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# A Performance Optimization Approach for 5G Network-Based Mobile Edge Computing in Smart City Construction

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**Abstract** Mobile edge computing technology has a wide range of applications in enhancing the capability of wireless network devices in the construction of smart cities, which is the core driving force in the construction of smart cities. In this paper, the IRS auxiliary channel model, one of the key technologies in 5G networks, is combined into the design of mobile edge computing system, and the optimization model of mobile edge computing system is proposed in the light of the basic requirements in the construction of smart cities. The alternating iteration algorithm is used to decompose the optimized model to obtain the sub-optimization model, and the particle swarm optimization algorithm is used to solve the sub-optimization model, and the performance-optimized 5G network-based mobile edge computing system is constructed. The results show that under the 10Mbit computing task volume, the latency of this paper's system (M=2) is reduced by about 63.81% (2.148s) compared with that of the local computing-only scheme (5.935s), and good convergence performance can be guaranteed. It is also found that the application platform based on this system can guarantee fairness among users and can satisfy their respective performance requirements when used by multiple users. The mobile edge computing optimization method proposed in this paper has low-latency performance, which provides a strong technical guarantee for the construction and development of smart cities, and lays a foundation for improving the management efficiency and service level of cities.

**Index Terms** mobile edge computing, IRS, alternate iteration, particle swarm optimization algorithm, smart city construction

## I. Introduction

With the research progress of space information technology, IT technology and wireless communication technology, city informatization has become the main trend of international city modernization and development, and has become an important content to measure the competitiveness of cities. Urban informatization has a great role in enhancing the carrier function of cities, integrating social resources, allocating production factors, and strengthening the comprehensive management function of cities, thus liberating productive forces [1]-[3]. According to the strategic deployment of China's informatization, spatial information infrastructure construction, urban informatization construction and industrial informatization construction are the three main construction contents. As an important part of China's informatization strategy, urban informatization construction, its construction status and development trend will have an important impact on the overall development direction of national informatization [4], [5].

With the development of sensor networks, grid computing and other breakthrough technologies, the future of the digital city, which is commonly studied, is also an issue worth thinking about, and smart city will become a new direction for the development of urban informatization [6], [7]. Smart city will better reflect the function of modern city “information distribution center”, which means that the city functions to fully realize the intelligence, and better promote the improvement of urban habitat and sustainable development. With the advancement of urban informatization process, smart city has begun to step into our lives, and it is worthwhile to further study the theoretical system of smart city [8]-[10].

As one of the core technologies of 5G, Mobile Edge Computing (MEC) has a promising development prospect. MEC enables localized and proximity-distributed deployment of applications, services, and contents by migrating the computing storage capacity and business service capacity to the edge of the network [11]-[13]. The construction of smart cities is in a process from concept to gradual realization. In many smart city application scenarios from intelligent transportation, autonomous driving to real-time surveillance and real-time monitoring, many types of data need to be processed at the edge of the network rather than in the cloud. Therefore, edge computing plays an important role in many smart city application scenarios [14], [15].

With the rise of Internet of Things (IoT), 5G, industrial automation, and smart manufacturing, mobile edge computing, which lies between physical entities and industrial connectivity, is increasingly playing an important role.

Literature [16] proposes a cognitive radio-mobile edge computing framework that considers local computing and partial offloading schemes and supports UAVs, and introduces an equivalent reconstruction of the EE maximization problem, aiming to alleviate the computational and spectral demands of the exploding mobile edge computing. Literature [17] achieves virtual mobile edge computing optimization through gradient-based dual-delay deep deterministic policy intelligent computational offloading, optimal stopping theory, software-defined networking, and network function virtualization concepts, and proposes an offloading method based on TD3PG-OST, which is validated through a large number of comparative analyses, to improve the quality of service of service offloading networks and to meet the next-generation application Demand. Literature [18] proposes a strategy for scheduling edge computing tasks in the IoT cloud environment using the hybrid bacterial foraging optimization (HBFA) method, and verifies the effectiveness of the proposed strategy through simulation and comparison experiments with state-of-the-art algorithms, which not only minimizes the completion time, but also maximizes the resource utilization of the edge network.

The development of modern science and technology provides the possibility for the construction of smart cities, especially the arrival of the 5G network era, which makes the construction of smart cities with basic data prerequisites. Literature [19] constructs a hotspot data processing framework for UAVs and 5G edge computing infrastructure, aiming at realizing the monitoring of abnormal hotspots through the collaboration of subsystems, and proposes an ensemble multi-objective cooperative learning method that can deal with different types of hotspot data, and experimentally verifies the validity of the proposed framework and method, which is of certain application value in the construction and governance of smart cities. Literature [20], in order to protect the user privacy of smart devices in smart cities, proposed a framework using a Quad-tree retrieval based zoning method, LDP perturbation scheme, and blockchain, and verified the effectiveness of the framework in real-world scenarios through simulation experiments, in addition to pointing out that the integration of emerging technologies, such as 5G, in edge computing environments can help to protect the privacy of data collection and analysis. Literature [21] proposes a multi-joint optimization method for edge computing resource allocation in smart cities based on the Internet and verifies the feasibility of the method through experiments, which can provide efficient computing resources for latency-sensitive jobs.

In this paper, we optimize the mobile edge computing system by using IRS-assisted channel model to calculate the normalized gain and realize the mobile edge computing system to offload and calculate the related tasks. Then the original optimization problem of maximizing the amount of user offloading tasks by the system is constructed according to the user usage requirements in the construction of smart cities based on 5G networks. Subsequently, an alternating iteration algorithm with lower complexity is proposed to decompose the original optimization problem using maximum ratio merging to obtain the sub-optimization problem. Then the particle swarm optimization algorithm is used to solve the sub-optimization problem until it reaches convergence by using MATLAB simulation to optimize the performance of the mobile edge computing system. Finally, a simulation experiment environment is established to analyze the convergence and delay performance of the mobile edge computing system, and analyze the user expansion performance of the smart city construction related application platform constructed based on the system, in order to explore the optimization effect of the system performance.

## II. Application of mobile edge computing systems in the construction of smart cities

The arrival of the 5G era has injected new kinetic energy into the digital transformation of the city, and 5G will reshape the city's intelligent system, empower thousands of industries, promote the development of intelligent innovation and application, and become a new engine for the development of the digital economy, so as to make the city intelligent to a higher level. The development process of smart city has been decades long in general. In recent years, with the development and application of new generation of information and communication technology, the degree of city informatization has been deepening, which makes the overall architecture of smart city construction basically take shape, and points out the direction for the development of smart city. The overall architecture of smart city is divided into perception layer, network layer, service layer, intelligent application layer and user layer according to layers, and its specific architecture is shown in Figure 1. The service layer consists of three sub-layers: public information platform, public database and public facilities, which are usually planned and constructed uniformly in the intelligent cloud platform. The integration of 5G network with artificial intelligence + Internet of Things (AIoT), Mobile Edge Computing (MEC), and Intelligent Operation and Management Platform (IOC) is able to connect the “end-edge-hub” hierarchical intelligent scenarios, and empower the city to be intelligent throughout the entire region. Therefore, optimizing the performance of 5G network-based mobile edge computing system plays an important role in the development of smart city construction.

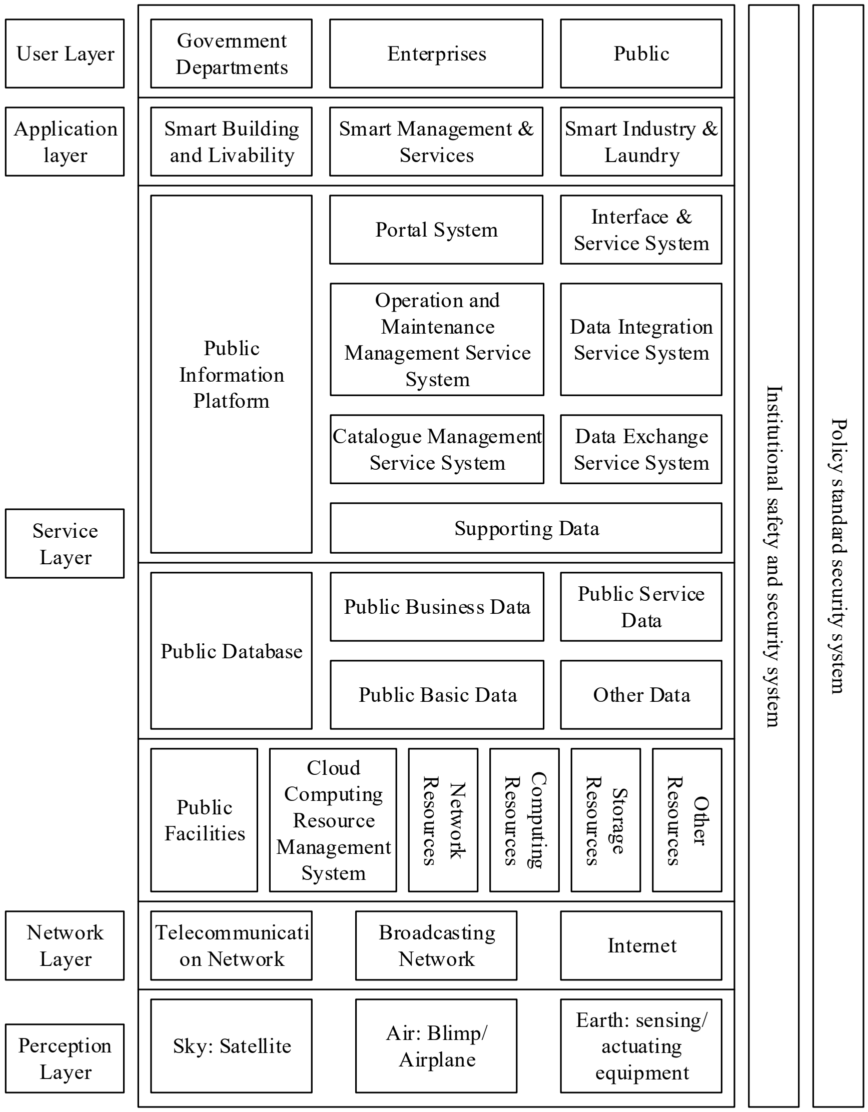


Figure 1: The overall framework of intelligent urban construction

# III. Performance optimization methods for mobile edge computing systems

## III. A. System modeling based on IRS-assisted communication

### III. A. 1) IRS channel modeling approach

IRS [22] is a fundamental innovative technology involving multidisciplinary contents such as metamaterials, electromagnetic information, interfacial electromagnetism, electromagnetic computation, cybernetics, wireless communication, etc., which is one of the key technologies for 5G. The basic idea of the model is to divide the channel between the original transmitter $(Tx)$ and receiver $(Rx)$ into two parts: the IRS auxiliary channel of Tx-IRS-Rx and the direct-connect channel of Tx-Rx, as shown in Equation (1):

$$H = \frac{1}{\sqrt{PL_{RU}}} h_{RU}^{T} \Phi \frac{1}{\sqrt{PL_{TR}}} h_{TR} + \frac{1}{\sqrt{PL_{TU}}} h_{TU} \tag{1}$$

In Eqs. $h_{TR}$ and $h_{RU}$ are the channel response vectors from the transmitter to the IRS and from the IRS to the receiver, respectively, and $PL_{TR}$ and $PL_{RU}$ are the path losses of the corresponding channels. $h_{TU}$ is the channel response vector, and $PL_{TU}$ is the corresponding path loss. The electromagnetic characteristics of the IRS itself can be characterized numerically, and the model uses the phase-controlled (amplitude-controlled) diagonal arrays $\Phi = diag\left(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_M e^{j\theta_M}\right)$ and $\beta_m \in [0,1]$, where $\beta_M e^{j\theta_M}$ represents the amplitude-control coefficients and phase-control coefficients of the $M$ th IRS electromagnetic unit.

The IRS auxiliary channel model makes the IRS itself independent of the two end channels, and the output of the model is the channel response matrix $h_{TR}$, $h_{RU}$, where the IRS-to-receiver channel response $h_{RU}$, for example, is the channel matrix:

$$h_{RU} = \left(h_{u,1}(t,\tau),\ldots,h_{u,k}(t,\tau),\ldots,h_{u,n\times n}(t,\tau)\right) \tag{2}$$

where the number of IRS cells is $n \times n$, treating each EM cell of the IRS as a transmitting cell, and $h_{u,k}(t,\tau)$ is the channel response from the $k$ rd EM cell on the IRS to the $u$ th antenna at the receiving end, expressed similarly to Eq. (2) above.

### III. A. 2) Optimization Model for MEC Systems

In this paper, we construct a mobile edge computing system based on IRS-assisted communication and OFDM collaborative relaying, which consists of a user end (UE) that is relatively far away from the AP, a relay that is relatively close to the AP, an IRS with $M$ reflection unit, and an AP with an integrated MEC server.

The user's application offloading task $L > 0$ in smart city construction needs to be divided into three parts $l_U$, $l_R$, and $l_A$, with the first part $l_U$ executed at the user's end, the second part $l_R$ offloaded to the relay node for collaborative execution, and the third part $l_A$ offloaded to the AP node for execution. Moreover, for applications with indivisible granularity, it can be flexibly assumed that there are multiple fine-grained applications that need to be offloaded by the user, so in this paper, we assume that partial offloading is used in the MEC system, i.e., a granularly divisible application is used. Therefore, the user offloading task satisfies the following relationship:

$$l_U + l_R + l_A = L \tag{3}$$

It is assumed that in one duration $T$, the system completes the offloading and computation of the $L$ -bit computation task, and thus a duration $T$ is called a time frame in this paper. Often, since a duration is very short, it is assumed that each link channel of the system is invariant at the same one time frame and obeys an i.i.d distribution across time frames. The direct link channel $h_{UA}$ from the user end to the AP is modeled as Rayleigh fading:

$$h_{UA} = \sqrt{\rho d_{UA}^{-a_{UA}}}\tilde{h}_{UA} \tag{4}$$

where $\tilde{h}_{UA}$ denotes the random scattering component modeled by a complex Gaussian distribution with zero mean and unit variance, $\rho$ is the path loss at the reference distance $d_0 = 1m$, and $a_{UA}$ is the path loss exponent between the user and the AP. Similarly, the direct channel $h_{UR}$ from the user to the relay node and the direct channel $h_{RA}$ from the relay node to the AP are obtained.

The channel from the AP to the IRS can be modeled as $g_A \in \mathbb{C}^{M\times 1}$, following the Rician distribution:

$$g_A = \sqrt{\rho d_{AI}^{-a_A}}\left(\sqrt{\frac{\zeta_A}{1+\zeta_A}}h_{AI}^{LoS} + \sqrt{\frac{1}{1+\zeta_A}}h_{AI}^{NLoS}\right) \in \mathbb{C}^{M\times 1} \tag{5}$$

where $\zeta_A$ is the Rician factor associated with small-scale fading. Similarly the channels from the user side to the IRS and the relay node to the IRS can be modeled $g_U \in \mathbb{C}^{M\times 1}$ and $g_R \in \mathbb{C}^{M\times 1}$ respectively.

The phase shift vector of the IRS reflection unit is denoted by $\theta = [\theta_1, \theta_2, \ldots, \theta_M]$, where $\theta_n \in [0, 2\pi]$, the diagonal matrices $\Theta = diag\left(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_M e^{j\theta_M}\right)$, $\beta_m \in [0,1]$ are the reflection coefficient matrices of the IRS, and $\beta_m e^{j\theta_m}$ denotes the phase shift and amplitude reflection coefficients of the $m$ th IRS reflection unit. Thus the $n$ th subcarrier combination channel normalized gain from the UE to the AP can be expressed as:

$$\gamma_n^{UA} = \frac{\left|g_A^H \Theta g_U + h_{UA}\right|^2}{\sigma^2} \tag{6}$$

where $\sigma^2$ is the receiver's additive Gaussian white noise (AWGN) at the relay and AP, respectively. Similarly, the $n$ nd subcarrier combination channel normalized gain from the relay to the AP can be expressed as $\gamma_n^{RA}$, and the $n$ th subcarrier combination channel normalized gain from the UE to the relay can be expressed as $\gamma_n^{UR}$.

### *III. B. Performance optimization algorithm design*

#### III. B. 1) Construction of the problem of maximizing the amount of data unloaded from the system

In $t_k$ time slot, the received signal of the $k$ nd edge device includes the signal sent by the user over the direct link, the signal reflected by the RIS, and the additive Gaussian white noise [23], and thus the received signal of the $k$ rd edge device can be expressed as:

$$y_k = \sqrt{P_k}\left(H_{r,k}\Theta_k g + h_{d,k}\right)s_k + n_k \tag{7}$$

where $P_k$ is the transmit power from the user to the $k$ nd edge device, $H_{r,k} \in \mathbb{C}^{M\times N}$ is the baseband equivalent channel from the RIS to the $k$ th edge device. $g_k \in \mathbb{C}^{N\times 1}$ is the baseband equivalent channel from the user to the RIS, $h_{d,k} \in \mathbb{C}^{M\times 1}$ is the baseband equivalent channel from the user to the $k$ th edge device. Diagonal matrix of the RIS $\Theta_k = diag\left(\theta_k\right)$, phase shift coefficient of the RIS $\theta_k = \left[e^{j\xi_{h}},e^{j\xi_{2,k}},\ldots,e^{j\phi_{N,k}}\right]^H$. $\phi_{N,K} \in [0,2\pi)$ is the phase shift of the $n$ th reflection cell of the RIS corresponding to the $k$ th edge device, $s_k \sim CN\left(0,1\right)$ is the data signal sent by the user to the $k$ th edge device during the $T$ th moment. $n_k \sim CN\left(0,\sigma^2\right)$ is the white noise of the $k$ th edge device. The signal is decoded at the signal access point of the $k$ th edge device using a receive beam fugue, wherein $w_k \in \mathbb{C}^{M\times 1}$ denotes a set of receive beam fugue vectors, and $\left\|w_k\right\|^2 = 1$. The signal recovered at the $k$ st edge device is denoted as:

$$r_k = w_k^H y_k \tag{8}$$

The received signal-to-noise ratio (SNR) of the edge device after decoding is denoted as:

$$Y_k = \frac{P_k\left|w_k^H\left(H_{r,k}\Theta_k g_k + h_{d,k}\right)\right|^2}{\sigma^2} \tag{9}$$

where $\sigma$ is the noise power. From Eq. (9), the amount of offloaded data $l_{off}$ for a user offloading a task to $K$ edge devices is expressed as:

$$l_{off} = \sum_{k=1}^{K}\left[t_k B_k \log_2\left(1+Y_k\right)\right] \tag{10}$$

where $t_k$ is the offloading time slot from the user's transmission task to the $k$ edge device and $B_k$ is the bandwidth from the user to the $k$ th edge device.

In this paper, we study the smart city construction in which the user maximizes the amount of offloaded data from the user's offloading task to the edge devices by optimizing the joint allocation of the received beam fugitive vector, phase shift, user's transmit power, and the time slot for the user's transmit data in time $T$. Therefore, the original optimization problem is constructed as follows:

$$\begin{aligned}
&\max_{w_k,\phi_n,P_k,t_k} \sum_{k=1}^{K}\left[t_k B_k \log_2\left(1+\mathrm{Y}_k\right)\right] \\
&s.t.\ C_1 : t_k P_k \le E_{\max} \\
&C_2 : \left\|w_k\right\|^2 = 1 \\
&C_3 : 0 \le \phi_{n,k} < 2\pi \\
&C_4 : \sum_{k=1}^{K} t_k \le T
\end{aligned} \tag{11}$$

where, constraint $C_1$ denotes that the energy consumption of the $k$ nd edge device in computing the task is less than the system maximum energy consumption and $E_{\max}$ denotes the system maximum energy consumption. Restriction $C_2$ denotes that the second-paradigm of the received beam assignment vector is to be equal to 1. Restriction $C_3$ denotes that the phase shift range of the RIS is between $[0,2\pi)$. Restriction $C_4$ indicates that the sum of the time slots for the user to offload the task to the $K$ edge device is less than the time for the user to compute the task locally, where $T$ denotes the user's local computation time.

#### III. B. 2) Alternate Iterative Optimization Algorithm

Since the original optimization problem (11) involves the optimization of four variables, it can be solved using the algorithm of alternating iterations [24] with lower complexity until the optimization problem reaches convergence. In the following, the received beam assignment vector $w_k$ is optimized first, and the original optimization problem (11) can be re-expressed as:

$$\begin{aligned} &\max_{w_k} l_{off} \\ &s.t. C_2 : \|w_k\|^2 = 1 \end{aligned} \tag{12}$$

Considering the use of Maximum Ratio Combining (MRC) [25] to solve the problem, the $w_k^*$ optimal solution can be expressed as:

$$w_k^* = \frac{H_{r,k}\Theta_k g_k + h_{d,k}}{\|H_{r,k}\Theta_k g_k + h_{d,k}\|} \tag{13}$$

where the optimal solution of the received beam assignment vector $w_k^*$ is known from (13), given the initial values of the optimization variables $P_k$ and $t_k$, the constraints of the irrelevant variables are removed, and the optimization variable $\phi_{n,k}$, denotes the phase shift of the $n$ th reflection unit of the RIS corresponding to the $k$ th edge device. Thus, the original optimization problem (11) can be re-expressed as:

$$\begin{aligned} &\max_{\phi_{n,k}} l_{off} \\ &s.t.\ C_3 : 0 \le \phi_{n,k} < 2\pi \end{aligned} \tag{14}$$

By looking at the structural features of the optimization problem and considering the use of the trigonometric inequality in mathematics, the sum of the two vectors is greater than the third side vector, denoted as $|a+b| \le |a| + |b|$, and hence, $\left|w_k^H \cdot \left(H_{r,k} \cdot \Theta_k \cdot g + h_{d,k}\right)\right|$ can be transformed into:

$$\begin{aligned} \left|w_k^H\left(H_{r,k}\Theta_k g_k + h_{d,k}\right)\right| &= \left|H_{r,k}\Theta_k g_k w_k^H + h_{d,k} w_k^H\right| \\ &\le \left|H_{r,k}\Theta_k g_k w_k^H\right| + \left|h_{d,k} w_k^H\right| \end{aligned} \tag{15}$$

where the optimization function is able to take the maximum value when and only when Eq. (15) takes the equal sign, denoted as:

$$\arg\left(H_{r,k}\Theta_k g_k w_k^H\right) = \arg\left(h_{d,k} w_k^H\right) \tag{16}$$

where $\arg(\cdot)$ in Eq. denotes the phase of a vector.

Introducing the auxiliary variable $\varphi_0 = \arg\left(h_{d,k} w_k^H\right)$ transforms Eq. (16) into:

$$\arg\left(M_k \Theta_k g_k\right) = \varphi_0 \tag{17}$$

where $\Theta_k = diag(\theta_k)$, $M_k = w_k^H H_{r,k}$.

Thus, the optimal solution for $\Theta_h$ can be expressed as:

$$\Theta_k = e^{j[\varphi_0 - \arg(M_k) - \arg(g_k)]} \tag{18}$$

The $\phi_{n,k}^*$-optimal solution can be expressed as:

$$\begin{aligned} \phi_{n,k}^* &= \varphi_0 - \arg(M_k) - \arg(g_k) \\ &= \arg\left(h_{d,k} w_k^H\right) - \arg\left(w_k^H H_{r,k}\right) - \arg(g_k) \end{aligned} \tag{19}$$

Based on the above analysis of $w_k$ and $\phi_{n,k}$, the original optimization problem can be decomposed into 2 sub-optimization problems P1 and P2 to be solved separately.

Based on the above analysis of the four optimization variables, the original optimization problem can be decomposed into the following two sub-optimization problems P1 and P2 for processing.

Sub-optimization problem (P1):

$$\begin{aligned} &\max_{w_k^*, \phi_{n,k}^*, P_k, t_k} l_{off} \\ &s.t. C_1 : t_k P_k \le E_{\max} \end{aligned} \tag{20}$$

Suboptimization problem (P2):

$$\begin{aligned} &\max_{w_k^*, \phi_{n,k}^+, P_k, t_k} l_{off} \\ &s.t. C_1 : t_k P_k \le E_{\max} \\ &C_4 : \sum_{k=1}^{K} t_k \le T \end{aligned} \tag{21}$$

For the above two sub-optimization problems, they are solved using particle swarm optimization algorithm [26] by using MATLAB simulation.

## IV. Performance analysis of mobile edge computing systems

### *IV. A. Simulation experiment setup*

The purpose of this simulation experiment is to model a scenario where there are multiple devices requiring computational offloading and resource allocation within the coverage area of a single base station in a smart city construction. The edge server on the base station side is equipped with a reinforcement learning intelligence that can make decisions about offloading schemes within the area. In addition to this, the computational resources in this system are constrained to be limited and the tasks cannot be computed locally. The performance of the proposed 5G network-based mobile edge computing system is simulated and analyzed in the constructed simulation experiment environment. In order to verify the performance enhancement of the mobile edge computing system by introducing IRS and optimization algorithms, the following five scenarios are proposed in this paper for comparison.

(1) Local-only computing scheme. The user's entire computing tasks are computed locally only.

(2) Full offloading scheme. All the computation tasks of TUs (multi-antenna task-oriented users) are assigned to MEC servers and RU users for computation, i.e., the amount of local computation is 0D=0bit.

(3) No IRS-assisted offloading. The TU offloads tasks to the MEC server and the M RUs (single-antenna resource-based users) offload tasks without using IRS-assisted offloading.

(4) Proposed in the related study using the D2D cooperative offloading scheme. the TU offloads only to the nearby RUs through the IRS with no edge offloading, $D_c$ =0bit.

(5) No optimization scheme. In the offloading scheme used in this paper, the user's computational task, the transmit power, the system bandwidth are randomly allocated, and the phase shift values of the reflection cells of the IRS are random values.

The specific settings of the parameters are as follows, the location of the TU is located at (0, 0), the location of the base station is located at (0, 45), the number of RUs is M = 2, which are located at (5, 2), and (4, 9), respectively, and the IRS location is located at (0, 6). The small-scale fading for all channel models is obeying an independent Rayleigh distribution, and the large-scale fading is $L(d)=C_0 d^{-a}$ . Where, $C_0=-30dB$ , $\alpha$ = 3, and the system bandwidth is B = 0.75 MHz. the computational frequencies of the TUs, the MEC server, and the two RUs are $f_1=1GHz$ , and $f_2=0.8GHz$ , respectively, and the maximum value of the TU's transmit power is $p_{\max}=1Watt$ , and the size of the TU's computational task is D = 1 Mbit, and the complexity of the computational task is C = 600cycle /The power spectral density of Gaussian white noise is $N_0=10^{-16}$ Watt/Hz, the number of reflection units of the intelligent reflective surface is N=64, assuming that there is an obstacle in the direct link between the TU and the 2nd RU that causes the channel link to be blocked, the algorithm latency is counted in the latency of each scheme, and the parameter is changed to make a special note.

### *IV. B. System delay analysis*

#### IV. B. 1) Analysis of the relationship between total bandwidth and delay

The results of the analysis of the relationship between the total delay of the mobile edge computing system and the total system bandwidth under IRS-assisted optimization are shown in Fig. 2, where A-G represent the local computing scenario, the full offloading scenario (M=2), the no-optimization scenario (M=2), the D2D offloading scenario (M=2), the no-IRS scenario (M=2), the scenarios of this paper (M=1), and the scenarios of this paper (M=2), respectively. The total bandwidth of the system is increased from 0.2MHz to 1.6MHz, it can be seen that the total delay of the mobile edge computing system decreases with the increase in the bandwidth of the system, this is due to the larger system bandwidth offloading the tasks with higher task offloading rate, which results in lower offloading delay of the user TUs while offloading the tasks to the MEC servers on the BTS as well as to the RUs, which results in the reduction of the overall system delay. It can be seen that the scheme adopted in this paper has the lowest system delay when the number of RUs is M=2, and the total system delay is only 0.0648 s when the total system bandwidth is 1.6 MHz. Compared with the unoptimized scheme, the user's computational task and the allocation of the transmit power, the allocation of the system bandwidth, and the phase shift value of the IRS are all randomized, which can result in the delay of a certain portion of the local processing, the MEC processing, and the D2D processing to be too large and thus affecting the overall system delay. Processing with excessive latency thus affecting the overall computational latency of the user. Compared to M=1, the system increases a part of the computational resources, thus the computational tasks assigned to other RUs and the MEC server are reduced thus the transmission delay of the computational tasks as well as the computational delay are reduced, which can verify the effectiveness of the introduction of the D2D communication in the MEC system to reduce the system latency. In the M=2 scheme without IRS-assisted offloading, the delay performance is close to that of the scheme adopted in this paper when M=1 because the link between the TU and the 2nd RU is blocked by obstacles due to the fact that IRS is not used for assisted offloading. However, since the IRS provides a portion of the channel gain in the reflective cascade channel of the D2D link between the TU and the first RU as well as in the cellular link with the base station, the scheme in this paper at M=1 is slightly lower than the delay under the no-IRS scheme. When the total bandwidth is 1.6 MHz, the total delay of this paper's system (M=1) and the IRS-free scheme are 0.0906s and 0.1276s, respectively. In the D2D offloading-only scheme, due to the lack of the richer computational resources of the MEC servers, the increase in the computational tasks assigned to the local and the RUs leads to the excessive system latency.

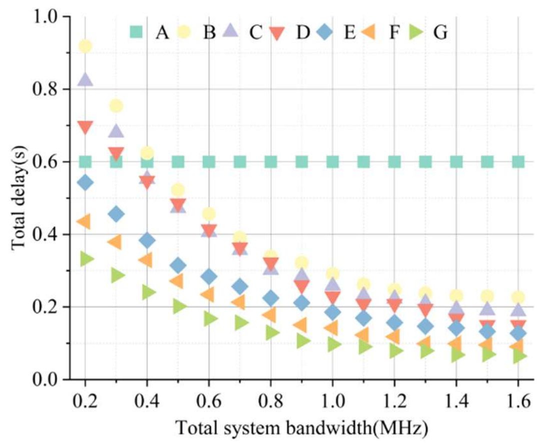


Figure 2: Analysis of the relationship between total time delay and total bandwidth

**IV. B. 2) System Latency Variation under Different Task Volumes**

The results of the analysis of the relationship between the total computational delay and the size of the computational tasks of the mobile edge computing systems are shown in Fig. 3, where A-G represent the local computation scheme, the full offloading scheme (M=2), the no-optimization scheme (M=2), the D2D offloading scheme (M=2), the no-IRS scheme (M=2), this paper's scheme (M=1), and this paper's scheme (M=2), respectively. The computational task size of the user TU increases from 1Mbit to 10Mbit, and it can be seen that the total computational delay of all systems increases with the computational task size. It is clear that larger task computation size leads to higher task computation latency as well as task offloading latency. It is also observed that the performance-optimized mobile edge computing system proposed in this paper outperforms other task computing schemes in reducing the total system latency. Especially it is more obvious in the case of very large size of computation tasks, in the case of 10Mbit computation task size, the system (M=2) latency (2.148s) of this paper is reduced by about 63.81% compared to the local computation only scheme (5.935s). The delay of the mobile edge computing system (M=2) in this paper is reduced by about 17.16% compared to the D2D offloading only scheme (2.593s). The system (M=2) latency is reduced by about 6.69% compared to the scheme used in this paper when M=1.

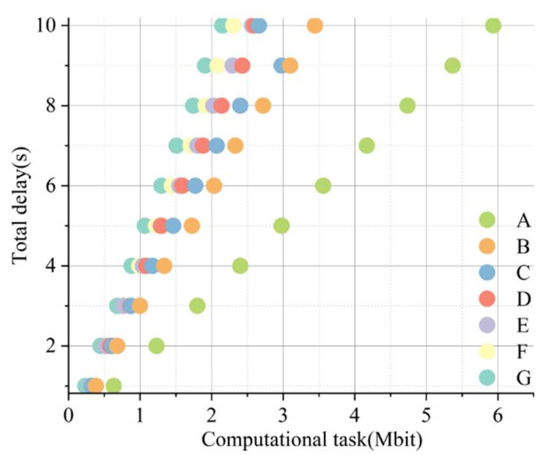


Figure 3: The relationship between total time delay and task calculation

### *IV. C. System convergence analysis*

The results of the analysis of the total user delay versus the number of iterations for the optimized performance system proposed in this paper with system bandwidth B = 0.8 MHZ and TU computational task size of D = 1 Mbit are shown in Fig. 4. The convergence of the mobile edge computing system in this paper can be seen to be guaranteed as it gradually starts to converge gradually when the number of iterations is 5 (t=0.1988s) at C=500 and N=4, while the number of iterations is 8 (t=0.1828s) at C=500 and N=64, so it can be seen that the convergence of the mobile edge computing system in this paper can be guaranteed. Meanwhile, it can be observed that when the number of reflection units of the intelligent reflective surface is higher, the convergence speed is slower but there will be a lower system delay, the number of reflection units of the IRS in the iteration number of 16 times N=64 (0.1819s) compared to N=4 (0.1988s) the delay is reduced by about 0.0169s. This is due to the fact that the more the number of reflection units of the IRS is, the more the number of reflected signal paths provided will also be higher, and the more the number of reflected signal paths provided at the user's place will be higher. Will be more and superimposed at the user, thus increasing the transmission rate when the computational task is offloaded. It can also be seen from the figure that as the computational complexity of the task increases, the total latency of the user's computational task increases accordingly.

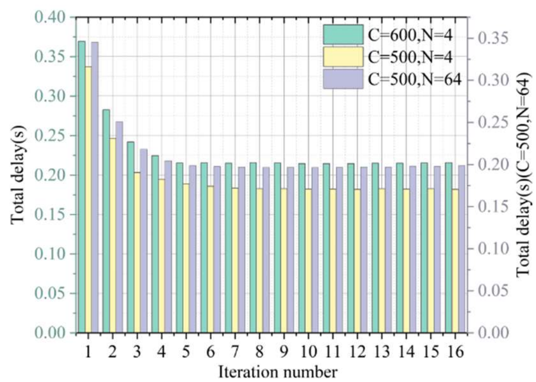


Figure 4: The relationship between total time delay and iterative number of systems

### *IV. D. Smart City Construction Platform Application Analysis*

This paper completes the realization and deployment of a smart city construction application platform based on 5G networks in accordance with SDN and NFV development principles. The platform consists of three main parts, the infrastructure layer and the physical abstraction layer constitute the platform's underlying pedestal, which is responsible for operating, managing and maintaining the network and cloud computing infrastructure. In order to facilitate the deployment of the mobile edge computing system performance optimization method, this paper carries out functional abstraction and interface encapsulation for the platform bottom layer base, and provides programmable user-plane and control-plane APIs to the upper layer. the functional management layer constitutes the middleware, which is used for deploying and maintaining the operation of the performance optimization method of the mobile edge computing system, and provides the application layer with an accessible program development portal. The application layer constitutes the upper layer service support, which is responsible for maintaining the operation of the application back-end program. The platform can meet the diversified needs in the process of smart city construction, and realize the precipitation and application of urban data assets through the urban data use of data collection, storage, computation, mining, and presentation as a whole.

In order to explore whether the platform based on the optimized mobile edge computing system has the ability to be scalable and ensure fairness, this paper uses the Linus Traffic Control tool to simulate the fluctuation of the 5G wireless link, while the real-world collected OD application data streams are fed into the simulated base station through the wired LAN. The results of the analysis of the platform's multi-user scalability are shown in Table 1, when the number of users is less than 20, the frame response latency is low and similar for all users (106.79-109.14ms) because there are enough PRBs in the base station's wireless resource pool. When the number of users is greater than 20 and less than 50, the frame response delay gradually increases but is limited to 200ms (147.81-183.14ms) because there is competition for wireless resources among multiple users. The frame response delay increases significantly when the number of users is greater than 80. For example, when the number of users is 100, the delay is even as high as 389.24 ms. However, the standard deviation of the frame response latency is small and stable in all cases, which implies that the performance-optimized mobile edge computing system proposed in this paper can guarantee the fairness among users in the smart city construction platform, and can satisfy the respective performance requirements when used by multiple users.

Table 1: Analysis of platform versatility

| Number of users | Response latency (ms) | Number of users | Response latency (ms) |
|---|---|---|---|
| 1 | 106.79 | 55 | 215.22 |
| 5 | 107.27 | 60 | 233 |
| 10 | 108.55 | 65 | 239.32 |
| 15 | 108.74 | 70 | 247.44 |
| 20 | 109.14 | 75 | 257.78 |
| 25 | 147.81 | 80 | 262.43 |
| 30 | 154.01 | 85 | 295.88 |
| 35 | 161.86 | 90 | 336.72 |
| 40 | 163.67 | 95 | 352.76 |
| 45 | 179.4 | 100 | 389.24 |
| 50 | 183.14 | —— | —— |

## V. Conclusion

While 5G network becomes a platform for integrated computing and communication technology, the application of mobile edge computing extends to various fields in smart city construction. In this paper, IRS technology, one of the 5G technologies, is used with alternate iteration algorithm to optimize the mobile edge computing system and improve the performance of mobile edge computing system in smart city construction. Numerical simulation experiments are conducted to verify the effectiveness of introducing IRS assistance in the mobile edge computing system, and the results show that the total delay of the mobile edge computing system decreases with the increase of the bandwidth of the system. This paper's system has the lowest system delay when the number of RUs M=2, and the total system delay is only 0.0648s when the total system bandwidth is 1.6 MHz. in the case of 10 Mbit computation task volume, the delay (2.148s) of this paper's system (M=2) is reduced by about 63.81% compared with that of the local computation only scheme (5.935s). In addition, the convergence of the mobile edge computing system in this paper is also ensured, which gradually starts to converge gradually at the number of iterations of 5 (t=0.1988s) at C=500, N=4. The scalability analysis of the smart city construction application platform designed based on the optimized mobile edge computing system reveals that when the number of users is less than 20, the frame response latency is low and similar (106.79-109.14ms) for all users due to the availability of sufficient PRBs in the wireless resource pool of the base station.

The research in this paper provides a solution to the problems of low spectrum utilization and high energy consumption of traditional mobile edge computing systems. In future work, the performance of mobile edge computing systems can be considered to be studied in dynamic user scenarios, which are more in line with practical application scenarios.

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