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ENHANCED VIDEO SURVEILLANCE IN AUTONOMOUS VEHICLES USING BLOCKCHAIN-ENABLED EDGE COMPUTING TECHNIQUES

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Abstract
The blockchain-based audio-visual transmission systems have been constructed to develop a distributed and adaptable smart transport system (STS), which gives consumers, video producers, and service providers direct contact. Blockchain-based STS devices need substantial computer resources to transcode diverse quality and formats of video feed into multiple versions and structures following varied user needs. Existing blockchains, however, cannot support live streaming because of their limited computing capability and high processing times. Large video data transfer and extensive analysis even put an excessive load on vehicular networks. In this work, a video surveillance approach has been proposed to optimize the blockchain system's traffic performance and reduce the latency throughout the multiple access edge computing (MEC) system. Integration of MEC and blockchain for video surveillance in autonomous vehicles (IMEC-BVS) has been proposed. To address this challenge, the joint optimization problem is represented based on the profound reinforcement training as a Markov Choice Progression (MCP) and the actor-critical asynchronous advantage (ACAA) method. Simulation findings show that the proposed method rapidly converges and enhances integrated MEC and blockchain performance for video surveillance in autonomous vehicles than existing methods.

Keywords: Blockchain, Multiple Access Edge Computing, Video Surveillance, Autonomous Vehicles

1. Introduction to Blockchain and MEC

As online services become more prevalent, mobile devices on wireless connections are growing at an explosive rate. Seventy-nine percent of worldwide mobile data traffic will be mobile video transmission by 2022, as per a study made by Cisco [1]. Over the past decade, flowing audio-visual platforms like Netflix and YouTube have been increasingly prevalent as the need for multimedia applications has grown. Various drawbacks are associated with video streaming services, including limited profits for video providers, hefty subscriptions, and low privacy for consumers [2]. On top of that, video streams have to be transformed into multiple bitrate versions to fulfill varied user needs owing to various policies and changing system circumstances. Numerous duplicates of audio-visual records with varying data rates are kept on the centralized servers, incurring enormous expenses in video collection and internet use [3].

As a viable decentralized alternative, blockchain has recently been presented and deployed in various distributed settings. These decentralized, innovative contract-based communications in communal or isolated peer-to-peer (P2P) networks and may be accessed by anybody in the system [4]-[5]. VideoCoin, flixxo, and others can construct decentralized, distributed video

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streaming networks using blockchain solutions. With blockchain-based streaming media, video providers (VP), listeners, and network operators (NOs) can all trade videos without the involvement of a third entity. The streaming video procedures may be self-organized as a bonus by employing consensus protocol [6]-[7].

Blockchain-based video systems cannot transcode videos owing to their limited computing requirements [8]. MEC, which delivers computing performance to the edges of the STS system, is viewed as a potential solution to enable content delivery facilities to the consumers [9]-[10]. Servers outfitted with MEC deliver reduced delay services to consumers and free up network bandwidth and storage expenses [11]. According to [12], a MEC-based architecture enables a MEC server to translate the bitrate form of the audio-visual data following link conditions and operator demands. A video bitrate adaption method is proposed in [13], taking into account wireless channel circumstances. Incorporating blockchains and MECs might have substantial advantages and be an excellent idea for this exciting field. Progress has been made on MEC and distributed ledger to make the most of both technologies' strengths and weaknesses.

In recent years, deep reinforcement learning (DRL) has become a powerful technique for solving resource allocation issues in wireless communications and networking with the aid of Artificial Intelligence (AI) [14]-[15]. The DRL-based methods have lower computational complexity than the standard optimization methods and can maximize the resources with low complexity in communication systems [16]-[17]. Using the MEC platform for video surveillance, throughput can be improved and reduce latency in blockchain-enabled autonomous vehicles. The study aims to contribute to the following points:

- This paper presents a unique video surveillance architecture for blockchain-enabled STS with the MEC system, in which philosophical transactions have been used to provide safe data gathering and processing.
- Video unloading and resource allocation have been defined as an MCP to improve operational throughput and reduce the delay of the MEC system. It is characterized as a normalized transaction throughput and aggregated delay.
- An ACAA-based DRL method is further presented, centered on a distributed management system with reduced complexity.

The remaining sections of the document are organized as follows. Section 2 explores related works on video surveillance in MEC and Blockchain. Integration of MEC and blockchain for video surveillance in autonomous vehicles have been proposed in section 3 for STS. Section 4 consists of the analysis and findings obtained from the proposed model. Finally, the conclusion and possible studies have been outlined in Section 5.

2. Related works on MEC, Blockchain, and STS

MEC for blockchain has been introduced by Wu et al. in [18], and commercial computational supply management teams based on Stackelberg game theory have been proposed. This method allows smartphone nodes (miners) to outsource their mining tasks to an edge computing network operator (ECNP). An allocation strategy for deep learning (DL) resources in mobile blockchain networks is proposed by Guo et al. [19] to optimize the income of the

ECNP. However, these works are inappropriate for video streaming because they use a proof-of-work (PoW) procedure to achieve agreement in the blockchain system. Data mining and block harmonization among all members affected by increased costs and extended delays.

Hu et al. [20] examine the agreement proliferation issue in Proof-of-Stake (PoS) public blockchains to overcome this challenge. Blockchain users and miners are modeled using machine learning models. To ensure automobile information sharing in blockchain-enabled IoV, Nguyen et al. in [21] present an improved Decentralized PoS (DPoS) consent system with a two-step lenient safety approach (miner choice and segment verification). Kang et al. in [22] present a systematic information sharing solution for effective information loading and distribution without endorsement in-vehicle computation and connections using collaborative blockchain and consensus mechanism. The game theory is a versatile and effective tool for studying the interplay and collaboration processes among diverse nodes and participants in systems. In edge buffering platforms, Xiong et al. in [23] examine an interrelationship among network service operators, subsidized information facility benefactors, and mobile consumers under a structured multiple Stackelberg control group. Several other applications of Stackelberg's game have been studied, including allocation of resources in portable fog calculating environment, simulated reserve administration in wireless transmitting networks, computational supply apportionment in fog networks, etc., [24]-[25]. They portray prospecting as a cooperative game amongst miners. To maximize their computing capacity and gain a regular income, miners establish a consortium.

To optimize the income of the ECNP and the usefulness of the blockchain, Misra et al. [26] model the mining procedure as Stackelberg game. This is not the first time Stackelberg's activities have been used to mimic reserve distribution and blockchain-based withdrawal processes. MEC now supports video transcoding as a practical method for delivering ad-hoc video streaming services. Using MEC and other technologies, we have explored several challenges related to video transcoding and delivery. It is proposed by Singh et al. [27] to strengthen the streaming service in information-centric heterogeneous networks by leveraging wireless virtualization techniques.

MEC, buffering, and soft-defined networks (SDN) are all considered by several researchers. A combined adaptive audio-visual frequency and circulation engineering challenges have been studied. Sun et al. in [28] proposed a heterogeneous computational unloading strategy, where operators have numerous autonomous activities that may be divested at fog nodes or a distant cloud jointly. The multimedia processing and distribution challenges in ultra-dense networks are investigated using MEC technology by Zhang et al. in [29]. A combined small BS selection, capacity planning, and resource distribution method are proposed for video streaming services. Transcoding and delivering video using blockchain and MEC may provide significant advantages and become an inspirational idea in this field[30].

Due to the high transaction throughput required by the blockchain system, this work aims at lowering the latency of video analytics applications using MEC systems and boosting the operational throughput of the blockchain. Markov decision process is used to represent a combined audio-visual offloading and reserve distribution challenge. To solve this challenge, the DRL technique is utilized in this study. Also, the critical control components have been distributed to solve various computational issues.

3. Integration of MEC and blockchain for video surveillance in autonomous vehicles

A video surveillance framework using MEC for STS has been introduced. The smart contract for video analytics is then described. The combination of Ethereum with edge devices can safeguard STS critical information systems and protect private information in the infrastructure and services. The overall model is presented for video unloading criteria in STS circumstances, which comprise STS systems that create interactions, the MEC scheme that supports video surveillance, and the blockchain scheme that interacts with the event.

3.1 The architecture of video surveillance

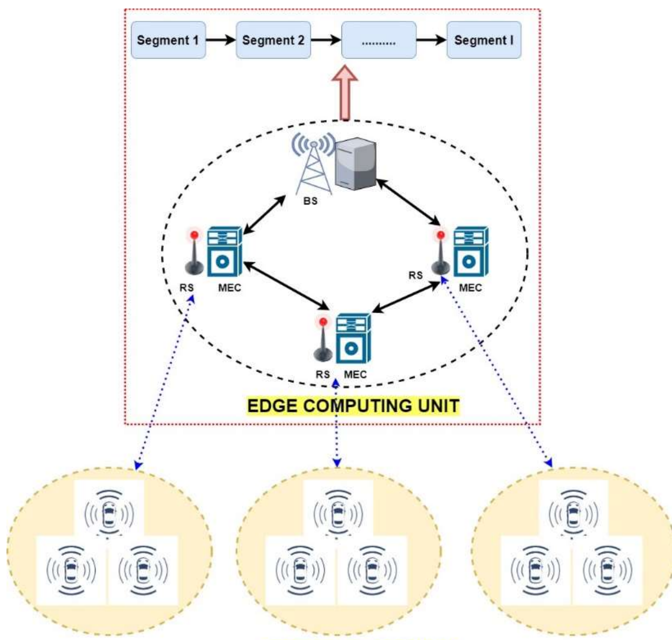


Fig. 1 Framework for the integration of MEC and blockchain for video surveillance in autonomous vehicles

Fig. 1 depicts the framework for the integration of MEC and blockchain for video surveillance in autonomous vehicles. MEC is used to unload video surveillance tasks from the STS, which has two aspects: a vehicle node with the camera and a Road Segments (RS) node with MEC. Cameras mounted on vehicle nodes can initiate audio-visual errands, wrap them into video blocks, and convey them to RS nodes through vehicular systems. MEC with RS node allows for sophisticated video analytics. It also ensures video retention on RS and information processing across nearby vehicles. For STS's perception and decision-making, cameras are an appealing sensor choice. Numerous contemporary professional driving support systems depend on cameras for carriageway and pedestrian identification, for example. In real-time, video analytics in STS may be performed using edge computing due to its extensive data volume, computation needs, and latency constraints.

3.2 System Model for STS

A blockchain-activated STS network using blockchain has been examined. The core of the coverage area is placed within the STS networks with a single macro-cell base station (BS). Various RSs are spread across the BS, and wired connections link all RSs. Assume a system without interruption, in which users employ coherent bandwidth for the communication of information. Let the RS set be marked $N = \{1,2,\ldots\ldots,N\}$. Therefore, $P = \{1,2,\ldots\ldots,P\}$, is indicated for the set of vehicles where n vehicles are provided with their respective RS n.

The blockchain nodes consist of all RSs in the blockchain system. These units have two characteristics: regular nodes and nodes of consensus. The blockchain system broadly addresses operations from the MEC network, i.e., the video download of data records. Blockchain technology requires two stages to accomplish the functions. One is the production of blocks, while the other is the procedure of accord. Normal nodes transmit and absorb register information solely, whereas agreement nodes create transactions and execute the consensus protocol. It has to be noted that L consensus nodes are chosen by a particular practice from N. Let $L = \{1,2,\ldots\ldots,L\}$ mark the agreement cluster. The reverse link produces a video bottleneck in vehicular communications. MEC servers have resource constraints that restrict download scaling. Vehicle to internet communication supports cellular system uplink communication when automobiles communicate RS visual information.

There is a need to enhance connectivity and computer abilities. Thus, reverse link MEC is taken into account in this research. Backhaul MEC will be examined in the future study because of the length constraint of this paper. Edge buffering is also crucial for on-demand cellular network video streaming. Video surveillance requests in automotive cyberspace have been considered, and the key responsibilities are video decryption, pre-processing and entity recognition. Therefore, connectivity and processing capabilities were examined to maximize the blockchain platform's transaction performance and reduce the MEC platform's delay. MEC-based RSs are used in video analysis platform tasks.

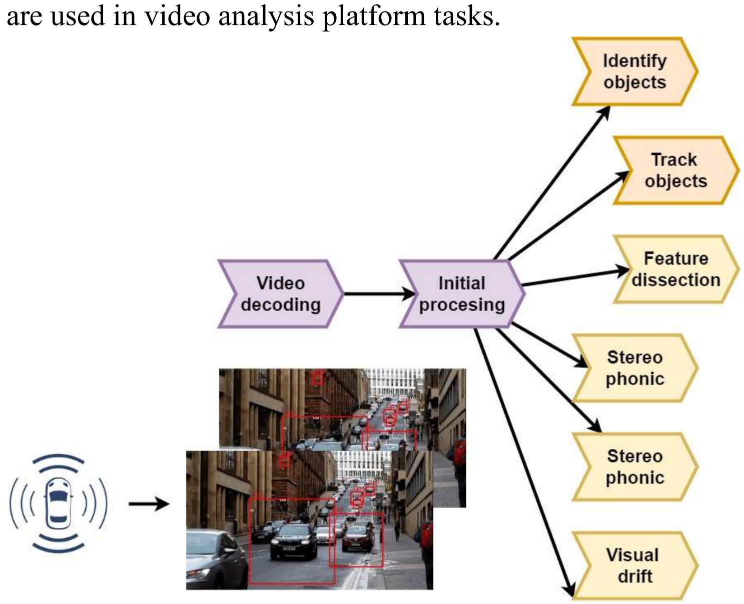


Fig. 2 Methodology of video surveillance in STS

Fig. 2 shows the methodology of video surveillance in STS. As illustrated in figure 2, many modules allow the video analysis process to be considered and explained.

1) Video deciphering: It is the decoding procedure or the decompression of encoded video instantaneously. The codec may extract and unwind the multimedia broadcasting in a sequential sequence constructed on the real-time streaming protocol (RTSP) or the real-time messaging protocol (RTMP). As a result, AVS, H.264/AVC, and H.265/HEVC are among the most commonly utilized video coding standards.

(2) Initial processing: the correction procedure is a non-uniform modification of brightness or colors and amplitude. Because of the poor contrast and blurring of the picture, lens correction and enhanced picture should improve the quality of the video sequences.

3) Object Recognition: Instances of semantic entities of a specific class need to be detected, which are essential in achieving independent navigation. STS's significant objects are automobiles, football, cycling, and road signs. Accordingly, a single-phase method comprised of the deep learning (DL) based object recognition methodologies has been used. The different classes include regional integration, spatial pyramid pooling network (SPP-Net), and regional proposition networks (RPN). The solitary technique model consists of a single screen detector (SSD).

4) Track objects: The status of one or more things must be estimated over runtime via sensor readings. The follow-up of other drivers is essential for autonomous vehicles. Object detection generally comprises four phases: function retrieval, navigation model, look-up framework, and online updating. Approaches for object detection and tracking include the generating, discriminating, and deep learning model.

5) Feature dissection: A tag consisting of a set of classes must be assigned to each pixel of the image. The division of pictures into semantic areas allows cars to comprehend their atmosphere so that autonomous vehicles may be securely included in our current roadways.

6) Stereo Phonic: the method of getting knowledge from inactive 2D pictures taken from a laser scanner is stereo prediction.

7) Visual Drift: It can offer important scene information and act as an interface to specific activities, including movement estimate and surveillance.

For the unburdening mission of video surveillance applications using MEC, the transmission of data from intelligent vehicles to road segments is given as follows:

$$S = BW \times log[1 + \frac{Po(m)G(m)}{\delta + P_j G_j(m)}] \quad (1)$$

Let $Po(m)$ and $G(m)$ depict the transmission energy and gain of the channel. There are p vehicles and n RSs for a period of m. δ is the power of interfering signal. The transmission bandwidth is given by BW. $P_j G_j(m)$ is the sum of all interfering signals.

The latency to download the video information (E_o) is given by

$$E_o = \emptyset^J / S \quad (2)$$

Where $\emptyset^J$ is the volume of video information in bits received from the road segments, S is the transmission of data from intelligent vehicles to road segments for the unburdening mission of video surveillance applications using MEC. The power consumed for the information of video data from the autonomous vehicle to RS is given by

$$D_o = Po(m)\, E_o \tag{3}$$

E_o is the latency to download the video information. $Po(m)$ is the transmission energy of the channel. It would incur the computing resources to carry out the video surveillance work on the MEC server p. The processing latency that MEC server p performs on the autonomous vehicle n is therefore determined by the following equation:

$$E_d = \emptyset^J Y / F_0 \tag{4}$$

The number of computational resources needed for evaluating a bit of the video data may be determined using $F = \{F_0\}$ in cycles/s to signify the processor frequency needed by the nth MEC server. Y denotes calculation intensity for video surveillance (in cycles/bit).

The power consumed for video surveillance using the MEC server is given by

$$D_d = L \times (F_o^2) \times E_d \tag{5}$$

L is the effectiveness of power consumption of the dispensation unit. F_0 represents the processor frequency needed by the nth MEC server. E_d is the processing latency that MEC server p performs on the autonomous vehicle.

The total transmission latency is given by

$$E = E_o + E_d = \emptyset^J / S + \emptyset^J Y / F_0 \tag{6}$$

Therefore, the completion of the video surveillance task by the nth MEC server is given as the total delay in transmission and processing latency. The actual power consumption is provided by

$$D = D_o + D_d = [Po(m)\, E_o] + [L \times (F_o^2) \times E_d] \tag{7}$$

E_o is the video information delay to be downloaded. $Po(m)$ is the channel energy transfer. L is the efficiency of the unit's electricity usage. An nth MEC server requires CPU-cycle frequency F_0. E_d is the autonomous vehicle delay performed by MEC server p.

3.3 Blockchain process

Blockchains can possess three characteristics of a scalability trilemma law: (1) versatility, (2) safety, and (3) decentralization.

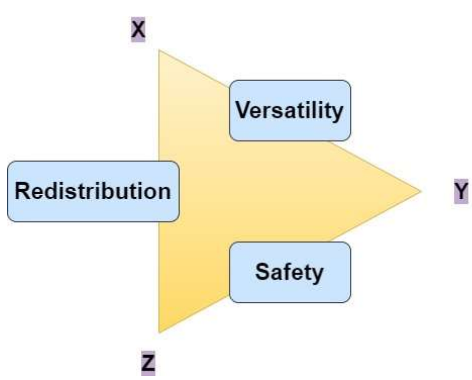


Fig. 3 Features of blockchain

The three key features of blockchain have been depicted in Fig. 3. Each of these features has been explained in detail as follows:

3.3.1 Versatility

It defines the network infrastructure, including how many nodes the network can handle, the number of transactions the network can take, etc. Operations to the blockchain network have been recorded. Based on the suggested timetable approach, a block producer is selected, and a block producer is then generated by gathering, verifying, and packing operations [31]. The operational throughput ∂ can be specified by

$$\partial = \{[\frac{T^C}{T^U}]/\ U^J\} \tag{8}$$

where T^C be the segment size. The segment interval and the transaction size are denoted by U^J and T^U, respectively. The segment size can thus be increased or the time interval reduced to enhance the information flow. However, additional variables like delay, safety, and decentralization impact the scalability of blockchain systems.

3.3.2 Safety

Safety refers to the amount of blockchain's defensiveness against exterior assaults and the platform's resilience to manipulation. A blockchain system contains various attack vectors, including dual expenditure attack, wormhole attack, DDoS assault, and 51 percent assault [32]. The amount of malevolent verifiers k should thus be constrained by the following restriction to guarantee the safety of smart contracts:

$$k < K, where\ K = \lfloor (L-1)/2 \rfloor \tag{9}$$

K is the number of malevolent nodes which is maximally acceptable.

3.3.3 Redistribution

Redistribution refers to the extent of authority, dominance, and value diversity of the blockchain. All activities and blocks are disseminated, validated, and recorded in a decentralized way across all stakeholders in a private blockchain, ensuring that the whole structure is unchangeable, robust, and durable. At the same time, more than 1/2 of the computer resources stay fair. When blockchain is used in STS settings, scaling becomes a big problem. Firstly, by boosting segment size or lowering block intervals, the transaction output may be enhanced. Second, the reduction in the break of the block enforces a more substantial restriction on the latency. The segment size and periodic modification or the choice of block manufacturers and consensus methods should thus be carried out carefully to bring blockchain sustainability up to a standard level.

3.3 Process flow of contract in Blockchain for STS

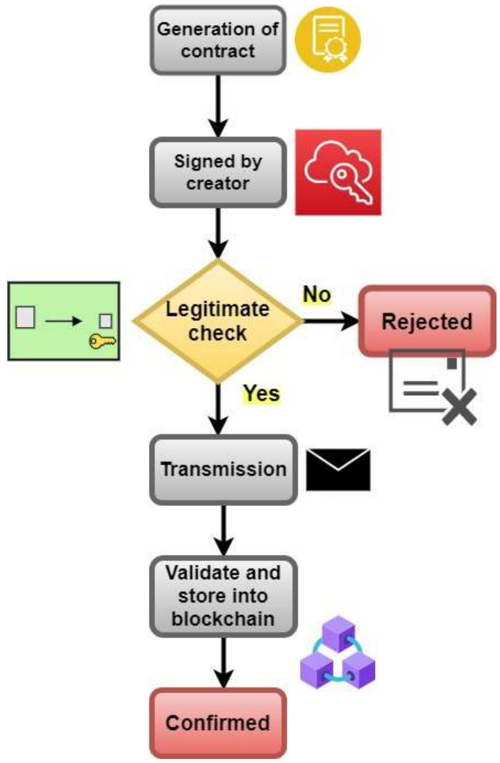


Fig. 4 The process flow of contract in Blockchain for STS

Fig. 4 depicts the process flow of contracts in blockchain. An intelligent contract is an agreement of conscience, autonomous and manipulative programs. A centralized repository with the interoperability and security of blockchain expertise proficient in audio-visual surveillance in low-cost STS situations has been given. Fig. 4 shows the STS blockchain topology, with data stock and data sharing records included in the transaction data. The interactions created as STS environments are presented in Fig. 4 with intelligent contracts for data storage and share procedures. The blockchain network has to accomplish two stages: (1) Transaction bundling and segment generation, (2) segment registration with agreement q.

3.4 Markov Chain Process (MCP)

The problem of video download and the allocation of resources is presented as a discrete decision-making process by Markov for maximizing system rewards. Two primary types of DRL techniques are generally available, including worth-based and regulation-based. The ACAA technique approaches temporal differences using a distinct memory structure to reflect an active policy irrespective of the value. Actor-Critics want to use all of the exceptional items based on both weight and procedure while at the same time removing all their inconveniences.

ACAA has been employed in discontinuous and ongoing activity spaces faster and more resilient than conventional methods. The method focuses primarily on the simultaneous formation of several players with universal characteristics. The ACAA uses several actors and reviewers to break down the reliance of the data on multiple threads of a CPU. This increases convergence in training considerably and enables DRL agents to train for CPUs quickly. This problem is solved by using the ACAA algorithm.

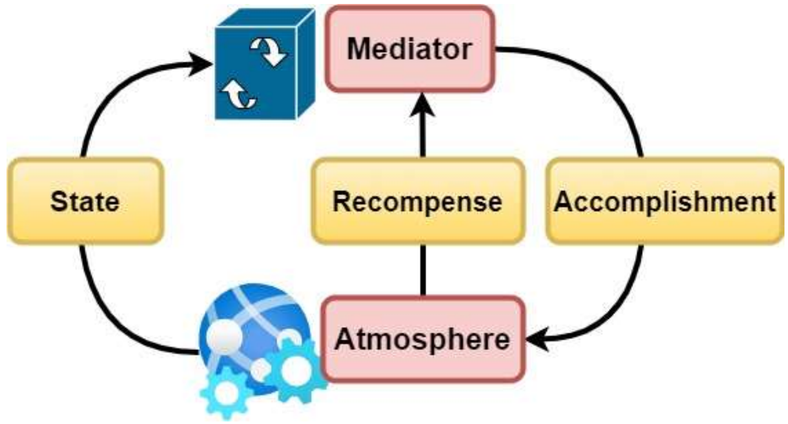


Fig. 5 Mediator and atmosphere in DRL for proposed IMEC-BVS framework

Fig. 5 shows the mediator and atmosphere in DRL for the proposed IMEC-BVS framework. The DRL method can resolve synchronous policy decisions by optimizing the reward function in the unknown environment. The resource apportionment issue based on DRL may be stated as an MCP, as seen in Fig. 5. The MCP is well-defined by three factors: $[T(m), B(m), Q(m), S(m)]$, where $T(m)$ is the system state set, $B(m)$ the structure accomplishment set, $Q(m)$is the probabilities for the status transition and $S(m)$ is the function for recompense. The objective of learning is to create a strategy that optimizes the benefits predicted. Network entities can make observations using the DRL methods and get the optimal policy on location with the least or without sharing of information.

This work aims to maximize the operation output of the distributed ledger and reduce the delay of MEC systems, which is based on video analytics apps within an STS. The MEC system's overall latency comprises queuing delay and computer latency defined by E. As stated in equations for E_o and E_d, the volume of the data is utilized to estimate the delay and calculate the computational latency. The magnitude of information and processor frequency have also been used. The output may be defined by network capacity, segment interval, and average transaction size in the blockchain network. In STS systems, vehicles generally anticipate to be finalized in a short period, and the Stay to Final (STF) meets the limitation. Therefore, the resource assignment issue defines data quantity, processing capacity, and delay for video surveillance tasks. Then the combined objective function has been formulated as follows:

$$max_{B(m)} F\left[\sum_{m=0}^{\infty} (\alpha_1 \partial / (\alpha_1 + 1)) \times \alpha_2 E\right] \quad (10a)$$

Given that GT 1: $\sum_{n=1}^{N} Po(m) \times (\emptyset^J / S) > F^{min}$ (10b)

GT 2: $U^{STF} < \tau < U^J$ (10c)

F and F^{min} are the summation of overall MEC server computing capability and minimum energy consumption. $\emptyset^J$ is the volume of video information in bits received from the road segments, S is the transmission of data from intelligent vehicles to road segments. N is the number of RS in STS using MEC. $Po(m)$ is the transmission energy of the channel. Transaction size is given by U^J and STF period is denoted as $U^{STF}.\tau$ is the segment interval. The recompense function can therefore be stated as:

$$S(m) = \begin{cases} \alpha_1 \partial/(\alpha_1 + 1) \times \alpha_2 E, & if\ GT1 \cap GT2 \\ 0, & otherwise \end{cases} \quad (11)$$

Where α_1 refers to a weight factor in which the goal function is combined into the same, and α_2 is a charting factor in assuring the objective function in the same grade. Operational throughput is given by ∂ , and E denotes the overall latency of the proposed IMEC-BVS framework.

4. Results and discussion for the proposed IMEC-BVS framework

The effectiveness of the suggested method has been tested in this section under various parameter settings. Simulations that used a Python-based simulator are carried out with Tensorflow. Different interventions have been examined to check the performance of the proposed algorithm: 1) Conventional Deep Q-Network (DQN) method: A standard DQN approach creates a DNN to identify and assess behaviors that eventually lead to extrapolation. 2) Suggested approach with Static segment size (SSS): block size generated by the block provider will be the same. 3) Suggested approach with Static Segment Period (SSP): the producing frequency of segments are equal.

Table 1: Simulation parameters used in the proposed IMEC-BVS framework.

Parameter	Value
Minimum energy consumption $\boldsymbol{F^{min}}$	1 J
Duration of video sequence $\boldsymbol{M}$	2.5 secs
Video size $\emptyset^J$	250 bytes
Channel Bandwidth $\boldsymbol{BW}$	1.3 MHz
Power of interfering signal $\boldsymbol{\delta}$	-180dBm
Calculation intensity for video surveillance $\boldsymbol{Y}$	500 bit/Hz
Segment size $\boldsymbol{T^C}$	10MB
Transaction size $\boldsymbol{T^U}$	150KB
$\boldsymbol{\alpha_1, \alpha_2}$	0.85, 0.02

The simulation parameters used in this work have been summarized in Table. 1. The proposed IMEC-BVS framework, comprising 15 RS units and 50 autonomous vehicles, is assessed in this study. The CPU has a 64G memory for Intel Core i5-8400. Tensorflow 1.10.0 and Python 3.6 on Ubuntu 18.04.2 LTS are the programming environments employed.

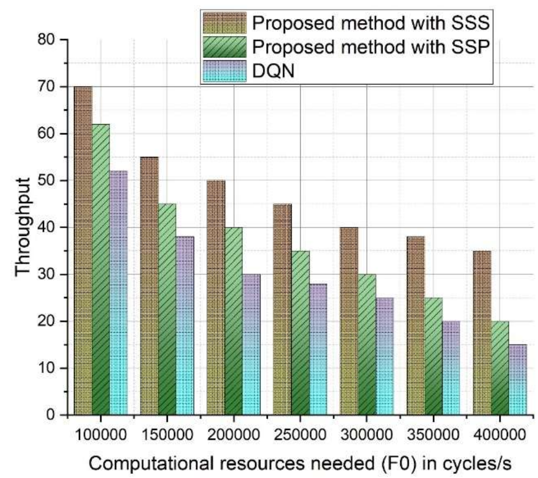


Fig. 6 Comparison among throughput (%) and computational resources (F_0) for the proposed IMEC-BVS framework

Fig. 6 shows the comparison among throughput (%) and computational resources (F_0) for the proposed IMEC-BVS framework. When the computational resources of MEC grow for all techniques, the average throughput drops, as can be seen in the graph. Further, the suggested approach provides greater throughput under the same processing power of MEC, while the conventional DQN method obtains the minimum value of throughput. The throughput of the proposed IMEC-BVS framework with SSS is higher than the approach with SSP for all deals of computational resources. As a result, the blockchain network has fewer computer resources available, whereas the MEC system has more computing resources available to execute the video unloading job.

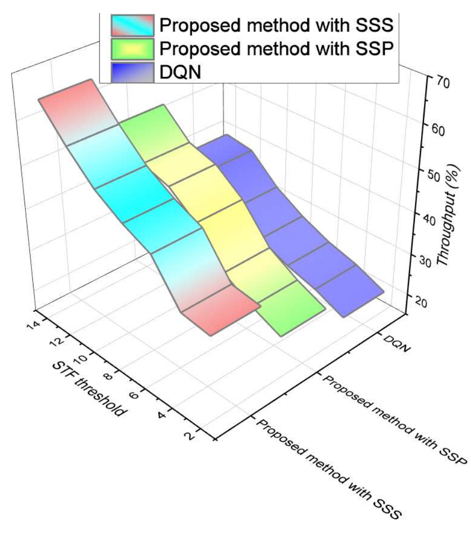
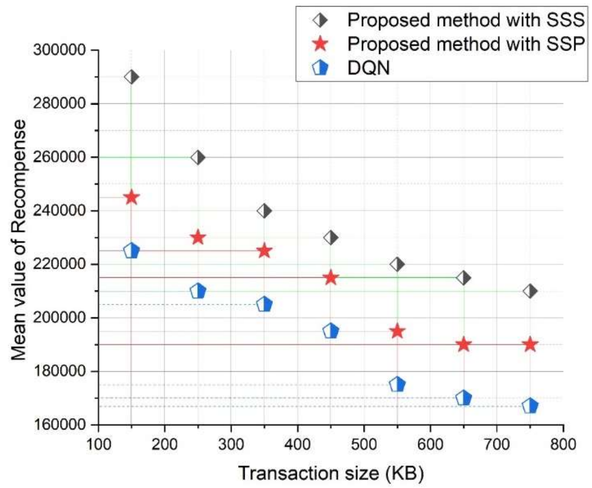
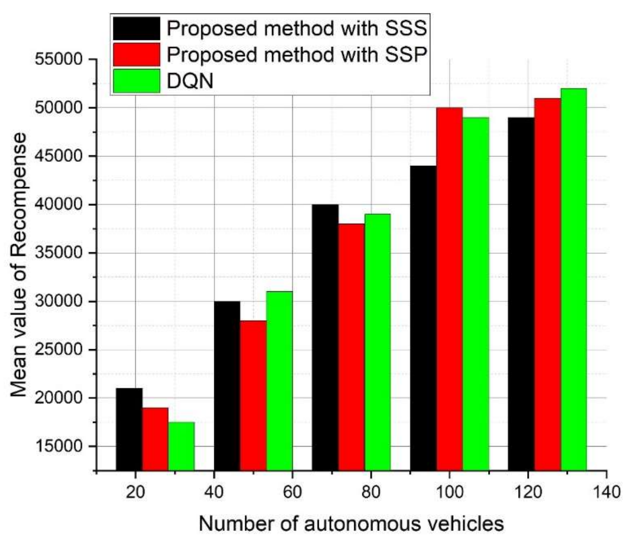


Fig. 7 Comparison among throughput (%) and STF threshold for the proposed IMEC-BVS framework

Comparison among throughput (%) and STF threshold for the proposed IMEC-BVS framework has been depicted in Fig. 7. The figure shows the effect of the STF threshold on the average transaction rate. As the threshold of the STF is increased, the average throughput improves for all methods. It is possible to produce more transactions due to the reduced latency limitation. The proposed IMEC-BVS method with SSS has a maximum throughput of 63%. The proposed approach with SSP has a maximum throughput of 60%, which is less than that obtained in the SSS approach. The DQN method has the most negligible throughput value of 38% at an STF threshold value of 14.



(a) Mean value of recompense versus transaction size (T^U)



(b) Mean value of recompense versus the number of autonomous vehicles

Fig. 8 Comparison of the mean value of compensation among the proposed approach (with SSS and SSP) and the existing DQN approach.

Fig. 8 compares the mean value of recompense among the proposed approach (with SSS and SSP) and the existing DQN approach. As seen in Fig. 8(a), transaction size has a significant influence on averaging rewards. For all techniques, the average compensation falls as the average transaction size increases. As the mean transaction size increases, so does the throughput, and the two are strongly associated. In addition, the suggested method yields the most significant mean compensation relative to the baseline methods, indicating that it is the most effective. Fig. 8(b) compares the mean value of recompense versus the number of autonomous vehicles for various approaches. With the rising number of autonomous cars, the average incentive rises. Moreover, the proposed method with SSS can achieve higher compensation than the proposed approach with SSP and existing approaches.

Table 2(a): Effect of various parameter values (α) on the mean value of recompense for varying processor frequency.

Processor frequency (GHz)	Mean value of recompense		
	$\alpha_1 = 0.15$	$\alpha_1 = 0.45$	$\alpha_1 = 0.85$
1	100	300	510
1.5	150	360	530
2	200	400	540
2.5	250	420	550

Table 2(b): Comparison among various methods on the mean value of recompense for varying segment intervals (U^J).

Segment interval U^J (mins)	Mean value of recompense		
	DQN	The proposed method with SSS	The proposed method with SSP
0.2	7200	9100	6200
0.4	5800	6300	4500
0.6	5200	5800	2100
0.8	5200	5100	2100
1.0	5180	5100	2100

Table 2(a) shows the effect of various parameter values (α) on the mean value of recompense for varying processor frequencies

Using different weight factors, the influence of processor frequency on average reward is explored (see table 2(a)). The total compensation increases as α_1 increases. Further, it can be noticed that the mean compensation for a given α_1 increases with processor frequency as a function of α_1. Comparison among various methods on the mean value of recompense for varying segment intervals (U^J) has been given in Table 2(b). As the maximum segment interval U^J for all approaches is increased, the mean compensation drops for all methods. This is attributed to the fact that, as the segment interval increases, throughput reduces.

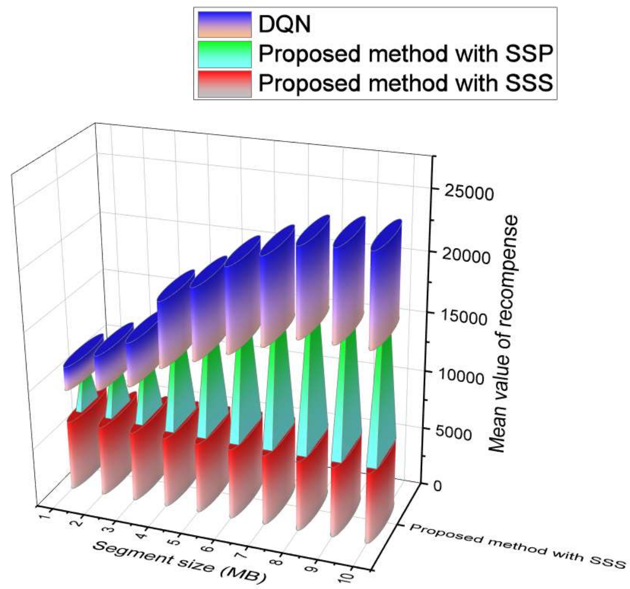


Fig. 9 Comparison of the segment size (T^C) versus mean value of recompense using the proposed IMEC-BVS framework.

Fig. 9 depicts the assessment of segment size (T^C) versus the mean value of compensation using the proposed IMEC-BVS framework. Except for SSS, the mean value of compensation increases with the increase in the segment size. The value of the reward is the maximum for the proposed approach with SSP than SSS and DQN. This is due to the STF limitation. As a result, the optimum number of transactions in a segment is limited to a maximum of 11.

A combined optimization issue has been developed to optimize the operational throughput of the blockchain process and reduce the delay of the MEC system. An excellent convergence efficiency has been provided by the proposed IMEC-BVS method. For video surveillance applications in STS scenarios, the framework justifies using the decentralized approach with blockchain.

5. Conclusion

For video surveillance in autonomous cars, the integration of MEC with blockchain technology has been suggested. As a result, the joint optimization issue has been modeled as MCP. The ACAA method has also been utilized to unravel the problem. The effectiveness of the suggested algorithm has been tested using a variety of inputs. For all values of computing resources, the proposed IMEC-BVS architecture with SSS has a greater throughput than the method with SSP. The average incentive increases as the number of autonomous automobiles increases. A decrease in the mean compensation is observed for all techniques when the maximum segment interval U^J increases. An additional benefit is that a suggested strategy with SSS can result in greater average rewards than a proposal with SSP or existing alternatives. With SSP, the maximum throughput is 60 percent. Throughput and convergence performance are improved compared to the baseline method.

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