificial bee colony algorithm are as follows.

5.1 Nectar Source

A nectar source corresponds to a feasible solution, namely the migration selection from the source server ES_i to the candidate target server ES_j. The algorithm generates N initial nectar source solutions $\{Z_1, Z_2, \ldots, Z_k, \ldots, Z_N\}$ during initialization, each nectar source solution includes the following parts: the source server ES_i ID, the candidate target server ES_j ID and 3 properties of the nectar source.

$$Z_k \leftarrow \left\{(i, j_k), location_{i,j_k}, quality_{i,j_k}, count_{i,j_k}\right\} \tag{11}$$

1) Nectar source location $location_{i,j}$

It records the server IDs and deployment positions of ES_i and ES_j, expressed by 2D coordinates.

$$location_{i,j} = \left\{i\colon (x_i, y_i), \ j\colon \left(x_j, y_j\right)\right\} \tag{12}$$

2) Nectar source quality $quality_{i,j}$

It records the suitable degree of ES_j as the migration target for ES_i, which should be jointly evaluated by the migration time $\mathcal{M}_{i,j}$ and the service time $\mathcal{S}_j$. However, the service time $\mathcal{S}_j$ is hard to calculate accurately, so this paper utilizes 3 parameters related positively or negatively with $\mathcal{S}_j$ as described in Eq. (7) to reflect its value size. In general, $quality_{i,j}$ is evaluated by the normalized weighted equation of $\mathcal{M}_{i,j}$, d_{v2j}, $\langle \vec{V}, \overrightarrow{O_{v2j}} \rangle$ and Q_j^{offer}.

$$quality_{i,j} = \begin{cases} \rho_1 \dfrac{T_{max} - M_{i,j}}{T_{max}} + \rho_2 \dfrac{d_{v2j}}{d_{thr}} + \rho_3 \dfrac{\cos\langle \vec{V}, \overrightarrow{O_{v2j}} \rangle + 1}{2} + \rho_4 \dfrac{Q_j^{offer} - Q_A}{Q_{max} - Q_A} & , \text{if } valid\,(i,j) = 1 \text{ and } i \neq j \\ 0 & , \text{otherwise.} \end{cases} \tag{13}$$

where $\rho_1, \rho_2, \rho_3, \rho_4$ are score weight coefficients, satisfying $\rho_1, \rho_2, \rho_3, \rho_4 \in (0, 1)$ and $\rho_1 + \rho_2 + \rho_3 + \rho_4 = 1$, and their respective values can be adjusted.

Eq. (13) shows that within the valid migration range, the less the migration time $\mathcal{M}_{i,j}$, the farther the distance d_{v2j}, the smaller the azimuth deviation angle $\langle \vec{V}, \overrightarrow{O_{v2j}} \rangle$ and the larger the service traffic capacity Q_j^{offer} of the candidate target server ES_j, the larger the value of $quality_{i,j}$, namely the more suitable ES_j is as the migration target, which means the app migrated to ES_j can cost less migration time to gain more service time.

3) Nectar source mining degree $count_{i,j}$

It records the un-updated times of the feasible migration solution from ES_i to ES_j during the iteration. The initial and the maximum mining degree of each nectar source is 0 and *limit*, respectively.

Algorithm 3: CBM decision algorithm based on improved artificial bee colony algorithm (CBM-IABC)

Input: t_{end}, itr_{max}, $limit$, $(x_A, \ y_A)$, src, $\{\rho_{CBM-IABC}\}$
Output: dst^*

```
1:  for t = t_cur : t_end do
2:     update src and (x_A, y_A)
3:     if Alg.1 return true then
4:        initialize {Z_1, Z_2, ..., Z_k, ..., Z_N}
```

(Continued)

Algorithm 3: Continued

5: **for** $itr = 1\ :\ itr_{max}$ **do**
6: *//1. Employed Phase*
7: update *valid* and *ICol*
8: **for** $k = 1\ : N$ **do**
9: generate Z'_k by Eq. (14)
10: **if** $quality_{src,j'_k} > quality_{src,j_k}$ **then**
11: $Z_k \leftarrow Z'_k$
12: **else**
13: $count_{src,j_k} \leftarrow count_{src,j_k} + 1$
14: **end if**
15: **end for**
16: *//2. Onlooker Phase*
17: **for** $k = 1\ : N$ **do**
18: update P_{Z_k} and G_{Z_k} by Eq. (15)
19: **end for**
20: select Z_k by roulette selection
21: update Z_k by Line 9–14
22: *//3. Scout Phase*
23: **if** $count_{i,j_k} \geq limit$ **then**
24: find Z_{new} by initialization method
25: update Z_k by Line 9–14
26: **end if**
27: record the best solution Z^* obtained so far
28: **end for**
29: $dst^* \leftarrow Z^*$
30: **end if**
31: **end for**

5.2 *Bee Colony*

There are 3 kinds of bees in the colony. The employed bee is responsible for discovering excellent solutions. The onlooker bee is responsible for speeding up the convergence. The scout bee is responsible for avoiding local optimal traps.

The initial colony size is $2N$, where each number of employed bees and onlooker bees is N while scout bees are not present initially. The employed bees match with the initial nectar source solutions one by one and record their respective 3-property information. Each iteration of the algorithm will go through the following 3 phases.

Algorithm 4: CBM & SDM decision algorithm based on improved artificial bee colony algorithm (IABC)

Input: t_{end}, itr_{max}, $limit$, $(x_A,\ y_A)$, src, $\{\rho_{IABC}\}$
Output: dst^*
for $t = t_{cur}\ :\ t_{end}$ **do**
update *src* and $(x_A,\ y_A)$

(Continued)

Algorithm 4: Continued

```
    if Alg. 1 return true || Alg. 2 return true then
        initialize {Z_1, Z_2, ..., Z_k, ..., Z_N}
        repeat
            //Line 5–28 from Alg. 3
            Employed Phase
            Onlooker Phase
            Scout Phase
            record the best solution Z* obtained so far
        until itr_max
        dst* ← Z*
    end if
end for
```

1) Employed phase

At the migration trigger moment of the IoV app A in ES_i, this paper first determines the valid migration range *valid* at the trigger position (x_A, y_A) and records all the column labels where $valid\,(i, :) = 1$ into a set $ICol$. Then each employed bee randomly searches from $ICol$ to form a new solution $Z_k^{'}$ and decides whether to update its original matched solution Z_k $(k \in [1, N])$ according to the nectar source quality.

$$Z_k^{'} \leftarrow \left\{ i, j_k^{'} = \text{rand}\,\{ICol\}\,, location_{i,j_k^{'}}, quality_{i,j_k^{'}}, count_{i,j_k^{'}} \right\}, \text{ s.t. } valid\left(i, j_k^{'}\right) = 1 \tag{14}$$

If the $quality_{i,j_k^{'}}$ of the new solution $Z_k^{'}$ is greater than the $quality_{i,j_k}$ of the original solution Z_k, then replace Z_k with $Z_k^{'}$, otherwise do not update Z_k and add 1 to the $count_{i,j_k}$ of the original solution Z_k.

The employed bees will transfer their latest matched nectar source information to onlooker bees after the above process.

2) Onlooker phase

Based on the information shared by employed bees, onlooker bees first calculate the quality level evaluated value (the individual selected probability) P_{Z_k} and the corresponding cumulative probability G_{Z_k} for each solution Z_k.

$$\begin{aligned} P_{Z_k} &= \frac{quality_{i,j_k}}{\sum_{m=1}^{N} quality_{i,jm}} \\ G_{Z_k} &= \sum_{m=1}^{k} P_{Zm} \end{aligned} \tag{15}$$

Then N onlooker bees select the solution according to the probability P_{Z_k} based on the roulette selection method, search and update the selected solution according to Eq. (14).

3) Scout phase

Scout bees are not present at the beginning, their numbers will be adjusted dynamically in the iteration as following rules.

When the $count_{i,j_k}$ of Z_k reaches *limit*, its matched employed bee will turn into a scout bee, and a new solution Z_{new} will be searched randomly like the solution initialization. If the $quality_{i,jnew}$ of Z_{new} is greater than the $quality_{i,j_k}$ of Z_k, then replace Z_k with Z_{new}, otherwise do not update Z_k.

6 Simulations

Simulation experiments are carried out via MATLAB to verify the performance of the proposed migration strategy based on IABC. The comparative strategies include 4 kinds.

1) Nearest selection (NS) migration strategy aiming to minimize the distance from the vehicle to the target server.
2) Greedy selection (GS) migration strategy aiming to minimize the current migration time at the migration trigger moment.
3) Shortest path (SP) migration strategy aiming to minimize the sum of migration time within the observation period.
4) Discrete particle swarm (DPS) migration strategy aiming to minimize the current ratio of migration time to service time at the migration trigger moment.

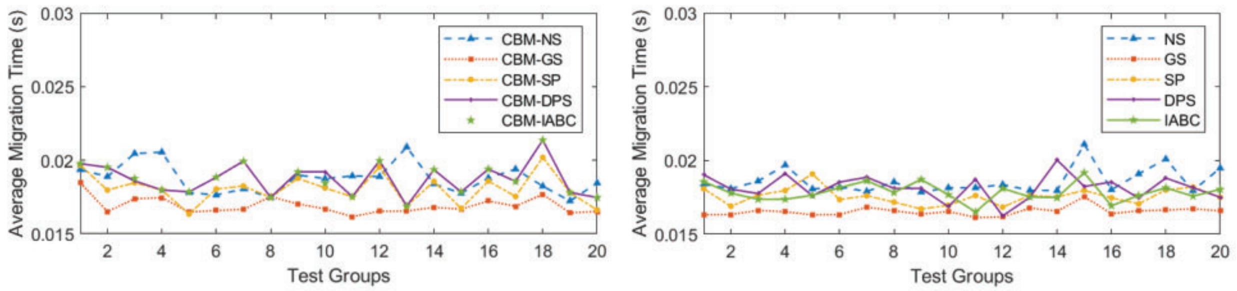
The simulation map contains 2 crossroads and 30 edge servers. The edge servers are seamlessly deployed on both roadsides (sparsely and evenly beside straight roads and more densely near the crossroads or fork roads). The vehicle drives at a constant speed of 10 m/s without parking on the way. The coverage radius of each edge server is 300 m. The parameters involved are shown in Table 1.

Table 1: Parameter values

Parameter	Value	Parameter	Value
d_{pre}	290 m	T_{create}	4 ms
d_{thr}	300 m	T_{queue}^{trans}	100 μs
v_{min}	30 km/h	T_{queue}^{comp}	200 μs
$Q_{i,t}$	[240, 700] MB	$D_{i,j}^{A}$	1 Mbit
Q_A	100 MB	$\eta_{i,j}$	[100, 500] Mbps
Q_{max}	600 MB	ω	[0, 1]
Q_{hold}	100 MB	p_j	[100, 800] Mbps
pri_{Apps}	[1, 10]	T_{access}	1 ms
pri_A	[1, 10]	T_{return}	1 ms
SN	30	$\{\rho_{CBM-IABC}\}$	$\rho_1 = 0.5, \rho_2 = 0.25, \rho_3 = 0.25, \rho_4 = 0$
t_{end}	250 s	$\{\rho_{IABC}\}$	$\rho_1 = 0.5, \rho_2 = 0.1, \rho_3 = 0.1, \rho_4 = 0.3$
T_{hold}	6 ms		

To show the performance of each strategy in various migration trigger situations more clearly, this paper sets two simulation backgrounds: (a) only CBMs occur; (b) both CBMs and SDMs occur. 20 groups of tests are conducted under the conditions of the same observation period and same vehicle route, where each strategy in each test group faces the same state of edge servers and networks that will change after each test group. Then this paper compares the performance of each strategy in terms of average migration time, migration times, the sum of migration time, average service time and frequency of SDM. Finally, this paper analyzes the adaptability and stability of each strategy for various migration situations.

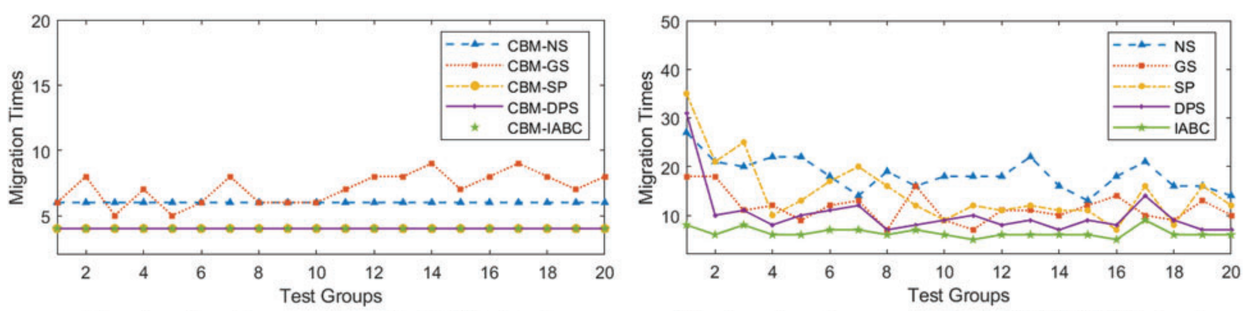
Fig. 6 compares the average migration time of each strategy within the observation period. GS is basically the smallest, but the overall gaps between NS, GS, SP, DPS and IABC are not significant. It indicates that this paper can't accurately distinguish the merits of each strategy via average migration time alone.



(a) avg-migration-time under only-CBM situation (b) avg-migration-time under both-CBM&SDM situation

Figure 6: Comparison of average migration time within observation period of different strategies in 20 test groups, evaluated under two migration situations

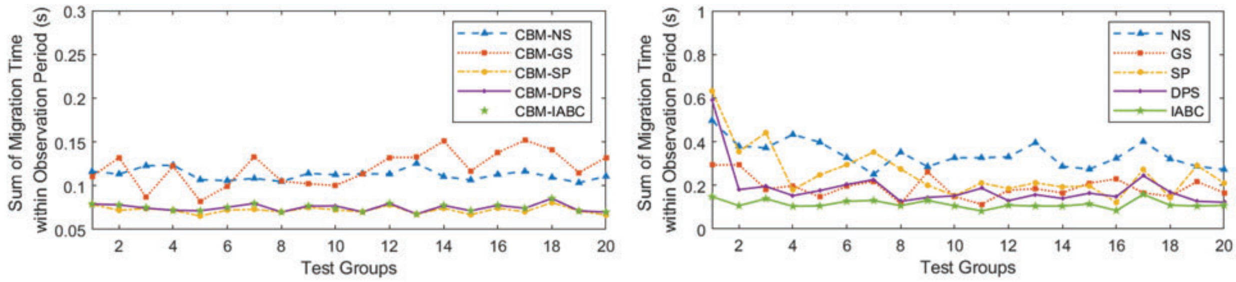
Fig. 7 compares migration times of each strategy within the observation period. In Fig. 7a, IABC, DPS and SP always generate the lowest migration times and remain stable enough, NS is also stable but somewhat higher, while GS shifts frequently and is often the highest. In Fig. 7b, IABC varies little and is obviously less than NS, GS, SP and DPS, where DPS is slightly less than GS and both SP and NS are higher, but SP is slightly less than NS. It indicates that IABC performs excellently and stably in terms of migration times.



(a) migration-times under only-CBM situation (b) migration-times under both-CBM&SDM situation

Figure 7: Comparison of migration times within observation period of different strategies in 20 test groups, evaluated under two migration situations

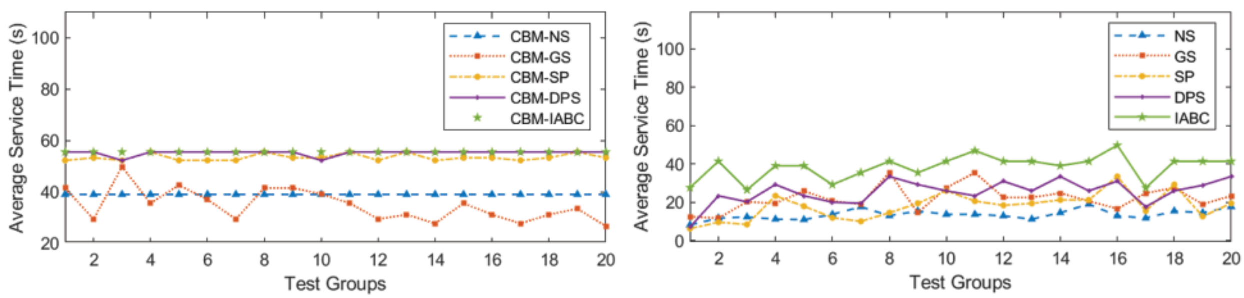
Fig. 8 compares the sum of migration time within the observation period for each strategy. In Fig. 8a, IABC, DPS and SP are always in the smallest value echelon where SP is occasionally slightly less than IABC and DPS, while NS and GS are obviously larger where GS fluctuates the most. In Fig. 8b, IABC is still the smallest; and the fluctuation range of DPS becomes larger, which is significantly higher than IABC and appears to be similar to GS; while both the result value and fluctuation range of SP are significantly larger; although NS fluctuates smaller than SP, its value remains the largest in the long term. It indicates that IABC performs best and stably in terms of the sum of migration time.



(a) sum-migration-time under only-CBM situation (b) sum-migration-time under both-CBM&SDM situation

Figure 8: Comparison of sum of migration time within observation period of different strategies in 20 test groups, evaluated under two migration situations

Fig. 9 compares the average service time of each strategy within the observation period. The average service time can also be reflected by migration times, where lower migration times mean longer average service time. Therefore, it also indicates that IABC performs best and stably in terms of average service time.



(a) avg-service-time under only-CBM situation (b) avg-service-time under both-CBM&SDM situation

Figure 9: Comparison of average service time within observation period of different strategies in 20 test groups, evaluated under two migration situations

Fig. 10 compares the frequency of SDM within the observation period for each strategy. As each strategy in each test group faces the same state of edge servers and networks, it means that all existed moments and positions that can trigger SDMs are fixed. Therefore, the ratio of SDM times triggered by each strategy to the total migration times, namely the frequency of SDM, can reflect its ability to avoid SDMs. This critical ability is directly related to the adaptability and stability of the strategy in situations where existing high risk of triggering SDMs. The results indicate that IABC has the best ability to avoid SDMs.

Fig. 11 averages the results of the above indicators separately and directly displays the long-term average performance of each strategy through the bar charts, which verifies the above analysis.

This paper also carried out corresponding simulation experiments under the conditions of different vehicle speeds or different edge server coverage radius, as shown in Fig. 12, which verifies the applicability of the above conclusions in more variable scenarios.

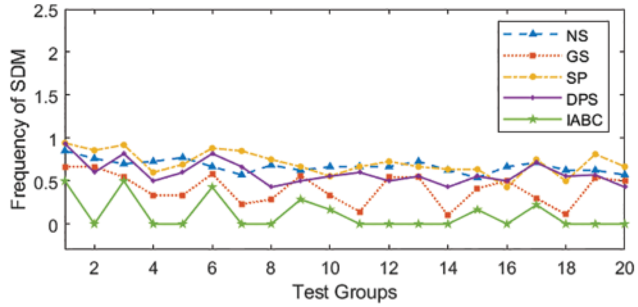
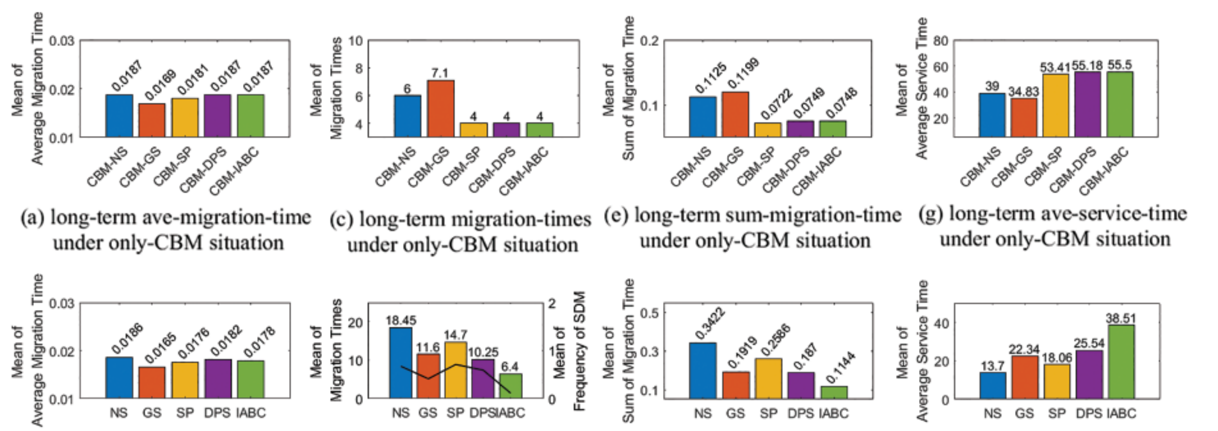


Figure 10: Comparison of frequency of SDM within observation period of different strategies in 20 test groups, evaluated under the situation where both CBMs and SDMs occur



(a) long-term ave-migration-time under only-CBM situation
(c) long-term migration-times under only-CBM situation
(e) long-term sum-migration-time under only-CBM situation
(g) long-term ave-service-time under only-CBM situation
(b) long-term ave-migration-time under both-CBM&SDM situation
(d) bar: long-term migration-times line: long-term SDM-frequency under both-CBM&SDM situation
(f) long-term sum-migration-time under both-CBM&SDM situation
(h) long-term ave-service-time under both-CBM&SDM situation

Figure 11: Comparison of long-term average performance of each indicator within observation period of different strategies

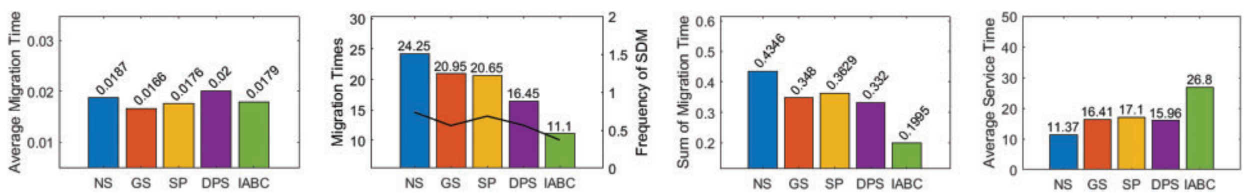


Figure 12: Comparison of each indicator within observation period of different strategies under the conditions of different vehicle speeds or different edge server coverage radius

7 Conclusion

This paper studies the IoV edge application migration mechanism, focusing on optimizing the migration cost and reward in the migration process. First, a migration trigger determination algorithm for CBM and SDM is separately proposed to improve the determination accuracy. Then, a migration target decision calculation model oriented to minimize the average migration time and maximize the average service time is constructed to reduce migration times while optimizing the migration decision. Finally, a migration decision algorithm based on the improved artificial bee colony algorithm is proposed to avoid local optimal migration decisions. Simulation results show that the proposed migration mechanism can reduce the average migration time and migration times, improve the average service time and the ability to avoid SDMs, and enhance the stability and adaptability of IoV application services.

In future work, this research will investigate the IoV edge application migration problem under more complex scenarios to further optimize the performance and availability.

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