Journal of Urban Development and Smart Cities
2025, 2(1), 73-84

PERFORMANCE OPTIMIZATION OF 5G-ENABLED MOBILE EDGE COMPUTING FOR SMART CITY DEVELOPMENT

Mukesh Sharma
Naresh K Malhotra
Khushwant Singh

Mobile edge computing (MEC) plays a central role in smart-city construction by strengthening the computing capability of wireless devices and supporting responsive urban services. This study integrates an intelligent reflecting surface (IRS)–assisted channel model—an important 5G technology—into MEC system design and formulates an optimization framework aligned with smart-city performance requirements. An alternating-iteration strategy is used to decompose the overall problem into manageable subproblems, which are then solved using particle swarm optimization to build a performance-optimized 5G-based MEC system. Experimental results show that for a 10 Mbit computing task, the proposed system (M = 2) reduces latency by about 63.81%, lowering delay to 2.148 s compared with 5.935 s under a local-computing-only baseline, while maintaining good convergence behavior. The results also indicate that the resulting application platform can preserve fairness among multiple users and meet heterogeneous performance demands. Overall, the proposed MEC optimization approach delivers low-latency performance that supports efficient smart-city services, strengthens urban management capability, and contributes to improved service quality.

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

https://doi.org/10.66033/judsc2025-207

INTRODUCTION

With the continuous advancement of space information technologies, information technology (IT), and wireless communication systems, urban informatization has become a dominant trend in global urban modernization. It now serves as a key indicator of a city's comprehensive competitiveness. Urban informatization plays a vital role in enhancing a city's carrying capacity, facilitating the integration of social resources, optimizing the allocation of production factors, and strengthening overall urban governance, thereby stimulating productivity and socio-economic development [1, 2, 3]. According to China's national informatization strategy, spatial information infrastructure, industrial informatization, and urban informatization constitute the three core construction pillars. As a central component of this strategy, the development level and evolution path of urban informatization significantly influence the broader direction of national informatization [4, 5].

With breakthroughs in sensor networks, grid computing, and related technologies, the concept of the digital city is evolving toward a more advanced paradigm—namely, the smart city. Smart cities emphasize the deep integration of information technologies into urban functions, enabling cities to act as intelligent information distribution hubs. This transformation enhances urban sustainability, improves living conditions, and promotes high-quality development. As smart city applications become increasingly embedded in daily life, it is necessary to further explore and refine their theoretical foundations and implementation frameworks [6, 7, 8, 9, 10].

As one of the key enabling technologies of fifth-generation (5G) communication systems, Mobile Edge Computing (MEC) has demonstrated substantial potential. MEC shifts computing, storage, and service capabilities from centralized cloud platforms to the network edge, allowing localized and low-latency service provisioning [11, 12, 13]. Many smart city scenarios—such as intelligent transportation, autonomous driving, real-time surveillance, and environmental monitoring—require real-time processing of large volumes of data close to the data source. Consequently, edge computing plays a critical role in supporting these latency-sensitive and computation-intensive applications [14, 15].

Driven by the rapid growth of the Internet of Things (IoT), 5G networks, industrial automation, and intelligent manufacturing, MEC has become a core component connecting physical devices with industrial communication infrastructures. Recent studies have proposed various MEC optimization frameworks. For example, a cognitive radio–MEC model supporting unmanned aerial vehicles (UAVs) was introduced to jointly optimize local computing and partial task offloading, thereby improving energy efficiency and spectrum utilization [16]. A dual-delay deep reinforcement learning–based offloading strategy was proposed to enhance service quality through the integration of software-defined networking and network function virtualization [17]. Additionally, a hybrid bacterial foraging optimization algorithm was developed for IoT–cloud edge task scheduling, achieving reduced completion time and improved resource utilization [18].

The emergence of 5G has further accelerated the realization of smart cities by providing high bandwidth, ultra-low latency, and massive connectivity. Several studies have explored the integration of MEC with emerging technologies to address key challenges in smart city governance. For instance, a UAV-assisted 5G edge computing framework was proposed for hotspot data processing and abnormal event monitoring [19]. A privacy-preserving data collection architecture based on quad-tree zoning, local differential privacy, and blockchain was designed to protect user data in smart city environments [20]. Furthermore, a joint optimization strategy for edge resource allocation was introduced to support latency-sensitive services [21].

In this work, we propose a performance optimization framework for a 5G-based mobile edge computing system using an intelligent reflecting surface (IRS)–assisted channel model. The normalized channel gain is computed to support efficient task offloading and execution. An optimization model is formulated to maximize the total offloaded computation tasks under user demand constraints in smart city scenarios. To reduce computational complexity, the original problem is decomposed using a maximum ratio combining strategy, and an alternating iterative algorithm is developed. The resulting subproblems are solved using particle swarm optimization, with convergence verified through MATLAB simulations. Finally, a comprehensive simulation environment is established to evaluate system convergence behavior, latency performance, and scalability, thereby demonstrating the effectiveness of the proposed framework.

APPLICATION OF MOBILE EDGE COMPUTING IN SMART CITY DEVELOPMENT

The advent of the 5G era has injected new momentum into urban digital transformation. By enabling high-speed connectivity, ultra-low latency, and large-scale device access, 5G reshapes the intelligent infrastructure of cities, empowers diverse industries, and fosters innovation-driven economic growth. As a result, smart cities are evolving toward more integrated, adaptive, and sustainable ecosystems.

Over recent decades, the conceptualization and realization of smart cities have progressed steadily. With the widespread deployment of next-generation information and communication technologies, the overall architecture of smart city systems has gradually matured. Typically, this architecture is organized into five layers: the perception layer, network layer, service layer, application layer, and user layer.

The service layer comprises three major submodules: the public information platform, public databases, and public facilities, which are usually integrated into a unified cloud-based intelligent platform. By combining 5G networks with artificial intelligence, the Internet of Things (AIoT), mobile edge computing, and intelligent operation centers (IOC), an end–edge–cloud collaborative ecosystem can be formed. This architecture enables real-time sensing, intelligent analysis, and autonomous decision-making across the entire urban domain.

Therefore, optimizing the performance of 5G-enabled MEC systems is essential for enhancing smart city infrastructure, improving service responsiveness, and supporting large-scale intelligent applications. Efficient MEC deployment not only reduces system latency but also enhances resource utilization, reliability, and scalability, thereby serving as a foundational technology for future smart city development.

PERFORMANCE OPTIMIZATION OF MOBILE EDGE COMPUTING SYSTEMS

System Modeling with IRS-Assisted Communication

IRS Channel Modeling

The Intelligent Reflecting Surface (IRS) is an emerging enabling technology that integrates concepts from metamaterials, electromagnetic wave manipulation, computational electromagnetics, cybernetics, and wireless communications. As one of the core technologies envisioned for 5G and beyond, IRS provides a flexible means to control wireless propagation environments [22].

The fundamental modeling principle is to decompose the conventional direct transmission channel between the transmitter (Tx) and the receiver (Rx) into two components: (i) a direct Tx–Rx link, and (ii) an IRS-assisted reflected link following the Tx–IRS–Rx path. The composite channel can be expressed as

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

where h_{TR} and h_{RU} denote the channel response vectors from the transmitter to the IRS and from the IRS to the receiver, respectively, while PL_{TR} and PL_{RU} represent the corresponding path losses. The direct channel between the transmitter and the receiver is characterized by h_{TU} with path loss PL_{TU}.

The IRS electromagnetic behavior is modeled through a diagonal reflection matrix

$$\Phi = \mathrm{diag}\left(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_M e^{j\theta_M}\right), \tag{2}$$

where $\beta_m \in [0,1]$ and $\theta_m \in [0,2\pi)$ denote the amplitude and phase shift of the m-th reflecting element, respectively.

The IRS-assisted channel is independent of the terminal-side channels, and the resulting response matrices h_{TR} and h_{RU} can be obtained separately. For instance, the IRS-to-receiver channel response matrix is written as

$$h_{RU} = [h_{u,1}(t,\tau), \ldots, h_{u,n}(t,\tau)], \tag{3}$$

where the IRS is assumed to contain $n \times n$ reflective elements, and $h_{u,k}(t,\tau)$ denotes the channel coefficient between the k-th IRS unit and the u-th receiving antenna.

MEC System Optimization Model

In this work, we consider an IRS-assisted mobile edge computing architecture combined with OFDM-based cooperative relaying. The system consists of a user equipment (UE) located far from the access point (AP), a relay node positioned closer to the AP, an IRS with M reflecting elements, and an AP integrated with an MEC server.

The user application task of size L is partitioned into three components: l_U, l_R, and l_A, corresponding to the portions executed locally, offloaded to the relay, and offloaded to the AP, respectively. Thus, the task satisfies

$$l_U + l_R + l_A = L. \tag{4}$$

Within each time frame of duration T, the entire task is offloaded and processed. Channel conditions are assumed to remain constant during one time frame and follow an i.i.d. distribution across different frames.

The direct link from the user to the AP is modeled using Rayleigh fading:

$$h_{UA} = \rho d_{UA}^{-a_{UA}} \tilde{h}_{UA}, \tag{5}$$

where $\tilde{h}_{UA}$ represents the small-scale fading component modeled as a complex Gaussian random variable, ρ is the reference path loss at $d = 1$ m, and a_{UA} is the path loss exponent. Similar models apply to the user-to-relay and relay-to-AP channels.

The AP-to-IRS channel follows a Rician distribution:

$$g_A = \sqrt{\frac{\zeta_A}{\zeta_A + 1}} h_{LoS} + \sqrt{\frac{1}{\zeta_A + 1}} h_{NLoS}, \tag{6}$$

where ζ_A denotes the Rician factor. The channels from the UE to the IRS and from the relay to the IRS are defined analogously.

Let $\theta = [\theta_1, \theta_2, \ldots, \theta_M]$ denote the IRS phase shift vector. The corresponding diagonal reflection matrix is

$$\Theta = \text{diag}(\beta_1 e^{j\theta_1}, \beta_2 e^{j\theta_2}, \ldots, \beta_M e^{j\theta_M}). \tag{7}$$

The normalized channel gain for the n-th subcarrier between the UE and the AP is

$$\gamma_{UA}^{(n)} = \frac{|g_A^H \Theta g_U + h_{UA}|^2}{\sigma^2}, \tag{8}$$

where σ^2 denotes the noise variance. Similar expressions hold for the UE–relay and relay–AP links.

Optimization Algorithm Design

Problem Formulation

At time slot t_k, the received signal at the k-th edge device consists of the direct signal, the IRS-reflected signal, and additive white Gaussian noise [23]. It is expressed as

$$y_k = \sqrt{P_k}(H_{r,k}\Theta g_k + h_{d,k})s_k + n_k, \tag{9}$$

where P_k is the transmit power, $H_{r,k}$ is the channel from the IRS to the k-th edge device, g_k is the channel from the user to the IRS, $h_{d,k}$ is the direct channel, s_k is the transmitted signal, and n_k denotes noise.

With a receive beamforming vector w_k, the recovered signal is

$$r_k = w_k^H y_k. \tag{10}$$

The resulting SNR is

$$\gamma_k = \frac{P_k |w_k^H (H_{r,k}\Theta g_k + h_{d,k})|^2}{\sigma^2}. \tag{11}$$

The total offloaded data volume is given by

$$l_{\text{off}} = \sum_{k=1}^{K} t_k B_k \log_2(1 + \gamma_k), \tag{12}$$

where t_k and B_k denote the offloading time and bandwidth, respectively.

The optimization objective is to maximize l_{off} by jointly optimizing beamforming vectors, phase shifts, transmit powers, and time allocations:

$$\begin{aligned} \max_{\{w_k, P_k, t_k, \phi_{n,k}\}} \quad & \sum_{k=1}^{K} t_k B_k \log_2(1+\gamma_k) \\ \text{s.t.} \quad & C_1 : E_k \leq E_{\max}, \\ & C_2 : \|w_k\|^2 = 1, \\ & C_3 : 0 \leq \phi_{n,k} < 2\pi, \\ & C_4 : \sum_{k=1}^{K} t_k \leq T. \end{aligned} \tag{13}$$

Alternating Optimization Strategy

Due to the coupling of multiple variables, the above problem is non-convex. We adopt an alternating iterative optimization approach [24]. First, the receive beamforming vector is optimized using maximum ratio combining (MRC) [25]:

$$w_k^* = \frac{H_{r,k}\Theta g_k + h_{d,k}}{\|H_{r,k}\Theta g_k + h_{d,k}\|}. \tag{14}$$

Fixing w_k, P_k, and t_k, the phase shift optimization reduces to

$$\max_{\phi_{n,k}} \quad l_{\text{off}}, \quad \text{s.t. } 0 \leq \phi_{n,k} < 2\pi. \tag{15}$$

Using triangle inequality properties, the optimal phase alignment condition is

$$\arg(H_{r,k}\Theta g_k) = \arg(h_{d,k}), \tag{16}$$

which yields

$$\phi_{n,k}^* = \arg(h_{d,k}^H w_k) - \arg(g_{k,n}^H H_{r,k}^H w_k). \tag{17}$$

Based on this decomposition, the original problem is split into two subproblems: one for power and time allocation, and the other for phase shift optimization.

Numerical Solution

Both subproblems are solved using the particle swarm optimization (PSO) algorithm [26]. MATLAB simulations are used to evaluate convergence behavior and system performance.

PERFORMANCE EVALUATION OF THE MOBILE EDGE COMPUTING SYSTEM

Simulation Environment Setup

The objective of the simulation experiments is to emulate a smart city scenario in which multiple devices within the coverage area of a single base station require computational offloading and resource scheduling. The edge server deployed at the base station is equipped with a reinforcement learning–based decision-making module, enabling intelligent task offloading within the network. In this setting, computational resources are assumed to be limited, and tasks cannot be fully processed locally.

To comprehensively assess the performance gains achieved through the integration of IRS and the proposed optimization strategies, five benchmark schemes are considered for comparison:

1. Local computing only: All user tasks are processed locally without offloading.
2. Full offloading: All computation tasks of task-oriented users (TUs) are offloaded to MEC servers and resource users (RUs), i.e., $D_0 = 0$.
3. Offloading without IRS: Tasks are offloaded to MEC servers and RUs without IRS assistance.
4. D2D cooperative offloading: Tasks are offloaded only to nearby RUs via D2D links without MEC server participation, i.e., $c_D = 0$.
5. No optimization: Transmission power, bandwidth, offloading decisions, and IRS phase shifts are randomly allocated.

The simulation parameters are configured as follows: the TU is located at $(0,0)$, the base station is positioned at $(0,45)$, and two RUs ($M = 2$) are located at $(5,2)$ and $(4,9)$. The IRS is placed at $(0,6)$. All small-scale fading channels follow independent Rayleigh distributions, while large-scale fading is modeled as $L(d) = C_0 d^{-\alpha}$, where $C_0 = -30$ dB and $\alpha = 3$.

The system bandwidth is set to $B = 0.75$ MHz. The computational frequencies of the TU, MEC server, and RUs are $f_1 = 1$ GHz and $f_2 = 0.8$ GHz, respectively. The maximum TU transmit power is $P_{\max} = 1$ W. The task size is $D = 1$ Mbit, with computational complexity $C = 600$ cycles/bit. The power spectral density of noise is $N_0 = 10^{-16}$ W/Hz, and the number of IRS reflection units is $N = 64$. An obstacle is assumed to block the direct link between the TU and the second RU. Algorithm execution delay is included in the total system latency.

System Delay Analysis

Impact of Total Bandwidth on System Delay

Figure 1 illustrates the relationship between total system bandwidth and overall latency under IRS-assisted optimization. Scenarios A–G correspond to local computing, full offloading ($M = 2$), no-optimization ($M = 2$), D2D offloading ($M = 2$), no-IRS ($M = 2$), the proposed scheme with $M = 1$, and the proposed scheme with $M = 2$, respectively.

As the total bandwidth increases from 0.2 MHz to 1.6 MHz, the system delay consistently decreases. This trend occurs because a larger bandwidth enhances the offloading rate, thereby reducing transmission latency and improving task processing efficiency. Among all schemes, the proposed method with $M = 2$ achieves the lowest delay, reaching only 0.0648 s at 1.6 MHz.

In contrast, the unoptimized scheme exhibits higher delay due to random resource allocation, which may result in excessive latency at certain processing nodes. Furthermore, increasing the number of RUs reduces computational load per node, thereby lowering both transmission and processing delays. This confirms the effectiveness of D2D-enabled MEC architectures.

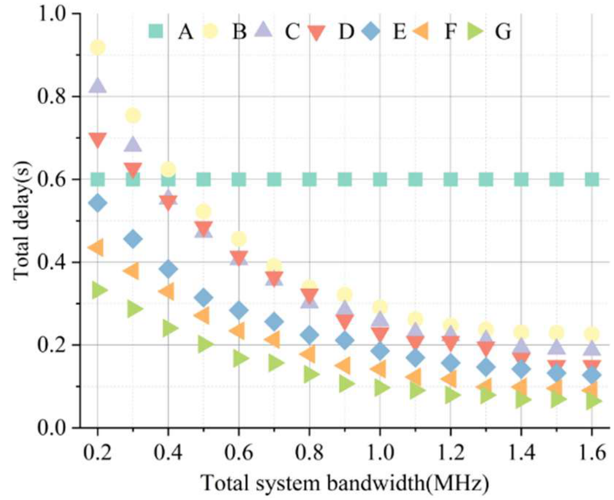

Figure 1: Analysis of the relationship between total time delay and total bandwidth

Effect of Task Size on Latency

Figure 2 depicts the variation of total system latency with respect to the task size. The task size increases from 1 Mbit to 10 Mbit, and it is observed that latency grows accordingly for all schemes. Larger tasks inevitably lead to longer transmission and processing times.

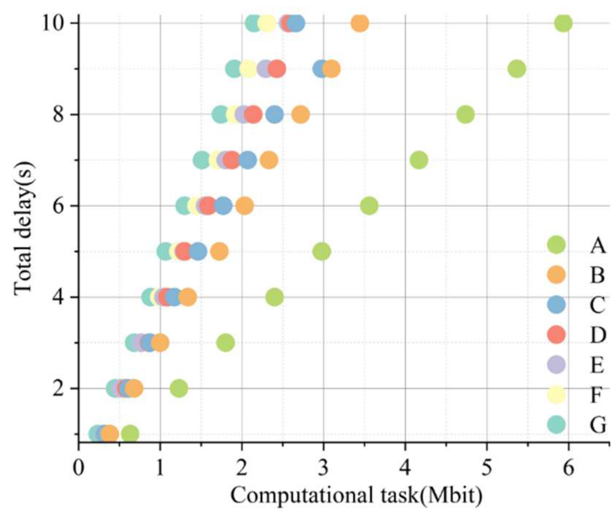

Figure 2: The relationship between total time delay and task calculation

Nevertheless, the proposed optimized MEC system consistently outperforms all baselines. For example, when the task size reaches 10 Mbit, the latency of the proposed method ($M = 2$) is 2.148 s, which represents a reduction of approximately 63.81% compared with the local-only scheme (5.935 s). It also achieves a 17.16% improvement over the D2D-only scheme and a 6.69% improvement compared to the $M = 1$ configuration.

Convergence Performance

Figure 3 presents the convergence behavior of the proposed system under $B = 0.8$ MHz and $D = 1$ Mbit. The system converges after approximately 5 iterations when $C = 500$ and $N = 4$, and after about 8 iterations when $C = 500$ and $N = 64$. This confirms the stability and reliability of the proposed optimization framework.

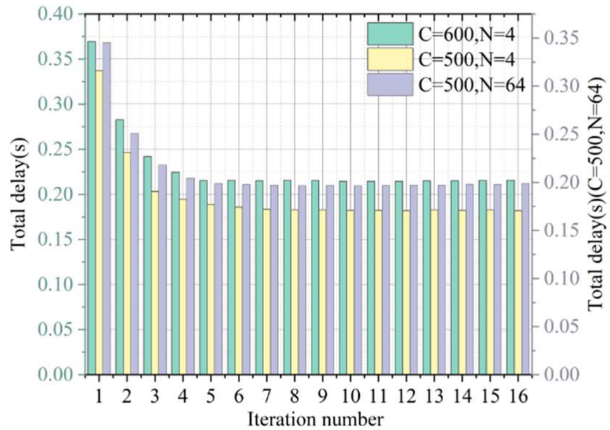

Figure 3: The relationship between total time delay and iterative number of systems

Although increasing the number of IRS reflection units slows down convergence, it also yields lower final latency. For instance, at 16 iterations, the delay for $N = 64$ is 0.1819 s, which is 0.0169 s lower than that for $N = 4$. This improvement stems from the enhanced signal diversity enabled by additional reflection paths.

Application-Level Analysis in Smart City Platforms

A smart city application platform based on the optimized MEC architecture is developed in accordance with SDN and NFV principles. The platform consists of three layers: (i) the infrastructure and physical abstraction layer, (ii) the functional management layer, and (iii) the application service layer. Together, these layers enable efficient data collection, storage, processing, mining, and visualization.

To evaluate scalability and fairness, the Linux Traffic Control tool is employed to emulate fluctuating 5G wireless conditions. Real-world OD traffic data are injected into the simulated base station via a wired LAN. The response latency for varying numbers of users is summarized in Table 1.

When the number of users is below 20, latency remains low and uniform due to sufficient physical resource blocks (PRBs). As the number of users increases, latency grows gradually due to competition for wireless resources. However, the low variance across all cases indicates that the proposed system ensures fairness and stable quality of service.

CONCLUSION

This study integrates IRS technology with an alternating optimization framework to enhance the performance of 5G-based mobile edge computing systems in smart city environments. Simulation results demonstrate that system latency decreases as bandwidth increases, with the proposed scheme ($M = 2$) achieving the lowest latency of 0.0648 s at 1.6 MHz. For a 10 Mbit task, the proposed method reduces latency by 63.81% compared to local computing.

Table 1: Scalability Analysis of the Smart City Platform

Users	Latency (ms)	Users	Latency (ms)
1	106.79	55	215.22
5	107.27	60	233.00
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	179.40	100	389.24
50	183.14	–	–

The convergence of the system is guaranteed, and the smart city platform built on the optimized MEC architecture exhibits strong scalability and fairness. These results indicate that the proposed framework effectively addresses the limitations of traditional MEC systems in terms of spectral efficiency and energy consumption.

Future work will focus on dynamic user mobility scenarios and adaptive task arrival patterns to further align the system with real-world smart city deployments.

REFERENCES

[1] Lv, Y. , & Tan, W. . (2022). Infrastructure smart service system based on microservice architecture from the perspective of informatization. Mobile information systems, 2022(Pt.14), 1344720.1-1344720.11.

[2] Hu, L. , Wen, J. , Yu, H. , Zhu, Y. , & Du, Y. . (2017). Research on Public Satisfaction Index Model of Urban Management Informatization. 2017 International Conference on Advanced Materials Science and Civil Engineering (AMSCE 2017).

[3] Wang, G. , & Fen, L. I. . (2020). Construction of new smart city powered by informatization —effects and thinking of covid-19 epidemic on urban development. Bulletin of Chinese Academy of Sciences, 35(8), 1024-1031.

[4] Zheng, C. , Yuan, J. , Zhu, L. , Zhang, Y. , & Shao, Q. . (2020). From digital to sustainable: a scientometric review of smart city literature between 1990 and 2019. Journal of Cleaner Production, 258, 120689.

[5] Zhao, Z. , & Zhang, Y. . (2020). Impact of smart city planning and construction on economic and social benefits based on big data analysis. Complexity, 2020(4), 1-11.

[6] Yang, J. , Lee, T. Y. , & Zhang, W. . (2021). Smart cities in china: a brief overview. IT Professional, 23(3), 89-94.

[7] Peng, Y. , Wang, X. , Shen, D. , Yan, W. , Fu, Y. , & Deng, Q. . (2018). Design and modeling of survivable network planning for software-defined data center networks in smart city. International Journal of Communication Systems, 31(16), e3509.1-e3509.14.

[8] LvZhihan, QiaoLiang, Singhamit, K. , & WangQingjun. (2021). Ai-empowered iot security for smart cities. ACM Transactions on Internet Technology.

[9] Li, C. , Liu, X. , Dai, Z. , & Zhao, Z. . (2019). Smart city: a shareable framework and its applications in china. Sustainability, 11(16), 4346.

[10] Zhao, H. , Wang, Y. , & Liu, X. . (2021). The evaluation of smart city construction readiness in china using critic-g1 method and the bonferroni operator. IEEE Access, PP(99), 1-1.

[11] Hajisami, Abolfazl, Tran, Tuyen, X., & Pandey, et al. (2017). Collaborative mobile edge computing in 5g networks: new paradigms, scenarios, and challenges. IEEE Communications Magazine Articles News & Events of Interest to Communications Engineers.

[12] Zhou, F. , Hu, R. Q. , Li, Z. , & Wang, Y. . (2020). Mobile edge computing in unmanned aerial vehicle networks. IEEE Wireless Communications, PP(99), 1-7.

[13] Ma, B. , Guo, W. , & Zhang, J. . (2020). A survey of online data-driven proactive 5g network optimisation using machine learning. IEEE Access, PP(99), 1-1.

[14] Qi, B. , Kang, L. , & Banerjee, S. . (2017). A vehicle-based edge computing platform for transit and human mobility analytics. ACM, 1- 14.

[15] Tang, B. , Chen, Z. , Hefferman, G. , Pei, S. , Wei, T. , & He, H. , et al. (2017). Incorporating intelligence in fog computing for big data analysis in smart cities. IEEE Transactions on Industrial Informatics, 13(5), 2140-2150.

[16] Pan, Y. , Da, X. , & Hu, R. Z. H. . (2020). Efficient design optimisation for uav-enabled mobile edge computing in cognitive radio networks. IET communications, 14(15), 2509-2515.

[17] Fu, Q. , & Yang, T. . (2024). Enhancing service offloading for dense networks based on optimal stopping theory in virtual mobile edge computing. Journal of Grid Computing, 22(2).

[18] Jaiswal, K. , Sobhanayak, S. , Turuk, A. K. , Sahoo, B. , & Jena, D. . (2020). Container-based task scheduling for edge computing in iot-cloud environment using improved hbf optimisation algorithm. International Journal of Embedded Systems, 13(1).

[19] Song, P. C. , Pan, J. S. , & Chao, S. C. . (2023). Collaborative hotspot data collection with drones and 5g edge computing in smart city. ACM Transactions on Internet Technology, 23(4).

[20] Yao, A. , Pal, S. , Li, X. , Zhang, Z. , Dong, C. , & Jiang, F. , et al. (2024). A privacy-preserving location data collection framework for intelligent systems in edge computing. Ad Hoc Networks, 161.

[21] Liu, Z. R. . (2023). A multi-joint optimisation method for distributed edge computing resources in iot-based smart cities. Journal of grid computing, 21(4).

[22] Gyana Ranjan Mati & Susmita Das. (2024). Orthonormal pilot-based channel estimation with low complexity phase shift optimization and coverage enhancement for IRS-assisted B5G communication. Physical Communication102286-.

[23] Yongqi Hu & Gen Ge. (2024). Response of Gaussian white noise excited oscillators with inertia nonlinearity based on the RBFNN method. Probabilistic Engineering Mechanics103637-103637.

[24] Mihai Bucataru & Liviu Marin. (2024). FDM-based alternating iterative algorithms for inverse BVPs in 2D steady-state anisotropic heat conduction with heat sources. Journal of Computational and Applied Mathematics116051-116051.

[25] Princewill Kum Kumson,Mahmoud Aldababsa,Khalid Yahya,Mahmoud Obaid & Allam Abu Mwais. (2023). Performance analysis of majority-based transmit antenna selection and maximal ratio combining in MIMO-NOMA networks. Annals of Telecommunications(7- 8),567-576.

[26] Alessandra F. Picanço,Antônio C. Zambroni de Souza & Andressa Pereira Oliveira. (2024). Natural logarithm particle swarm optimization for loss reduction in an island power system. MethodsX102924-102924.

Mukesh Sharma, Rice Housing Department, Rice University

Naresh K Malhotra, Rice Housing Department, Rice University

Khushwant Singh, Rice Housing Department, Rice University

Manuscript Published; 06 April 2025.