Q-learning-based Opportunistic Communication for Real-time Mobile Air Quality Monitoring Systems

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Abstract—We focus on real-time air quality monitoring systems that rely on devices installed on automobiles in this research. We investigate an opportunistic communication model in which devices can send the measured data directly to the air quality server through a 4G communication channel or via Wi-Fi to adjacent devices or the so-called Road Side Units deployed along the road. We aim to reduce 4G costs while assuring data latency, where the data latency is defined as the amount of time it takes for data to reach the server. We propose an offloading scheme that leverages Q-learning to accomplish the purpose. The experiment results show that our offloading method significantly cuts down around 40-50% of the 4G communication cost while keeping the latency of 99.5% packets smaller than the required threshold.

Index Terms—Air quality monitoring, Mobile sensor, Opportunistic Communication, Reinforcement learning.

I. INTRODUCTION

In the last decades, with the rapid development of industrialization and urbanization, air pollution has become an increasingly crucial issue. Over the years, many studies have been conducted and showed that air pollution could cause diseases, allergies, and even death to humans [1], [2]. In that context, monitoring air quality is one of the critical factors that help the government make policies and people plan for life. Traditionally, air quality monitoring has been carried out by static monitoring stations located at fixed locations. However, due to the high deployment and operating costs, the density of deployed monitoring stations is insufficient. For example, in Hanoi, Vietnam, with more than 3000 km^2 , there are only 50 air quality monitoring stations [3].

Recently, there have been several studies proposing a new approach, namely the vehicle-based mobile air quality monitoring system [4] [5]. The vehicle-based mobile air quality monitoring systems leverage lightweight air quality monitoring devices mounted on vehicles to broaden the monitoring area. In [6], the authors considered a mobile air quality monitoring system that relies on low-cost mobile sensors deployed on trash trucks. They proposed techniques to detect pollution hot spots and identify pollutant source signatures. Nguyen et al. in [5] studied how to deploy air quality monitoring sensors on buses for maximizing the monitored regions. The authors first mathematically formulated the problem and then provided an approximation algorithm to determine optimal buses for placing sensors.

In this research, we focus on real-time vehicle-based mobile air quality monitoring systems, in which the devices continuously collect the air quality information and transfer it to the server. There are two challenges when dealing with such real-time monitoring systems. Firstly, we need to ensure the freshness of the information, i.e., guaranteeing that the time from when the data is measured till arriving at the server does not exceed a threshold. The second challenge is to minimize the communication cost. The targeted problem, which we name as OCMA (stands for Opportunistic Communication for Mobile Air quality monitoring) can be stated as follows. Air quality monitoring devices are mounted on buses. These devices perform air quality measurement with frequency f. The data collected by the devices are transmitted to the cloud server via one of the following communication planes. Firstly, devices can transmit data directly to the cloud server via the 4G communication. Secondly, the devices can transmit data to Road Side Units (RSUs) located along the roads through the Wi-Fi channel. These Road Side Units will transfer data to the cloud server through a high speed wired network. Finally, a device can relay data to another device on the vehicle next to it. This neighbor vehicle will then aggregate the data and transfer it to the cloud server or Road Side Units. We assume that the 4G communication is available everywhere. Thus, device can transmit data by 4G at any time. In contrast, Wi-Fi communication can only be used when devices enter the communication ranges of the RSUs or other devices. On the other hand, it is well-known that 4G communication is usually much more expensive than Wi-Fi. Besides, the 4G communication also consumes much more energy compared to Wi-Fi. Therefore, our OCMA problem asks to minimize the use of 4G communication while guaranteeing that the information latency does not exceed a threshold. Here, the term "information latency" is defined by the time interval from when the data is collected until it reaches the server. To the best of our knowledge, this study is an early attempt to minimize communication costs while maintaining the freshness of information in mobile air quality monitoring systems.

The OCMA problem can be categorized as an offloading problem in V2X (i.e., Vehicle-to-Everything) networks. In [7], K. Zhang et al. addressed the energy optimization problem in Mobile Edge Computing (MEC)-enabled 5G networks. They first mathematically formulated the targeted problem and then proposed an approximation algorithm to allocate the radio resource. The work in [8]-[10] addressed the offloading decision of collaborative task execution between platoons and a MEC server. Both [8], [9] considered how to determine the location of task execution either on a vehicle, offloading to other platoon members, or an associated MEC server. However, [8] focused on minimizing the offloading cost, while [9] aimed at reducing the average energy consumption. [10] targeted the reduction of offloading latency between the vehicles, each of which necessarily maintains the information of its 1-hop neighbors. Whenever with a task, a vehicle calculates the offloading latency for all the relay hop candidates. A neighbor vehicle with minimum latency is chosen as the best relay node. The authors in [11] proposed a federated offloading method that exploits horizontal offloading path between vehicles, with the objective of minimizing total latency. In [12], the authors aimed at minimizing the power consumption of MEC servers and vehicles.

Zhao et al. recently utilized MEC and cloud computing resources simultaneously for offloading [13]. In that work, vehicles could offload their computation tasks to an MEC server or the cloud via RSUs. The objective was to maximize the system's utility by optimizing both the offloading strategy and resource allocation. In [14], Y. Lin et al. addressed the traffic and capacity allocation problem in a three-tier model and proposed an optimization algorithm consisting of two phases. The first was adjusting the capacity allocation, optimizing the traffic allocation. Their objective was to minimize total capacity and guarantee that at least some traffic has satisfying latency constraints.

Unlike previous research, we use three communication planes simultaneously, namely, vehicle-to-cloud, vehicle-to-RSU, and vehicle-to-vehicle, with the goal of reducing 4G communication costs while maintaining information freshness. Our idea is to exploit Q-learning in offloading tasks. In our Q-learning paradigm, each air quality monitoring device is considered as an agent that keeps track of its O-table. The action space consists of four values: keeping data in the local memory, sending to the RSU, relaying to the neighbor device, and transmitting to the server. An entry in a Q-table represents the quality of an action. The agent (i.e., air quality monitoring device) chooses the action whose Q-value is the greatest at every time slot. The Q-table is updated after performing an action, based on a so-called reward function. Our reward function is designed to encourage actions that reduce 4G communication cost while ensuring the data latency constraint. Our contribution is as follows:

- We are the first to handle the challenge of opportunistic communication in real-time mobile air quality monitoring systems.
- We propose a Q-learning-based opportunistic communication protocol that attempts to reduce the cost of 4G communication while ensuring data latency.
- We perform extensive experiments to evaluate the performance of the proposed protocol. The results show the superiority of our proposal to the existing works.



Fig. 1. Network model.

The remainder of the paper is organized as follows. We present the network model and a brief introduction to Q-learning framework in Section II. Sections III describes our proposed protocol in details. We present the numerical results in Section IV and conclude the paper in Section V.

II. PRELIMINARIES

In this section, we first present our network model, and then we give a brief introduction to Q-learning, the technique that will be used in our solution.

A. Network Model

Figure 1 depicts the network model which comprises of three components: air quality monitoring devices, Road-Side-Units (RSUs), and a cloud server. We assume that there are n air quality monitoring devices that are mounted on n buses. Each device $D_i(i = 1, ..., n)$ has a computing capacity of C_i^* and the transmission range of r_{D_i} . The RSUs are computing units located along the roads. We also assume that there are m RSUs denoted as $R_j(j = 1, ..., m)$ which has the transmission range of r_{R_j} . The cloud server is named as the *air quality server*. The air quality monitoring devices continuously measure the air quality indicators and transfer the measured data to the air quality server via one of the following three communication planes:

- 1) Air quality monitoring device \rightarrow Air quality server.
- 2) Air quality monitoring device $\rightarrow RSU \rightarrow Air$ quality server.
- Air quality monitoring device A → Air quality monitoring device B (device B then transfers the data to a RSU or the air quality server, or another device).

The air quality monitoring devices use the 4G connection, which is relatively expensive, to interact with the air quality server. Communication between air quality monitoring devices and RSUs, on the other hand, takes place via a free Wi-Fi channel, as does communication between two air quality monitoring devices. It's worth noting that 4G service is available everywhere. As a result, a device can send data to a server via the 4G channel nearly instantly. In order to send data to the RSU or another device, the device must first move into that RSU's or device's communication range. We aim at proposing an offloading mechanism that accomplishes both of the following goals: 1) Reducing the amount of data with a



Fig. 2. Q-learning overview.

latency larger than a given threshold δ , where "data latency" refers to the time it takes for data to reach the server from when it is measured; and 2) Minimizing the amount of data transmitted by 4G communication.

B. Q-learning

Q-Learning [15] is a Reinforcement Learning technique that learns from experiences in order to achieve a certain optimization target. Figure 2 depicts the Q-learning process, which consists of four components: an environment, an agent, a state space, and an action space. The agent uses the so-called Q table to determine the action at each stage. Each entry in the Q table represent the goodness of performing an action at a given state concerning the agent's final goal. The Q-table is updated by the following Bellman equation:

$$Q(S_t, A_t) \leftarrow (1 - \alpha)Q(S_t, A_t) + \alpha[\mathcal{R}_t + \gamma \max_{a} Q(S_{t+1}, a)]$$
(1)

where $Q(S_t, A_t)$ is the Q-value at a state S_t when taking action A_t at time-step t. \mathcal{R}_t is the reward received for performing action A_t in the state of $S_t \cdot \max_a Q(S_{t+1}, a)$ is the maximum value that may be obtained for all possible actions a at the next state S_{t+1} . In addition, the α and γ (ranges from 0 to 1) represent the learning and discount rates, respectively.

III. PROPOSAL

In our Q-learning-based model, the network is considered the environment, while each air quality monitoring device is an agent. We utilize the distributed approach where each monitoring device runs its own Q-learning-based model. To facilitate the reading, we summarize the notations in Table I.

A. State space

For each device D_i , the state at a time slot t is a quadruple consisting of the following items:

- $\mu_i(t)$: the timing D_i generates the last packet.
- $c_i(t)$: the computing resource of D_i that is remaining at time slot t.
- c_N(t): the remaining resource of the nearest device N, if N is in the communication range of D_i.
- $\mathcal{N}_i^R(t)$: a binary variable indicating whether D_i is in the communication range of a RSU.

TABLE I Notions

Notion	Description
n	the number of air quality monitoring devices
m	the number of RSUs
D_i	the <i>i</i> -th air quality monitoring device
r_{D_i}	the transmission range of D_i
C_i^{*}	the maximum computing capacity of D_i
$\vec{R_j}$	the <i>j</i> -th RSU
r_{R_i}	the transmission range of R_j
δ	the data latency threshold
$S_i(t)$	the state at a time slot t of agent D_i
$A_i(t)$	the action taken by agent D_i at a time slot t
$\mu_i(t)$	the timing agent D_i generates the last data at a time slot t
$c_i(t)$	the remaining computing resource of D_i at time slot t
$c_{\mathcal{N}}(t)$	the remaining computing resource of the nearest device at time slot t .
$\Delta_i(t)$	the time interval from when D_i generates the last data until the time slot t , $\Delta_i(t) = t - \mu_i(t)$
$\Delta c(t)$	the difference in remaining capacity of D_i and nearest device at time slot t , $\Delta c(t) = c_N(t) - c_i(t)$
θ	the priority factor

B. Action space

An air quality monitoring device can conduct one of the following actions at each time slot t:

- i) Keeping the data in the local queue,
- ii) Sending the data directly to the air quality server via 4G communication channel,
- iii) Sending the data to the nearest RSU, if D_i is in the communication range of a RSU,
- iv) Sending the data to the nearest device, if they are in the communication range of each other.

C. Reward function

We denote by $\mathcal{R}_i(t)$ the reward received when device D_i performs action $A_i(t)$. Our goal is to minimize the total amount of data transmitted by 4G while guaranteeing that the data latency does not exceed a predefined threshold δ . The reward function is defined as follows.

$$\mathcal{R}_{i}(t) = \begin{cases} \frac{\theta \times C_{i}^{*} - c_{i}(t)}{1 + \Delta_{i}(t)} &, \text{ sending to the} \\ & \text{air quality server} & (2) \\ \frac{C_{i}^{*} - \theta \times c_{i}(t)}{1 + \Delta_{i}(t)} &, \text{ sending to a} \\ \frac{BSU}{1 + \Delta_{i}(t)} &, \text{ sending to the} \\ \frac{\Delta c(t)}{[1 + \Delta_{i}(t)] \times |\Delta c(t)|} &, \text{ sending to the} \\ nearest device & (4) \\ -n & \text{if } c_{i}(t) > C_{i}^{*} \end{cases}$$

0 or
$$\Delta_i(t) > \delta$$
 (5)
, keeping in the local memory (6)

where $\Delta_i(t) = t - \mu_i(t)$ is the time elapsed from when the data is collected, $\Delta c(t) = c_N(t) - c_i(t)$ in that $c_N(t)$ is the remaining resource of the nearest device, and p is a significantly large positive number. θ is a parameter in the range of [0, 1]. The value of θ is adjust based on the remaining capacity $c_i(t)$ and the elapsed time $\Delta_i(t)$. Specifically, when $c_i(t)$ is large and $\Delta_i(t)$ is small, θ tends to be small as sending the packet to RSU is prioritized than sending it to the gNB. The rationale behind the reward function is as follows. Formula (2) means that when the device's remaining capacity is sufficient $(\theta \times C_i^* - c_i(t) \leq 0)$, the device will avoid transmitting packets directly to the cloud server (due to the negative reward value). Instead, it will either send the data to the RSU or a nearest device, or hold the packet in local memory until it can take another action. In contrast, when the remaining capacity is no longer sufficient ($\theta \times C_i^* - c_i(t) > 0$), the device cannot hold the packet in the local memory; thus, transmitting the data directly to the cloud server gets more priority. Moreover, when $\theta \times C_i^* - c_i(t) \leq 0$, the reward of action sending to the cloud server is proportional to $\Delta_i(t)$. It means that the smaller the $\Delta_i(t)$, the more likely the device will not send the packet to the air quality server. The reward of action transferring data to a RSU is represented by Formula (3), which is inversely proportional to $\Delta_i(t)$. When $\Delta_i(t)$ is small, the device will prioritize delivering data to the RSU. When $\Delta_i(t)$ is significant large, however, communicating over the RSU is no longer a viable alternative because the device is not always within the RSU's communication range. Therefore, the reward of this action is lowered. Formulas (4) mean that the action of relaying data to the neighboring device is only encouraged when the available resource of the neighboring device is greater than that of the current device. Moreover, the greater the $\Delta_i(t)$, the smaller the reward of action sending to the neighbor device (because $\frac{1}{1+\Delta_i(t)}$ is inversely proportional to $\Delta_i(t)$). Finally, Formula (5) depicts that when the available resource of the current device exceeds its capacity or when the data's latency exceeds the threshold, the agent will be punished by a substantial negative reward.

IV. EVALUATION

A. Methodology

In this section, we evaluate the efficiency of our proposed algorithm in terms of optimizing the communication performance and cost.

Simulation model: we simulate the target network model (as shown in Figure 1) by extending the queue-model proposed in [16]. In which, air quality monitoring devices (sensors) iteratively generate packets with a same size in every λ_d time steps. Packets are then stored in a local queue and wait for processing in a first-in-first-out manner. If the queue is full at the time a packet is generated, the packet will be dropped. Thus, the *data latency* of a packet comprises two components: the transmission latency, e.g., the total time for transmitting packets from the vehicles to the server, and the time in the queue of this packet. The transmission latency on a given communication channel, i.e., Wi-Fi, 4G, or wired network, is proportional to the packet size and inversely proportional to the link bandwidth. In our simulation, the packet will be routed based on the corresponding decision algorithms, e.g., our proposed Q-learning method or the baseline method that



Fig. 3. The real vehicle trajectory.

uses random selection. Basically, a packet is decided between four actions: (i) keep in the local queue, (ii) send directly to the air quality server, (iii) send to the nearest RSU, or (iv) send to the nearest sensor/vehicle. In case a packet of a given sensor is decided to send to the nearest RSU (or sensor) while there is no available RSU (or sensor) in the transmission range of this sensor, the packet will continue keeping in the local queue for processing in the next time step (hereafter mentioned as the *offload-hit*) or sent directly to the server when the queue remaining capacity is not sufficient (hereafter mentioned as the *offload-missed* issue).

Simulation environment: we use the data set of bus routes in Seattle City, Washington [17] to simulate the movement of vehicles. Each data point includes the time and position of a bus. We use the data collected within 2 days (48 hours) from November 19th, 2001 till the end of November 20, 2001. We realized that in this data set, there are several buses that only appear in a short time, therefore we only collect data of buses whose active time is no less than 90 minutes per day. We then generate the RSUs' position on the map along each bus route. In which, the RSUs are concentrated in the city center, 1 - 3 km apart, while in the suburbs there will be a sparser number of RSUs, 4 - 8 km apart. We illustrate the bus routes (color lines) and the RSUs' positions (red pin) in Figure 3.

Evaluation metrics: It is worthy to note that the target of this work is to keep the number of packets that can reach the air quality server as much as possible (i.e., *maximizing the*

 TABLE II

 CONFIGURATION OF THE FIX-POSSIBILITY STRATEGIES

Strategies	P_{keep}	P_{server}	P_{rsu}	P_{sensor}
FP1	0.2	0.3	0.3	0.2
FP2	0.1	0.3	0.5	0.1
FP3	0.1	0.5	0.3	0.1

TABLE III SIMULATION PARAMETERS

Parameter	Value
Packet size	1 Mb
RSU transmission range	350 Meter
Sensor transmission range	120 Meter
RSU-server's link bandwidth (wired network)	10 Gbps
Sensor-RSU's link bandwidth (wifi network)	1 Gbps
Sensor-server's link bandwidth (4G communication)	500 Mbps
A time step \mathcal{T}	1 Min
Packet generation interval at a sensor (λ_d)	$1\sim 5~{\cal T}$
Data latency threshold δ	$5\sim 25~{\cal T}$
Sensor's computing capacity C^*	25 Mb
Number of RSUs m	384
Number of vehicles n	776

delivery ratio), while reducing the amount of data with a long latency (i.e., guaranteeing the information freshness) and lessening the 4G communication usage rates (i.e., *minimizing the* communication cost). Firstly, for the delivery ratio, we introduce the term rate of dropped packets (r_{drop}) , i.e., the relative number of packets that have been dropped at sensors when their remaining capacity is no longer sufficient. Secondly, for estimating the information freshness, we introduce the term δ -delayed packets. The δ -delayed packets are calculated by the total number of packets that have data latency greater than the threshold δ . We also define the evaluation metric rate of δ -delayed packets (or r_{delay}) as the ratio of δ -delayed packets over the total number of generated packets. Finally, the communication cost can be considered as the number of packets that directly send from a sensor to the air quality server via the 4G communication channel over the total number of generated packets (4G communication ratio or r_{server})¹. In this work, we also investigate the ratio of a packet sent from a RSU to the air quality server, denoted as r_{rsu} .

Comparison baseline: Because there is no current work that handles the same problem as ours, to show the efficiency of our proposed method, we compare it with a naïve offloading strategy named **FP**. In FP, at a given time step, a packet is randomly decided between four actions, namely keeping at the local, sending directly to the server, transferring to an RSU, and relaying to the nearest device, with fixed possibilities of P_{keep} , P_{server} , P_{rsu} and P_{sensor} , respectively. We consider three different configurations of FP, in which we change values of P_{server} , P_{rsu} and P_{sensor} . The detail settings of FP are is summarized in Table II.

In the following, we first compare the performance and cost of our proposed method with the baseline concerning a particular settings of the packet generation interval λ_d and the



Fig. 4. Relative breakdown of the simulation packets.

latency threshold δ in Section IV-B. We then investigate the impacts of λ_d and δ in Section IV-C.

B. Comparison of the proposed method and the baseline

In this experiment, we set the packet generation interval λ_d to 1, and the data latency threshold δ to 5 and 10. As mentioned in Section III, the value of θ is adjust based on the remaining capacity $c_i(t)$ and the elapsed time $\Delta_i(t)$. We heuristically increase θ from 0 to 1 when the remaining capacity decreases and the elapsed time increases. Other simulation parameters are summarized in Table III.

Figure 4 shows the rate of dropped packets r_{drop} , δ -delayed packets r_{delay} , and the communication cost r_{server} of our proposed method and the baseline strategies. The lower value the better performance. First of all, in the baseline, devices tend to hold the data in their queue until they can send it an RSU/or the nearest device (the offload-hit as mentioned in section IV-A). This strategy leads to a longer delay of a message and a higher number of dropped packets (when the queue is full). In contrast, by constructing a flexible priority factor θ which considers both the number of packets in the local queue and the elapsed time of packets, our proposed method can always guaranty all the generated packets can reach the server, i.e., $r_{drop} = 0$. As a result, the baseline strategies can not avoid the packet-dropped issue in all the cases, e.g., 15,1% and 3.5% of r_{drop} as in FP1 and FP2, respectively. The result also shows that our method provides a small number of δ -delayed packet, e.g., 0.5% and 0.24% which are $3-5 \times$ lower than those of FP1 and FP2 as shown in Figure. 4(a) and 4(b), respectively.

In addition, although the r_{delay} of FP3 is lower than that of our proposed method in the case of $\delta = 10$, it requires much more 4G cost than ours. Specifically, in all the experiments, our method requires the lowest communication cost (r_{server}), i.e., only around 50% of packets travel through the 4G network. It is interesting to note that the *offload-missed* issue mentioned in Section IV-A increases the communication cost, i.e., r_{server} of the FP strategies is much higher than the expected value (which should be around P_{server}). The reason can be explained as follows. When a packet is decided

¹Assumption: the cost of sending a packet via the 4G communication channel is much higher than that of using Wi-Fi or wired network.



Fig. 5. Impacts of the packet generation interval (λ_d) . δ is fixed to 5 time steps.



Fig. 6. Impact of the data latency threshold (δ). λ_d is fixed to 1 time steps.

to send to the nearest RSU/device but there is no available RSUs/devices around it, and the queue is full, the packet will be directly sent to server via the 4G communication channel. Thus, the 4G communication cost increases significantly. For example, in the FP1 and FP2, more than 60% of packets use the 4G communication channel (although it is designed with a fixed possibility of 30%). Those values are 80% and 50% for FP3, respectively.

In summary, the results imply that the performance/cost of the baseline FB approach is sensitive to the environment/network due to its coarse fixed configuration. Thus, it requires effort to manually figure out the best configuration when implementing this method in the real world (for a given specific environment). By contrast, our proposed method learns the environment/network information to make the decision flexibly so that it can avoid both the packet-dropped issue and *offload-missed* issue.

C. Discussion

In the following, we investigate the impacts of the packet generation interval and the data latency threshold to our proposed method.

1) Impacts of the packet generation interval λ_d : Figure 5 shows the impact of the packet generation interval, i.e., the frequency the devices measure the air quality indicators. In this evaluation, we set the data latency threshold to 5 while

changing the packet generation interval from $1 \rightarrow 5$ time steps. The result shows that there's a trivial impact of packet generation rate to our proposed method in both communication cost and performance. However, in the FB strategy, a higher number of messages are generated in a time unit, the higher possibility of a packet is dropped. On the other hand, when the packet generation interval is slow enough, instead of being dropped, a packet will be stored in a queue and, thus, the rate of delayed packets is increased. In general, this trend also appears when the relative packet size over the capacity of the local queue is too big (that leads to a smaller number of the packet can be store in the queue until the queue is full). Interestingly, the packet generation interval does not affect the communication cost of FB strategy.

2) Impacts of the data latency threshold δ : Figure 6 illustrates the impact of the data latency threshold, e.g., the maximum latency required by application, to our proposed method. In this experiment, we fix the packet generation interval $\lambda_d = 1$ while changing the latency threshold δ from $5 \rightarrow 25$ times steps. As expected that the rate of δ -delayed packets of both our proposed method and the baseline strategy decrease as the latency threshold increase because a packet has a longer time stay in the local edges, e.g., sensor or RSU. Furthermore, let us remind our strategy of the reward function in our Q-Learning method (as shown in the Formula (5)). When the data latency exceeds the threshold, there is a higher possibility of a packet to be directly sent to the server using the 4G communication channel. As the results, when the latency threshold increases, the number of packets meets such condition and use the 4G communication channel becomes smaller.

V. CONCLUSION

In this research, we focused on real-time mobile air quality monitoring systems which rely on devices mounted on vehicles. The devices continuously measure the air quality indicators and transfer them to the server via either 4G or Wi-Fi communication channels. We leveraged Q-learning to propose an opportunistic communication algorithm that minimizes the 4G communication cost while guaranteeing the data latency is under a predefined threshold. The experiment results showed that the proposed method can reduce 40-50% of the 4G communication cost while ensuring the latency of 99.5% packets smaller than the required threshold.

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