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Performance Analysis of Digital Twin Edge Network implementing Bandwidth Optimization Algorithm

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Abstract: Sixth Generation (6G) network is meant to allow wireless networking and computing by digitalizing and sharing everything, by providing a computer image of the actual network world. Mobile edge computation as one of the key factors in allowing mobile downloads faces unparalleled obstacles because the 6G network environment is incredibly dynamic and unforeseeable. In the latest literature on mobile edge computing, the implications of user mobility and the volatile mobile edge computing world are still ignored. In this paper, we propose a new methodology for the Digital Twin mirror that offers training data to offload decisions for digital edge servers to evaluate the edge servers' status and the Digital Twin for the whole edge computing environment. In the wireless twin edge networks, the proposed system is to reduce the download delay in the face of the cumulative expense of relocation from the accessed service Mobility for consumers. The Lyapunov approach's Optimization is used to simplify the cost constraint of Long-term transformation to an intra-functional enhancement challenge, which is then resolved by profoundly enhanced Actor-Critic (AC) learning. Replications demonstrate that, as opposed to benchmark systems, our proposed arrangements effectively decrease the average offload delay, discharge failure rate and operation migration rate and save device costs with Digital Twin help.

Keywords: Digital Twin Edge Network, 6G Network, Mobile Edge Computing, Actor-Critical learning

1. Introduction

6G has been suggested to combine Fifth Generation (5G) with global reach satellite networks. Multimedia video and high-speed internet access, and satellite earth imagery networks are used for resource tracking and weather information [1]. The three critical goals for 6G technologies are the convergence of all types of satellite systems like telecoms, browsing, multimedia networks offering worldwide areas, high-speed internet access and mobile Internet information facilities [2]. 6G technology and fast Broadband technology are known as inexpensive. It offers good Broadband speed and high data speeds to reach the air via cellular devices with data from far away to 11 Gigabytes per second. The goal of 6G technologies is to provide smartphone users with multimedia, internet and weather facilities [3]. The engineered Nano Antennas were used to propagate high-speed electromagnetic signals at various geographical locations such as along roadsides, towns, malls, airports and hospitals. With 6G technologies, the planet is decorated with fly sensors. Wireless networks send ultra-fast broadband signals via air at high-speed fiber cables [4], meaning that secure information can be sent from transmitters to destinations [5]. The following are the key contributions.

1. For mobile offloading determination, edge server states and supplying agency data sets are estimated. Furthermore, given that there is a difference between the actual value of its digital representation and its state of the edge server.

2. During portability, we introduce the optimization problem of an offloading decision sequence to limit the average delay of transferring under the constraint of deep utilization costs.

3. Using the deep reinforcement learning (DRL) system with the training agent, the offloading optimization issue is solved. In order to demonstrate that our suggested scheme significantly reduce discharge delay, task breakdown rate and transition rate while retaining the low system efficiency, comprehensive experiments are done.

A. Digital Twin Edge Network (DTEN)

A digital twin incorporates data regarding their real-world objects, which models need for the position and behavior. In certain instances, it can consist of data over the entire life span of the entity and, where machinery is involved, it can consist of data at the design period, development process [6]. It can also provide organizational data, such as purchase reports. A digital twin includes theoretical or predictive models to define, interpret and forecast the working conditions and behaviour of the natural world object and models that are used to recommend behaviour based on organizational reasoning and the goals of the relevant object. Models focused on physics or chemistry, engineering, simulation models, statistical data models, machine learning, and artificial intelligence may include [7]. It also may include 3D simulations and model of increased reality to help people understand the operating circumstances or actions of objects in the real world.

B. Mobile Edge Computing

The new Mobile Edge Computing (MEC) structure expands cloud-based services using mobile access points to the network's edge. The hardware and software systems at the edge nodes, near to end clients, are suitable for the application of smartphones as a scalable technology, broadband and wireline scenarios. MEC offers integrated connectivity to smartphone users, businesses and other vertical markets for various device service providers and vendors [8], [9]. The 5G structural design's main factor enables several creative applications and utilities requiring incredibly low latency. Edge computing was a significant factor in mobile cell networks' computing paradigms, particularly mobile edge computing [10], [11], [12].

C. Internet of Things (IoT)

IoT devices contain sensors and mini-computer processors that act on the data collected by the sensors via machine learning. Essentially, IoT devices are mini computers, connected to the internet, and are vulnerable to malware and hacking. In this paper, A fresh vision of the Digital Twin Edge Network is presented (DTEN). To reduce offloading delay under the limitation of cumulative used service migrate cost while user mobility, a movable offloading technique based on deep reinforcement learning (DRL) in Digital Twin Edge Network (DTEN) is presented. The following are the major contributions:

1. To begin, we explore a DTEN scenario in which DTs help with mobility offloading decisions by calculating edge server variables and supplying DRL agent data for training. Furthermore, given that the actual worth of edge server status and its digital representation differ, we investigate the impact of this difference on the offloading decision.

2. We formalize the optimization problem of a sequence of offloading decisions taken throughout user mobility, with the goal of minimizing average offloading delay while keeping long-term migration costs in mind. The Lyapunov dynamic queue optimization (LDQO) scheme is used to convert a multiple objective dynamic optimization problem with a long-term migration cost constraint.

3. The offloading optimization problem is tackled in an online way utilising an ActorCritic based DRL framework and a DITEN training agent. Our proposed methodology effectively reduces offloading delay, job failure rate, and migrate cost while retaining lower system cost, according to simulation experiments.

D. DRL Actor-Critic Framework

The DRL Actor-Critic Framework uses Q-learning to reward each state and action. Using traditional reinforcement learning methods requires a lot of storage space because DITEN's environment is dynamic. DRL uses a deep learning network instead of Q-tables, which was previously used. This change allows for less storage in the Q-table. In order to learn its environment's rules, the DRL agent uses information from DITEN. With a neural network to approximate the state value function V, the critic agent better fits the two [3].

The rest of this paper is laid out as follows. The relevant work is described in Section 2, and the proposed system is presented in Section 3. The simulation of the result is then proposed in Section 4. Finally, Section 5 includes conclusion and future work this paper.

2. Related Works

Recent developments and emerging tele communications infrastructure technologies will be implemented in the next generation of telecommunications services. Ioannis Tomkos et al. [13] review the incorporation and fusion of cellular networks and the Internet of Things (IoT) of the fifth generation into sixth-generation technologies to reinforce and enhance AI operations. The IoT is a platform and service that allows things and people to interact at any time, in any location, with everyone and everything. As a result, the Internet of Things (IoT) is a massive flexible global internet architecture of Internet-enabled devices that use web services. [14] Smart 5G and the next IoT network installations in the smooth 6G networks of the upcoming will be paired with modern edge computing hardware, allowing Artificial Intelligence to function powerfully across computational resources. The implementation of AI on the edge networks faces numerous issues because its dependent applications must run in different complex systems that should cooperate with memory space, stability, energy generation, power consumption, latency, and stringent end-to-end bit rate. In this 6G network, the communication structure linking the anticipated billions of intelligent link devices (gathering and transmitting information). While the link computer processing hardware implementing Artificial Intelligent and other frameworks must be seen as its nervous system (such as, for example, the trust and protection blockchain). It should be seen as it Software-Defined Networking (SDN) or Network Functions Virtualization (NFV) control and management software platform. Wang et al. [15] noted that the radio and network The software formula might be integrated to control several high-recurrence bands and real - time use sound waves, offering brilliant radio help. Huang et al. [16] To alter transmitter algorithms, a software platform and machine code based on complex disc data and AI techniques have been suggested. Smart radio assistance has also been proposed to satisfy these criteria. For e.g., the transmitted signal needs to be adapted to the hardware and the environment, AI-enabled spectrum sharing, online hardware power estimation, etc. Furthermore, Jiang et al. [17] Proof of any broadband interruption and message transmission problems can be found in the transmission process that could lead to data protection risk., whereas certain suspicious behaviours by malicious nodes should be proposed to Tariq et al. [18] for monitoring during communication processes. Chen et al. [19] Li-fi, a multi-access Visible light communication Visible light communication (VLC) system that could provide high-speed services for many connected smartphone devices, has been developed. Such disadvantages, however, restrict VLC technology's development. The main usage contexts for VLC, for example, should be indoors as transmissions are hampered by intense natural light. Ucar et al. [20] a protocol for SecVLC that could be used to protect transmit data security in a vehicle network was recommended. Mostafa et al. [21] to improve the safety of the physical layer, a pre coding method has been recommended for VLC connection. Besides, Cho et al. [22] It verified that collaboration between dos attacks would reduce VLC technology security. Challita et al. [23] A architecture based on a convolutionary neural network was suggested that would provide stable, realistic tasks in independent drone nets. Sanjab et al. [24]are proposing a new computational background to boost the safety of automated drone nets .While a new communication system is being introduced by Sun et al. [25] to avoid intruding attacks. Kim et al. [26]Suggest a confidentiality approach to fix permission problems that could be used in UAV networks. Dai et al. [27] though security for blockchain forms such as private blockchains is low, some highly protected blockchains can also be used in secure resource transactions such as blockchain consortiums. Jayalakshmi et al. [28], 5G is the fifth period of the organic molecules named in from of 4G and it is proposed to be delivered in 2020 as the following broadcast communications standard.

3. Proposed System

6G is obvious that the assistance of Machine Learning or Artificial Intelligence on board is important for fast speeds, low latency and efficient communications. The use of the upcoming generation wireless network at the link of the system will have additional innovative ideas than Artificial Intelligence is referenced at the network link.

In future, if that view exists, the intellectual analysis carried out remotely from robots, self-driving two wheeler or four wheeler, Internet of Things systems and additional machines can be used on a platform/server that is connected to and wirelessly connected to 6G Base stations. A future 6G mobile network architecture that is intelligent to the at the network edge, AI will make the most of physical and computing capital and receive smart networks that serve a whole fresh era.

Figure 1 demonstrates the block diagram of the proposed system. The block diagram includes four components

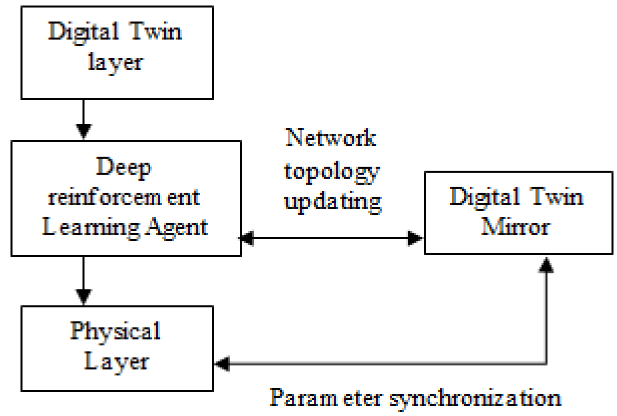

Figure 1. Block Diagram

are Digital Twin layer, Deep reinforcement Learning Agent, Digital Twin Mirror, Physical Layer which are linked by Network topology updating and Parameter synchronization.

Table I demonstrates the Notations and their meaning which are used in algorithm for proposed system. The experimental parameter in table I.

TABLE I. Notation

Notation	Meaning
Wt	Reward function set
ACt	Action set
Tt	State set
Dm	Digital Twin for Mobile
De	Digital Twin for edge server
γ	Required delay of the task
λ	Computation of unit data
η	Offloading task size
Lgap	Latency gap
LO	Offloading latency
Lcmp	Computation latency
Lcomm	Communication latency
Fe	Estimation error
F	Estimated edge server frequency
Lt	Migration cost deficit queue length
α	Migration rate
β	Service migration cost
ES	Service edge server
EC	Candidate edge servers
E	Edge servers

We suggest that on a scheduled time t where λ represents the length of the downloading task measured in bits, a user has the task allocation kt = {R, λt, vt}, yt is the cumulative amount for the Processor period needed to carry out the offloading task kt. We use Et E for indicating the existing edge nodes at time t and et Et for determining the mobile device (MD) edge server served at period t.

The proposed algorithm includes the movable device unload concluding unit is capable of determining on a number of Service link nodes d1, ..., dn during the mobility phase, depending on the measurement efficiency of the servers and on the tasks specifications of t. A user's satisfaction can be calculated during work discharge with the offloading latency ITglob(et) = $Icom(et)+Tcmp(et)$. User satisfaction typically increases as a Tg 1ob(et) is reduced, whereby Tglob(et) <= γt implies good task processing. The goal of the mobile discharge issue is to hit the update sequencing d1, ..., dn of the edge servers.

A. Algorithm: Mobile Offloading Optimization algorithm

Input: The Trained Network.
Output: The optimal offloading decisions Sequence d1, d2, ..., dn, The training center Array[].
Initialize the training center
Array[] ← 0 and state T1 ← 0
for i = 1 to n do
Calculate Probability α(T, Pa)
ACt = dt ← max ACt(α(TPa))
Do the action ACt.
Examine reward Wt and next state Tt+1
A[] – A[] ∪ ⟨Tt, ACt, Wt, Tt + 1⟩
end for
return {d1, d2, . . . , dn}, A[]

After training the proposed framework for mobile offloading determines that the agent is deployed in a mobile offloading management program to help to achieve the optimum digital twin decision-making strategy across the user nodes of the enabled edge servers. In addition, the user transition data is obtained during the running phase and placed into the preparation center for the user's further training. In the algorithm, the basic working process was included. First, when the Actor machine receives the results of an action stochastic process from the source data of the eligible user network, the decision agent gathers the edge node status across the client and selects the most likely yield decision as an exercise action. The action chosen will then be performed in the real world and the value of the environmental reviews is kept in the training center to enable further training for the mediator.

Figure 2 demonstrates that a customer produces the download tasks from edge servers for mobility computer services. During transit, the user can obtain different edge servers depending on the computing efficiency of the edge server as well as the position of the user. The decision module is responsible for the decision. If clients moved away from its original edge device because of system mobility and network dynamics, they can download the quality support to a reliable edge server.

For instance, a user in Figure 2, following a track, loads the edge server on the edge node, and then on the t+1 slot, 1 process chooses to install a task on another partially configured edge node. Relocating a service from a client to some other edge node causes the cost of transition. For

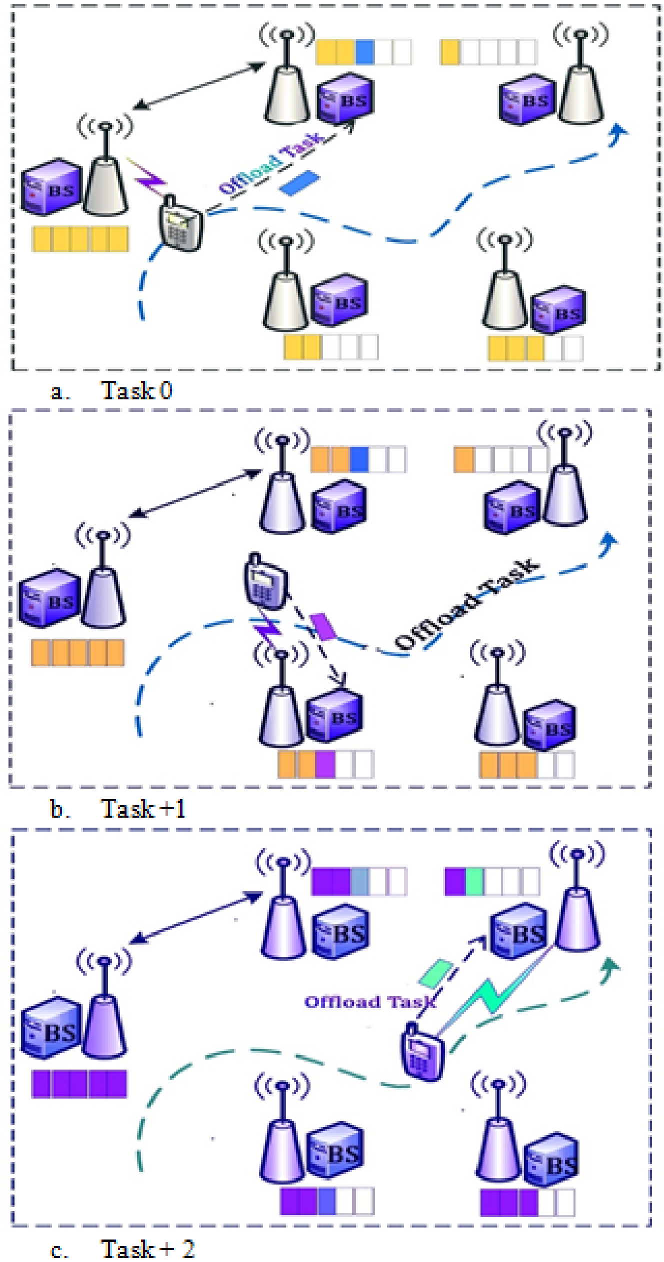

Figure 2. Customer produces the download tasks from edge servers for mobility computer services

convenience, we will be using to describe the rate of moving resources from one link node to another. The MD collection provision costs and the edge served may be expressed in the form of C(et) = htC in which ht 0, 1 is the result of the migration of the service migration module. ht is 1 if the slot t server is distinct from that of the slot t-1 edge server, otherwise the ht is 0.

Table II demonstrates the simulation parameter (i.e., experimental parameters) which includes various parameters used for simulation and their actual value are mentioned.

TABLE II. Parameters for Simulation

Parameter	Value
Sum of Servers Frequency	[25,35]GHz
Unit data Volume	[300,500]
Task Request Latency	[200,300]ms
Router Queuing Latency	4ms
Bandwidth for Transmission Channel	30MHz
Noise Power	2*10-2 W
Transmit Power	[0.4,0.8]W

With new and inaccessible services, software and applications that further challenge the limits of the infrastructure, N is going to continue driving the capacity and aspirations of mobile networks as the technological elements of 5G evolve. However, as the strategy leads to the life and availability of 5G networks, contemporary issues far beyond the eMBB (enhanced mobile broadband) and the IoT are anticipated in 6G. The position of the high-tech society with increasing demands and opportunities is far more prominent and integrated. The main issues for a 6G duration were envisaged. A main focus of 6G is the cost-effectiveness of service and implementation. This goal includes solutions to ensure that all related facets of society can be connected, access to adequate spectre, ease of use and deployment and a Significant level of integration of overall cost of ownership. A larger dimension of the same aim is to ensure cost-effective social activity and the reach and extent of innovative programs. Owed people to digitize and modernize and thereby probably fuel growth, market opportunities, and job development by providing a cost-efficient access to the global community. Other values can be intended to support from expanding the scope of the modern society.

4. Simulation of Results

After 2,850 rounds of preparation, the reward feature appears to converge. This demonstrates that the trained analysis is appropriate and has strong consolidation output for DTEN. As the proposed system is put after the training stage in the efficient mobile handling decision is carried out online by the mobile handling decision module, which ensures that the method is functional and satisfies the latency criteria.

Figure 3 represents the reward function's convergence pattern. Given the migration and latency cost, the reward is set. A small incentive means that the migration and latency expense of the job processing is comparatively small, which means that a better offloading service can be offered to the customer in an energy-saving manner. The proposed methodology is shown in Figure 3.

Figure 4 measures the overall latency over the changing total of users and applicant number of edge server E of the proposed model and the benchmark model. The average delay applies into the fraction between the overall potential of the jobs being unloaded and the quantity of tasks during the whole excursion. It tests the overall fulfilment of the customer with the service for job offloading during the journey.

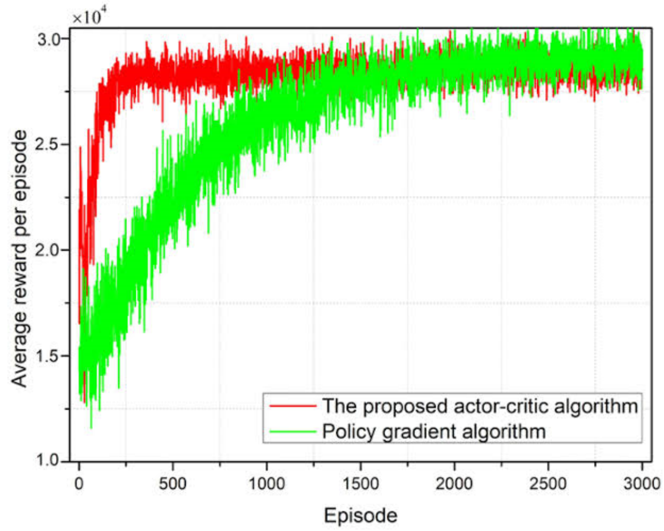

Figure 3. Convergence Performance

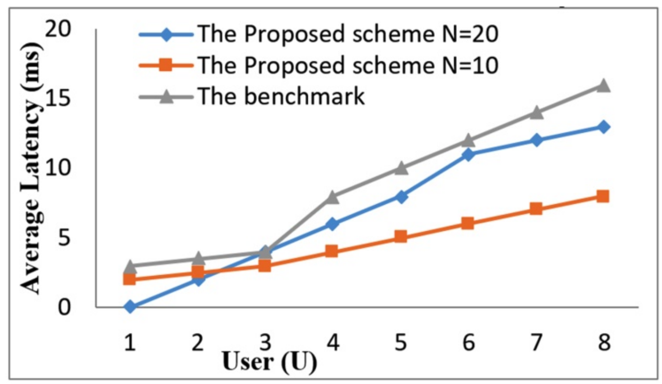

Figure 4. Contrast between different number of users and edge node candidates with average latency

Figure 5 calculates the overall latency over through the base station changing deployment volume and the digital twin estimation error. This will reduce the average latency provided that the digital double-estimated error remains unchanged as the amount of deployment of the base station increases. It calculates the average customer satisfaction during the trip with the task of offloading, measuring the latency of a single download task.

Figure 6 indicates the rate of job failure adjustments to the users and the edge servers accessible. The rate of failure of the task shall be well-defined as the part of a series of failed activities to the complete jobs that can compute the immediate success of a one activity.

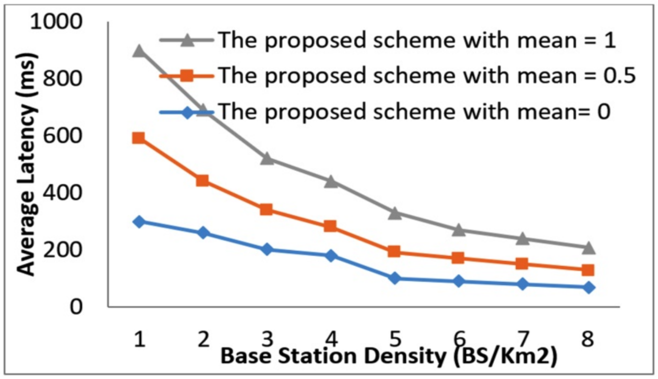

Figure 5. Contrast between varying BS density and DT estimation error mean with the average latency

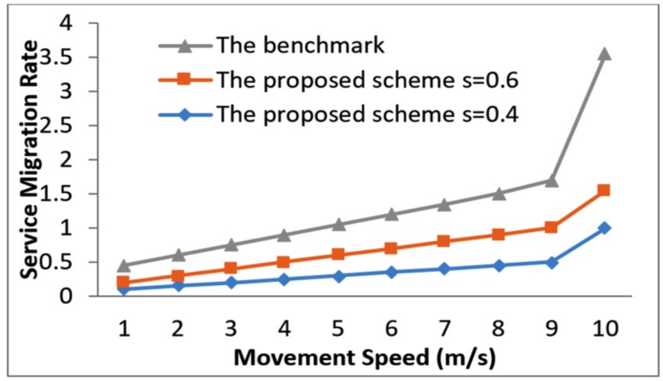

Figure 7. Contrast between varying movement speed with the service migration rate

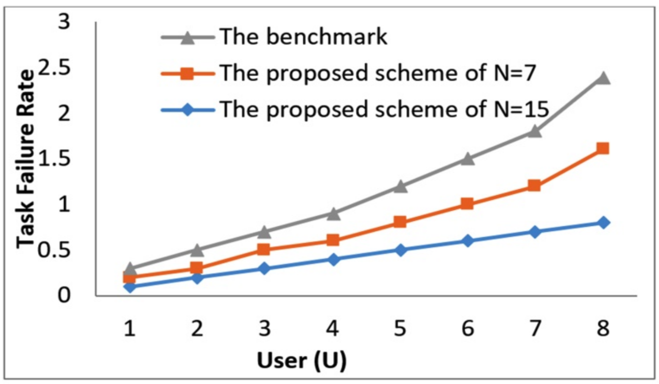

Figure 6. Contrast between different number of users and edge node candidates with rate for task failure

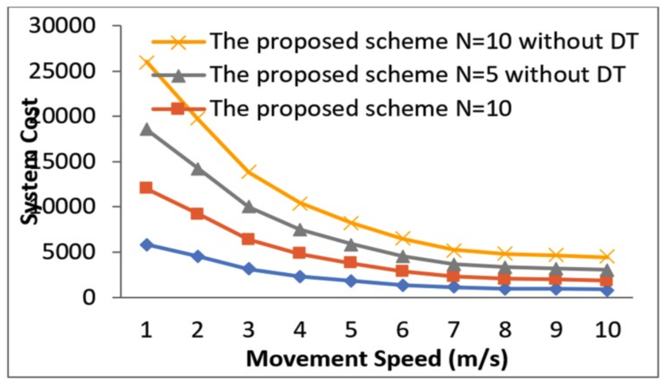

Figure 8. Contrast between varying movement speed with the system cost

Figure 7 describes the facility movement degree variations with client speed for movement and level of migration. The rate of movement of operation denotes measuring the total of network edge served with the total number of points during the path.

Figure 8 shows how system costs (cumulative cost for measuring the edge candidate database's status and during user path) vary with the speed at which the MD flies. As seen in the frame. 8, DT-assisted systems also cost less than that of No-DT, irrespective of the varying movement speed.

5. Conclusion and Future Work

With the goal of perceiving the Mobile Edge Computing environment, we built a digital doubling-edge 6G network in this article. In Digital Twin Edge Network, as a user travels through border servers and wants to offload the computation activities, the Mobile Downloading Problem was formalized to minimize the offload latency in the light of total immigration costs. By using Lyapunov is condensed the formal problem of complex multi-objective optimization, and Actor-Critic learning solves the simplified problem. Finally, we carried out simulations in order to test the results against other plans. The numerical findings defines approach decreases the interval and failure rate for work efficiently for details about effectiveness underneath the low device spending limits. In the future work, to obtain similar to the actual scene, we'll add more restriction elements like energy and signalling.

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