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Communication and computational resource optimization for Industry 5.0 smart devices empowered by MEC

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ABSTRACT

Smart devices in Industry 5.0, such as sensors and robots, are often limited by low battery life and finite computational resources, hindering their ability to perform complex tasks. By offloading computation-intensive tasks to Mobile Edge Cloud Computing (MEC) servers at the network's edge, businesses can achieve real-time data processing and analysis, reducing communication latency, quicker response times, and improved system reliability. This work presents an integrated framework for MEC and Industry 5.0, aimed at enhancing the performance, efficiency, and flexibility of industrial processes. In particular, we propose a joint optimization problem that maximizes computational energy efficiency by optimally allocating resources, such as processing power and computational resources, as well as device association, in the most efficient manner possible. The problem is formulated as nonconvex/nonlinear, which is intractable and poses high complexity. To solve this challenging problem, we first transform and decouple the original optimization problem into a series of subproblems using the block coordinate descent method. Then, we iteratively obtain an efficient solution using convex optimization methods. In addition, our work sheds light on the fundamental trade-off between local computation and partial offloading schemes. The results show that for small data size requirements, the performance is comparable among different schemes. However, as data size increases, our proposed hybrid scheme, which includes a partial offloading scheme, outperforms others, highlighting the effectiveness of the proposed joint optimization scheme.

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1. Introduction

The progression towards the fifth industrial revolution (known as Industry 5.0) is currently taking place on a worldwide scale, following the fourth industrial revolution, commonly referred to as Industry 4.0 (Aceto et al., 2019; Khan et al., 2023b). This transformative movement was initially conceptualized in the German government's High-Tech Strategy 2020 action plan, which was introduced in 2010 with a forward-thinking vision (Wollschlaeger et al., 2017). The main aim was to enhance the process of digitalization in smart manufacturing and achieve automated control within the context of mass production, similar to the previous industrial revolutions (Dai et al., 2022; Fang et al., 2022). The incorporation of various Information and Communication Technologies (ICT) has played a pivotal role in enabling the shift from the electronics-focused Industry 3.0 to the forward-thinking domain of Industry 4.0 (Jiang et al., 2022). The advent of Industry 4.0 has had a transformative impact on modern industries, as it has enhanced productivity and intelligence in production and automation procedures (Li et al., 2022). In recent times, there has been a scholarly and research-oriented discourse about the prospective trajectory of the forthcoming industrial revolution, commonly known as Industry 5.0 (Xiao et al., 2022). Industry 5.0 is presented as a natural and progressive extension of the existing Industry 4.0 paradigm, serving as a complementary framework that advances industrial innovation (Khan et al., 2022a).

Industry 5.0 is a conceptual framework that aims to realize mass-customized production, distinguished by eliminating waste, minimal costs, and maximum accuracy (Cao et al., 2023). This is a change from the focus of Industry 4.0, which prioritizes mass production with decreased waste and increased efficiency (Cao et al., 2020b). At the core of all Industry 5.0 concepts lies the essential notion of achieving a harmonic collaboration between human beings and robots, cultivating an intelligent society whereby humans actively contribute to the creative invention while robots, commonly called cobots, undertake many other responsibilities (Cao et al., 2019; Khan et al., 2022c). The European Commission (EC) has provided forward-thinking plans that place emphasis on resilience, human-centered methods, and sustainability in the context of Industry 5.0 (Wu et al., 2023). This framework enables various stakeholders, including employees and members of the digital society, to effectively align with the objectives of mass customization within efficient supply chains (Cao et al., 2020a; Khowaja et al., 2022). This encompasses the attributes of adaptability, a wide range of scalable product offerings, and significant positive effects in several societal domains, ultimately facilitating the achievement of the forthcoming industrial revolution (Khan et al., 2021d).

Mobile Edge Computing (MEC) is a conceptual framework that aims to enhance the efficiency of computing resources by positioning them in close proximity to the edge of the mobile network (Mahmood et al., 2023). This strategic placement enables the facilitation of applications and services that require a little delay and substantial data transfer capacity (Khan et al., 2021b). The deployment of computing capabilities in MEC occurs at the periphery of the network, often in close proximity to base stations (Khan et al., 2022b). This arrangement facilitates expedited data processing and diminished latency for mobile and Internet of Things (IoT) devices (Xu et al., 2023). The distributed computing approach described herein enhances service delivery efficiency through the reduction of data transmission between centralized cloud servers (Shome et al., 2022). The MEC platform provides support for various applications, encompassing augmented reality, virtual reality, and real-time analytics (Ahmed et al., 2022b). The proximity of computational resources to end-users is enhanced by MEC, leading to advancements in performance, responsiveness, and overall efficiency within the dynamic realm of mobile and connected devices (Ahmed et al., 2023b).

Integrating MEC servers and Industry 5.0 has significant potential to transform the manufacturing environment by enabling real-time data processing and analysis at the network's edge (Zeb et al., 2022). Industry 5.0 emphasizes the collaboration between humans, machines, and artificial intelligence (AI), and MEC servers can facilitate this collaboration by providing a more efficient, responsive, and safe manufacturing process (Chi et al., 2022; Maier, 2021). With MEC servers close to devices and sensors generating data, latency is reduced, allowing faster processing and real-time data analysis (Mahmood et al., 2020). This real-time analysis helps to identify and prevent problems before they occur, enabling predictive maintenance and reducing downtime (Ghosh et al., 2022). However, smart devices in Industry 5.0 experience latency and battery challenges. These challenges can be addressed by incorporating MEC servers, where data processing and analysis can be offloaded from smart devices to edge servers, reducing latency and power consumption (Maier et al., 2022; Deepa et al., 2022).

Besides the above advantages, integrating MEC servers with Industry 5.0 also improves manufacturing systems' performance, efficiency, and flexibility (Noor-A-Rahim et al., 2022). Companies can enable real-time data processing, analysis, and decision-making (Fraga-Lamas et al., 2021) by leveraging MEC servers (Qin et al., 2023). As a result, communication latency is reduced, response times are faster, and system reliability improves, ultimately increasing productivity and profitability (Ahmed et al., 2022a). Moreover, MEC servers provide a platform for real-time data analysis and machine learning algorithms, optimizing the manufacturing process and predicting equipment failures, reducing operational costs even further, and improving worker safety (Liu et al., 2017). In order to successfully adopt smart manufacturing processes, these two technologies must be combined because they have a major impact on industrial performance (Deepa et al., 2022; Zhang et al., 2023b).

By providing real-time data processing and analysis, integration of MEC servers and Industry 5.0 can assist the development of new business models and revenue streams in the manufacturing sector (Wu et al., 2021). Predictive maintenance, remote monitoring, and quality control are examples of value-added services that can be offered to clients using MEC servers, according to Mahmood et al. (2021). Manufacturers may stand out and create new revenue streams with the aid of these services. Additionally, MEC servers can help create more flexible and cooperative manufacturing systems where machines and people work together in a coordinated and effective way (Mahmood et al., 2022). This may make it possible to produce new products, customize existing ones, and respond to market changes more quickly (Ghosh et al., 2022). Combining MEC servers and Industry 5.0 can provide manufacturers with new business opportunities and competitive advantages (Ahmed et al., 2023a).

1.1. Related work

MEC servers have been employed and investigated in various communication network scenarios in recent years. Multiple studies have determined the most effective ways for mobile devices and MEC servers to share computational and communication resources to reduce total round-trip latency and power consumption. For instance, in Mao et al. (2016a) and Liu et al. (2016), the authors proposed an optimal framework for a single-user MEC network to minimize task latency. The proposed framework utilized a heuristic algorithm for the joint allocation of computation and communication resources to improve energy efficiency and load-balancing. In Zhang et al. (2013), the authors presented an optimal framework to minimize the total energy consumption of devices through the optimal allocation of computation and communications resources. Moreover, the authors in You et al. (2016) proposed a mode selection strategy between local and edge computing that enables the device to offload the computation to the edge server to minimize latency and energy consumption. In Kao et al. (2017), researchers investigated the weighted sum energy minimization under latency constraints for a multi-user MEC network. The authors proposed a joint optimization framework that considers computation and communication resources for each user in the network. The authors of Wang et al. (2017) focus on optimizing joint offloading and computing in wireless-powered mobile-edge computing systems. The key objective is to improve mobile devices' overall performance and energy efficiency by offloading computation-intensive tasks to the nearby edge servers, which are powered by wireless energy transfer. The authors of Wu et al. (2016) focus on user-centric energy efficiency maximization in wireless-powered communications. It aims to enhance the energy efficiency of wireless communication systems by considering user-specific characteristics and energy harvesting capabilities.

Considering the multi-user scenarios, in You and Huang (2016), the researchers considered an efficient decision policy for optimal resource allocation and offloading to minimize energy consumption. The proposed algorithm in this work employs a heuristic approach that considers the network topology, user preferences, and the status of the devices to perform resource allocation and offloading. Moreover, in Mao et al. (2017b), the authors focused on minimizing the long-term weighted energy consumption under buffer stability constraints. They proposed an optimization framework that considers the stability of the buffer in each device to prevent overflow and underflow, leading to an energy-efficient MEC network. Furthermore, in Mao et al. (2016b), the authors proposed an energy-latency trade-off in the MEC network. The proposed algorithm optimizes the trade-off between energy consumption and latency in a multi-user scenario. Using an adaptive offloading scheme which determines the optimal allocation of computation and communication resources for the devices to minimize energy consumption and latency.

Some researchers have also studied the potential advantages of combining MEC services and Industry 5.0. To increase manufacturing efficiency and adaptability, one study proposed a framework for integrating MEC and Industry 4.0, the forerunner of Industry 5.0, with the intention of shifting computation-intensive tasks to MEC servers (Mao et al., 2017a). The cognitive-edge computing approach proposed by these researchers makes use of MEC to bring near-real-time analytic and decision-making to applications in the emerging 4.0 and 5.0 industrial revolutions (Deepa et al., 2022). A joint optimization framework for offloading and resource allocation was proposed to further reduce power usage and communications delays in MEC-enabled Industry 5.0 networks (Wu et al., 2022). Another study introduced a hybrid cloud-MEC architecture for Industry 5.0, which permits dynamic and flexible resource allocation and task offloading (Chaudhry et al., 2020). A simulation-based evaluation of the performance of MEC-enabled Industry 5.0 networks with varying network topology and traffic patterns was also presented (Rafiq et al., 2022). These studies underscore the potential benefits of MEC integration with Industry 5.0 and demonstrate the feasibility of using MEC services to improve the performance and efficiency of Industry 5.0 applications. To this end, researchers in Qin et al. (2023) and Zhang et al. (2023a) have proposed task allocation frameworks and joint optimization frameworks for task offloading and resource allocation which aim to minimize energy consumption, communication latency, and task completion time.

1.2. Motivation and contribution

Even though various research works have been investigated on MEC networks, they have several limitations. For example, the works in Mao et al. (2016a), Liu et al. (2016), Zhang et al. (2013), You et al. (2016), Kao et al. (2017), Wang et al. (2017) and Wu et al. (2016) have considered MEC in traditional networks and consider the single user scenarios. Besides that, the work in You and Huang (2016), Mao et al. (2017b) and Mao et al. (2016b) have considered multi-user scenarios and do not consider industry 5.0. Further, only a few works (Mao et al., 2017a; Deepa et al., 2022; Wu et al., 2022; Chaudhry et al., 2020; Rafiq et al., 2022; Qin et al., 2023; Zhang et al., 2023a) have considered MEC in industry 5.0, and there are still several open problems that need to be investigated. Motivated by the above observations and existing literature, this study aims to present an integrated framework for MEC and Industry 5.0, which has the potential to transform the manufacturing industry by enhancing the performance, efficiency, and flexibility of industrial processes. In particular, we proposed a new framework integrating MEC with Industry 5.0, which has yet to be investigated to the best of our knowledge. We aim to design a partial offloading approach to maximize computational energy efficiency. More specifically, the idea of partial offloading is to divide the task into two parts (local part and edge part) to maximize the total computed bit while reducing energy consumption. The optimization problem is formulated as a mixed integer non-linear programming problem. Such problems have high complexity and are challenging to handle. To overcome the complexity and make it more tractable, we first transform the original problem and divide it into subproblems using the block coordinate descent (BCD) method. Then, we obtain an efficient solution using an iterative approach. The main contributions of this work are listed as follows.

(1) We consider multiple MEC networks which connected to a central cloud and provide services to multiple smart devices in Industry 5.0. All the devices are equipped with a single antenna scenario. The primary purpose is to maximize the total computed bits while reducing the computational energy efficiency of smart devices in Industry 5.0. To do so, we propose a partial offloading approach, where the task is divided into two parts: local and edge. More specifically, the task is locally processed at the smart device in the local part, while a part of the task is offloaded to the edge server for processing in the edge part.
(2) To achieve this goal, our work formulates a joint optimization problem for resource allocation. This involves identifying the different resources required by smart devices, such as processing power, computational resources as well device association. The objective is to allocate these resources in the most efficient manner possible such that computational energy efficiency is maximized. Our framework is also subjected to several practical constraints and bounds such as QoS constraint, energy consumption constraint, latency requirement constraint, and decision variables bounds.
(3) Solving the Joint Optimization problem is a challenging task, as it is non-convex, non-linear, and NP-hard in nature. In order to find the optimal solution, we employed a strategy of decoupling the problem into a series of subproblems and iteratively solving them. Item To demonstrate the effectiveness of our proposed schemes, we conducted extensive simulations using low-complexity algorithms and compared the results with other benchmark schemes. The findings revealed that our proposed scheme outperforms all other schemes.
(4) Additionally, our work sheds light on the fundamental trade-off between the local computation and partial offloading scheme. Our findings show that the system requiring small data size has a comparable impact on the performance of different schemes. However, as the data size increases, our proposed scheme outperforms others, highlighting its effectiveness in addressing the joint optimization problem.

The rest of the paper is organized as follows. Section 2 describes the system and network model, while Section 3 presents the mathematical formulation of the proposed system model. In Section 4, the proposed solution is explained. The results and discussion are provided in Section 5. Finally, Section 6 concludes the paper.

2. System and network model

This work focuses on the uplink Multiple MEC (MMEC)-enabled communication network used to provide services to the $N \in \mathcal{N}$ single-antenna devices in the Industry's 5.0 environment and connected to

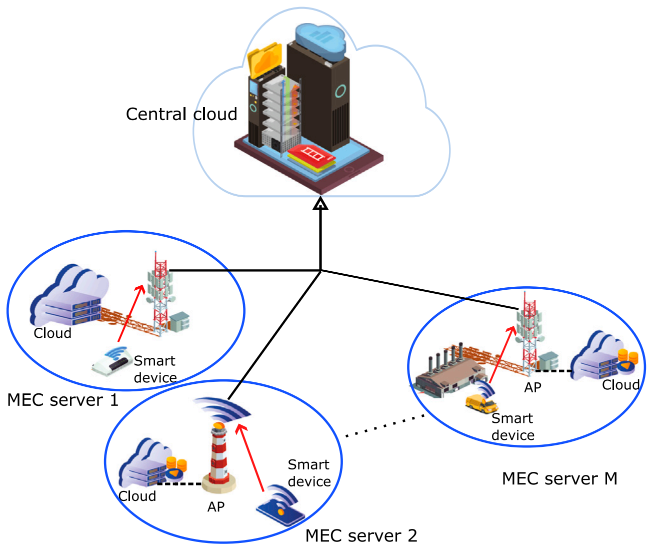

Fig. 1. Mobile edge computing network in Industry 5.0.

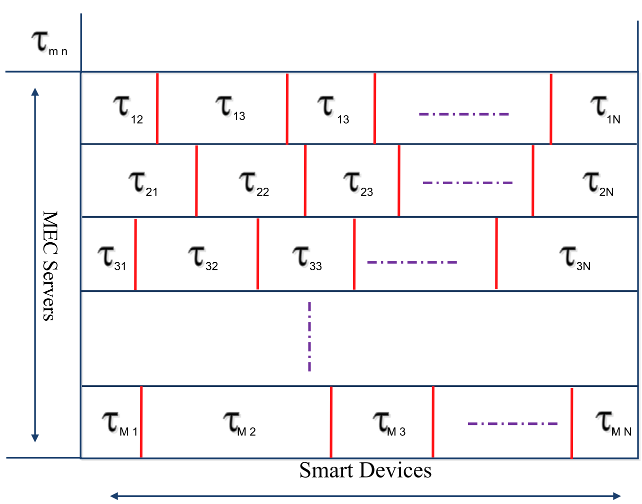

Fig. 2. Time division multiple access.

their associated access point(AP), where $M \in \mathcal{M}$ is the total number of AP (Li et al., 2016). Each AP is equipped with a MEC server, as shown in Fig. 1. Following that, we assume that the MEC server has access to the channel state information used to optimize data transmission between the smart devices and the MEC servers (Liu et al., 2022). The MEC servers are connected to the central cloud through a dedicated link that provides each MEC server with an orthogonal frequency band to prevent cross-cell interference. Moreover, to avoid user interference within a cell, we employ time division multiple access techniques; a comprehensive approach ensures optimal communication between the MEC servers, smart devices, and the central cloud, as illustrated in Fig. 2. Based on this, we will explain the communication and computational model used in this work in the following subsections.

2.1. Communication model

In the MMEC-enabled communication network, effective communication channels are critical parameters to ensure the effectiveness of the integration of MMEC servers and industry 5.0. In addition to optimizing the use of smart devices and preserving data accuracy, the quality of the communication channels between the MEC servers and smart devices plays a crucial role in the overall performance of the system (Khan et al., 2021a). Furthermore, for the sake of simplicity, we define the channel between the mth MEC server and the nth smart device as $g_{nm} = \xi_o d_{nm}^{-\mu}$, where ξ_o and μ represent the reference distance path-loss and pathloss exponent. Moreover, d_{nm} represents the distance between the devices and associated AP. Based on these definitions, the achievable rate of the nth user can be expressed as follows:

$$R_{nm} = W_m \log_2 \left(1 + \frac{p_{nm} g_{nm}}{\sigma^2}\right), \forall n, m. \tag{1}$$

In Eq. (1), W_m and σ^2 represent the system bandwidth and additive white Gaussian noise (AWGN) density, respectively, which are essential factors to consider in the design of a communication system. Where the transmission power of the nth user is represented by p_{nm}.

2.2. Computational model

This section describes the task computational model for smart devices. Let $alpha_m$ be a representation of the number of cycles needed to compute 1 bit. Whereas the total number of computational bits is represented by β_m. In this work, we assume that task computations were carried out using the partial offloading scheme, in which one portion of the task is computed locally. In parallel, the other portion of the task is offloaded to the MEC server for extensive computation. The following section will explain the local and edge task computational model.

2.2.1. Local computational model

When working in local computational mode, the effectiveness of the devices and the energy-efficiency of their local resources have a considerable impact on one another. The local computational mode can be a useful strategy in the context of Industry 5.0 and MEC servers for increasing the effectiveness and speed of data processing while reducing the strain on the central cloud. The task is computed utilizing the local computational resources denoted by $zeta_n$, where $zeta_m ax$ denotes the total computational power of the devices. The task is computed locally by the devices using the entire time period T. Using this, the number of bits computed locally using the local computational resources can be expressed as $\Psi_{nm}^{local} = \frac{T\zeta_n}{\alpha_n}, \forall n$. Furthermore, the energy consumption for the computation of the task can be expressed as $\Phi_{nm}^{local} = \varepsilon_n (\zeta_n)^3 T, \forall n$, where ε_n shows the efficiency of computational energy.

2.2.2. Edge computational model

It is worth noting that the effectiveness of the edge computational mode is heavily influenced by the coefficient of channel from devices to MEC server, as it affects the transmission of data between them. Edge computational mode can be a practical approach for offloading compute-intensive tasks and improving the speed and efficiency of data processing. Given that, the number of bits offloaded to the MEC server can express as $\Psi_{nm}^{edge} = R_{nm}\tau_{nm} = W_m \log_2\left(1 + \frac{p_{nm} g_{nm}}{\sigma^2}\right)\tau_{nm}, \forall n, m$. Similarly, the energy consumption while offloading the task to the MEC server can be expressed as $\Phi_{nm}^{edge} = p_{nm}\tau_{nm} + p_r \tau_{nm}, \forall n, m$. Similarly, the term p_r represents the constant circuit energy consumption for data offloading, Whereas it is the same for all devices.

2.3. User association

During MEC setup, it is necessary to identify which devices are associated with which MEC servers. The device's location, processing power, and demand on the MEC servers are all considered when making this choice. The goal is to balance the load among the MEC servers and ensure the devices are connected to the server best suited to handle their computational tasks. This process can be dynamic, with devices switching between MEC servers as needed. The device association plays a crucial role in determining the overall performance and efficiency of the MEC system. Thus, we define η_{nm} as a user association parameter for ease of simplicity. That represents $\eta_{nm} = 1$ means nth device is associated with the mth MEC server and otherwise, which is going to be optimized in Section 4.

3. Constraints definition and problem formulation

This section presents the mathematical framework for the integrated MEC and Industry 5.0 network. Our goal is to maximize the energy efficiency of smart devices in the Industry 5.0 environment subject to system and communication constraints. These constraints are introduced in the following.

3.1. Quality of Service (QoS) constraint

The first constraint is the Quality of Service (QoS) requirement, an essential parameter in Industry 5.0. The QoS requirement specifies that the total number of sensed bits should be completed within the time frame T if the total number of bits is computed as the sum of the number of bits computed locally by the device and the bits offloaded to edge, i.e., $\Psi_{nm} = \Psi_{nm}^{edge} + \Psi_{nm}^{local}, \forall n, m$. Then, the constraint that the total number of bits computed should be greater than or equal to a certain threshold, such as:

$$\Psi_{nm}^{edge} + \Psi_{nm}^{local} \geq \beta_n, \forall n, m \tag{2}$$

where β_n is the threshold for a minimum number of computed bits.

3.2. Energy consumption constraint

The integrated MEC and Industry 5.0 network must address the energy constraint. Smart devices must operate within the regulations of their battery life, and excessive energy consumption can result in reduced battery life and device performance (Khan et al., 2021b). As a result, the total energy consumption of the devices while performing local computations or offloading them to MEC servers must be considered (Raza et al., 2021). A device's total energy consumption can be expressed as the sum of the energy consumed for local computing and offloading the task to MEC servers which can be defined as $\Phi_{nm} = \Phi_{nm}^{local} + \Phi_{nm}^{edge}, \forall n, m$. The total energy consumption should be less than the maximum battery life, which is expressed as:

$$\Phi_{nm}^{local} + \Phi_{nm}^{edge} \leq \Phi_{max} \tag{3}$$

where Φ_{max} is the threshold for maximum energy consumption. This constraint guarantees the optimal and proficient operation of the devices within their energy limitations while simultaneously upholding their performance and durability.

3.3. Problem formulation

This section outlines the mathematical foundation for the integrated MEC-enabled Industry 5.0 network. This work aims to optimize transmission power, local computational resources, user association, and task offloading time to increase smart devices' computational energy efficiency. Following is the detailed mathematical problem formulation of the proposed system:

$$\max_{\substack{\zeta_{nm}, \eta_{nm}, \\ \tau_n, p_{nm}}} \sum_{n=1}^{N} \sum_{m=1}^{M} \frac{\Psi_{nm}}{\Phi_{nm}} = \frac{\Psi_{nm}^{edge} + \Psi_{nm}^{local}}{\Phi_{nm}^{local} + \Phi_{nm}^{edge}} \tag{4a}$$

$$s.t. \quad \Psi_{nm}^{edge} + \Psi_{nm}^{local} \geq \beta_n, \forall n, m, \tag{4b}$$

$$\Phi_{nm}^{local} + \Phi_{nm}^{edge} \leq \Phi_{max}, \forall n, m, \tag{4c}$$

$$\sum_{n=1}^{N} \tau_n \leq T, \forall m, \tag{4d}$$

$$0 \leq \zeta_{nm} \leq \zeta_{max}, \forall n, m, \tag{4e}$$

$$\eta_{nm} \in (0, 1), \forall n, m, \tag{4f}$$

$$\tau_{nm} \geq 0, \forall n, m, \tag{4g}$$

The constraints in (4b) ensure device QoS, while (4c) represents energy constraints. In addition, constraints in (4d) guarantee latency requirements, and (4e) to (4f) represent cision variables.

Since the optimization problem in (4) is mixed-integer, non-linear, and NP-hard (Khan et al., 2023a). Moreover, coupling decision variables also make it challenging. Therefore, to find the optimal best solution, we need to transform and reformulate the problem into a more trackable form by introducing slack variables, enabling more effective solution techniques, as detailed in the following sections.

4. Proposed solution

In this section, We aim to provide the efficient framework to find the efficient solution to the proposed optimization problem as mentioned in (4). To achieve this, we introduce slack variables, which are auxiliary decision variables that allow us to transform the original problem into a more tractable form (Khan et al., 2021e). This is particularly useful when dealing with mixed-integer and nonlinear problems like the one in (4), as the introduction of slack variables can help to reduce the complexity of the problem and make it easier to solve (Khan et al., 2021a). By reformulating the problem with slack variables, we can apply various optimization techniques and algorithms to efficiently find the optimal solution.

$$\max_{\substack{\zeta_{nm}, \eta_{nm}, \\ \tau_n, p_{nm}, \Gamma_{nm}}} \sum_{n=1}^{N} \sum_{m=1}^{M} \Gamma_{nm} \tag{5a}$$

$$C1 : \Psi_{nm} \geq \Gamma_{nm} \Phi_{nm}, \forall n, m. \tag{5b}$$

$$\text{Eqs. (4b) to (4g).} \tag{5c}$$

Lemma. *As perceived from the (5), if $\zeta_{nm}, \eta_{nm}, \tau_n, p_{nm}, \Gamma_{nm}$ is the solution of the optimization problem then there exits another variable ϑ_{nm} that satisfied the Karush-Kuhn–Tucker condition of the following optimization problem.*

$$\max_{\substack{\zeta_{nm}, \eta_{nm}, \vartheta_{nm} \\ \tau_n, p_{nm}, \Gamma_{nm}}} \sum_{n=1}^{N} \sum_{m=1}^{M} \vartheta_{nm} \left(\Psi_{nm} - \Gamma_{nm} \Phi_{nm} \right) \tag{6a}$$

$$\textit{Eqs. (4b) to (4g).} \tag{6b}$$

Proof. We can start by examining the objective functions in both problems to see this. We wish to maximize the sum of $Gamma_n m$ over all n and m in the first problem. In the second problem, we are trying to maximize the total amount of $\vartheta_{nm}(\Psi_{nm} - \Gamma_{nm}\Phi_{nm})$ over all n and m. Now observe that the second objective function may be rewritten as follows:

$$\sum_{n=1}^{N} \sum_{m=1}^{M} \vartheta_{nm} \left(\Psi_{nm} - \Gamma_{nm} \Phi_{nm} \right) = \sum_{n=1}^{N} \sum_{m=1}^{M} \Gamma_{nm} \left(\vartheta_{nm} \Phi_{nm} \right) - \sum_{n=1}^{N} \sum_{m=1}^{M} \vartheta_{nm} \Psi_{nm} \tag{7}$$

Given that $vartheta_n m$ and $Phi_n m$ are constants in the optimization problem, the first term in this expression is a constant with regard to the optimization variables. Thus, maximizing the second objective function is equivalent to minimizing the term $\sum_{n=1}^{N} \sum_{m=1}^{M} \vartheta_{nm} \Psi_{nm}$, which is the objective function in the first problem. Next, let us look at the constraints in both problems. In the first problem, we have the constraint $\Psi_{nm} \geq \Gamma_{nm}\Phi_{nm}$ for all n and m. In the second problem, we have the constraint $\vartheta_{nm} \geq 0$ for all n and m, which implies that $\Psi_{nm} - \Gamma_{nm}\Phi_{nm} \geq 0$ for all n and m. Therefore, we can rewrite the constraint in the second problem as $\Psi_{nm} \geq \Gamma_{nm}\Phi_{nm}$ for all n and m, which is the same as the constraint in the first problem. Finally, the optimization variables in both problems are the same: ζ_{nm}, η_{nm}, τ_n,

$$\mathcal{L}(\mathbf{x},\lambda)=\sum_{n=1}^{N}\sum_{m=1}^{M}\vartheta_{nm}\left(\Psi_{nm}-\Gamma_{nm}\Phi_{nm}\right)+\sum_{n=1}^{N}\sum_{m=1}^{M}\lambda_{1,nm}\left(\Psi_{nm}^{edge}+\Psi_{nm}^{local}-\beta_n\right)-\sum_{n=1}^{N}\sum_{m=1}^{M}\lambda_{2,nm}\left(\Phi_{nm}^{local}+\Phi_{nm}^{edge}-\Phi_{max}\right)$$
$$-\sum_{m=1}^{M}\lambda_{3,m}\left(\sum_{n=1}^{N}\tau_n-T\right)-\sum n=1^N\sum_{m=1}^{M}\lambda_{4,nm}\left(\zeta_{nm}-\zeta_{max}\right)-\sum_{n=1}^{N}\sum_{m=1}^{M}\lambda_{5,nm}\left(\eta_{nm}(1-\eta_{nm})\right)-\sum_{n=1}^{N}\sum_{m=1}^{M}\lambda_{6,nm}\left(\tau_{nm}\right), \quad (8)$$

Box I.

P_{nm}, and Γ_{nm}. Therefore, we can conclude that these two optimization problems are equivalent, and solving one will give us the same solution as solving the other.

Following that, the optimization problem (6) is mix integer in nature and also in more tackle form. Therefore we can write the Lagrange multiplier can be expressed as in (8) is given in Box I. where $\mathbf{x}$ represents the decision variables $\{\zeta_{nm},\eta_{nm},\vartheta_{nm},\tau_n,p_{nm},\Gamma_{nm}\}$ and λ represents the Lagrange multipliers associated with each constraint. Therefore, we may use the well-known block coordinate descent (BCD) approach to arrive at the best possible answer. A complex optimization problem is solved by BCD, an iterative optimization method, by dividing it into smaller subproblems. BCD modifies the decision variables one block at a time while keeping the other variables constant throughout each iteration. This method makes the overall problem easier to tackle by decreasing its computational complexity and memory requirements. Additionally, BCD may deal with issues including combinatorial, linear, and nonlinear restrictions. As a result, it is a viable solution for resolving the optimization issue raised in (4).

4.1. Dynamic resource allocation for local computation

The framework for the ideal distribution of computational resources, such as transmission power and local computational resources, is presented in this section. The partial derivatives of eqrefE21 with respect to $p_n m$ and $zeta_n m$, i.e., $\frac{\partial\mathcal{L}}{\partial p_{nm}}$ and $\frac{\partial\mathcal{L}}{\partial\zeta_{nm}}$, are taken and set to zero in order to obtain the closed-form equations for the best resource allocation. This optimization problem's Lagrangian function is expressed as Eq. (8) on the top of the page.

$$\begin{aligned}\frac{\partial\mathcal{L}(p_{nm})}{\partial p_{nm}}&=\left(\vartheta_{nm}+\lambda_{1,nm}\right)\frac{\partial\Psi_{nm}}{\partial p_{nm}}-\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\frac{\partial\Phi_{nm}}{\partial p_{nm}}\\&=\frac{\left(\vartheta_{nm}+\lambda_{1,nm}\right)W_m\tau_{nm}g_{nm}}{\left(\sigma^2+p_{nm}g_{nm}\right)\ln(2)}-\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\tau_{nm}\end{aligned} \quad (9)$$

In the similar fashion, $\frac{\partial\mathcal{L}}{\partial\zeta_{nm}}$ can be expressed as:

$$\begin{aligned}&\frac{\partial\mathcal{L}(\zeta_{nm})}{\partial\zeta_{nm}}=\left(\vartheta_{nm}+\lambda_{1,nm}\right)\frac{\partial\Psi_{nm}^{local}}{\partial\zeta_{nm}}-\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\frac{\partial\Phi_{nm}^{local}}{\partial\zeta_{nm}}\\&-\lambda_{4,nm}\zeta_{nm}=\left(\vartheta_{nm}+\lambda_{1,nm}\right)\frac{T}{\alpha_n}-\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)3\epsilon_n\zeta_n^2T-\lambda_{4,nm}\end{aligned} \quad (10)$$

Following that, to find the solution of the p_{nm} and ζ_{nm}, we put $\frac{\partial\mathcal{L}}{\partial p_{nm}}=0$ and $\frac{\partial\mathcal{L}}{\partial\zeta_{nm}}=0$ we have,

$$\begin{aligned}&\frac{\left(\vartheta_{nm}+\lambda_{1,nm}\right)W_m\tau_{nm}g_{nm}}{\left(\sigma^2+p_{nm}g_{nm}\right)\ln(2)}-\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\tau_{nm}=0.\\&\frac{\left(\vartheta_{nm}+\lambda_{1,nm}\right)W_mg_{nm}}{\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\ln(2)}-\sigma^2=p_{nm}g_{nm}.\\&p_{nm}=\frac{\left(\vartheta_{nm}+\lambda_{1,nm}\right)W_m}{\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)\ln(2)}-\frac{\sigma^2}{g_{nm}}.\end{aligned} \quad (11)$$

Similarly by putting $\frac{\partial\mathcal{L}}{\partial\zeta_{nm}}=0$, we have:

$$\begin{aligned}&\left(\vartheta_{nm}+\lambda_{1,nm}\right)\frac{T}{\alpha_n}-\left(\vartheta_{nm}+\lambda_{2,nm}\right)3\epsilon_n\zeta_n^2T-\lambda_{4,nm}=0.\\&\zeta_{nm}=\sqrt{\frac{\left(\vartheta_{nm}+\lambda_{1,nm}\right)\frac{T}{\alpha_n}-\lambda_{4,nm}}{3\epsilon_nT\left(\vartheta_{nm}\Gamma_{nm}+\lambda_{2,nm}\right)}}\end{aligned} \quad (12)$$

It is apparent from Eqs. (11) and (12) that the optimal values of p_{nm} and ζ_{nm} are contingent on the optimal values of other decision and slag variables. Consequently, finding the optimal values for these other variables will lead to the optimal values for p_{nm} and ζ_{nm}, respectively. Therefore, in the following section, we will propose a framework for determining the optimal values of these variables.

4.2. Device mating

In the context of Industry 5.0, the problem of user association refers to the association of smart devices to the MEC network for efficient data processing and communication. Matching theory can be used to solve the problem of device association in Industry 5.0 by formulating it as a many-to-one matching problem. In this problem, each smart device is considered a "proposer", and the MEC servers are considered the "receivers". The objective is to associate each smart device to a specific MEC server to ensure efficient processing of data. In this case, we have a set of N devices, $D=d_1,d_2,\dots,d_N$, and a set of M MEC servers, $S=s_1,s_2,\dots,s_M$. Each MEC server s_m has a capacity c_m that specifies the maximum number of devices it can handle. The goal is to match each device d_n with one of the available MEC servers, such that the total cost of the matching is minimized.

To formulate this problem mathematically, we can define a cost function, $C_{n,m}$, which represents the cost of matching device d_n with MEC server s_m. As we have already established, the cost function can be any metric that reflects the appropriateness of a device for a given MEC server. The matching problem seeks to discover a mapping between the devices and the MEC servers that minimizes the total cost of the matching, given the capacity constraints of the MEC servers. This can be written in mathematical terms as:

$$\min_{\eta_{\mathbf{nm}}}\sum_{n=1}^{N}\sum_{m=1}^{M}C_{n,m}\eta_{n,m} \quad (13)$$

where $\eta_{\mathbf{nm}}$ is a binary matrix of size $N\times M$, with elements $\eta_{\mathbf{nm}}$ that take on the value 1 if device d_n is matched with MEC server s_m, and 0 otherwise.

To ensure that each device is matched with one of the available MEC servers, we add a constraint for each device d_m that forces it to be matched with exactly one MEC server, which can be expressed mathematically as:

$$\sum_{m=1}^{M}\eta_{n,m}=1,\forall n=1,2,\dots,N \quad (14)$$

To ensure that the capacity constraints of the MEC servers are respected, we add a constraint for each MEC server s_j that limits the number of devices that can be matched to it, which can be expressed mathematically as:

$$\sum_{n=1}^{N} \eta_{n,m} \leq c_m, \forall m = 1, 2, \ldots, M \tag{15}$$

Finally, to ensure that the decision variables are binary, we add a constraint that forces each element of η to take on a value of either 0 or 1:

$$\eta_{n,m} \in \{0, 1\}, \forall n = 1, 2, \ldots, N \text{ and } m = 1, 2, \ldots, M. \tag{16}$$

The resulting optimization problem is a binary integer program, which can be solved using algorithms such as the Hungarian algorithm or the Gale–Shapley algorithm. These algorithms are designed to solve one-to-many matching problems efficiently and can provide an optimal solution to the problem of matching devices to MEC servers.

4.3. Optimal allocation of time

Given fixed values for transmission power, local computational resources, and user association, the sub-optimization problem for the optimal allocation of time can be expressed as follows:

$$\max_{\tau_n} \sum_{n=1}^{N} \sum_{m=1}^{M} \vartheta_{nm} \left(\Psi_{nm} - \Gamma_{nm} \Phi_{nm} \right) \tag{17a}$$

Eqs. (4b) to (4d) and (4g). (17b)

The optimization problem mentioned above is convex, which means it can be efficiently solved using a convex optimization toolbox, such as CVX.

4.4. Update Lagrange and auxiliary variables

After finding the optimal value of the decision variables in the current iteration, we provide the details for updating the values of the auxiliary and Lagrange multipliers (Khan et al., 2021c).

4.4.1. Auxiliary variable update

This section presents a framework for updating the values of ϑ_{nm} and Γ_{nm} based on the first-order derivative of (6). As this optimization problem is unconstrained with respect to these variables, their values can be calculated by utilizing the aforementioned derivative. Therefore their value can be expressed as:

$$\begin{aligned} \vartheta_{nm} &= \frac{1}{\Phi_{nm}(p_{nm}, \zeta_{nm}, \tau_{nm})}, \forall n, m \\ \Gamma_{nm} &= \frac{\Psi_{nm}(p_{nm}, \zeta_{nm}, \tau_{nm})}{\Phi_{nm}(p_{nm}, \zeta_{nm}, \tau_{nm})}, \forall n, m. \end{aligned} \tag{18}$$

Based on the equations presented in (18), it can be observed that the values of the auxiliary variables are dependent on the original decision variables. This implies that achieving optimal values for the decision variables will also result in optimal values auxiliary variables.

4.4.2. Lagrange multipliers update

In a similar fashion, the value of the Lagrange multiplier is updated using the gradient accent methods (Khan et al., 2020). whose mathematical expression can be expressed below:

$$\begin{aligned} \lambda^i_{1,nm} &= \lambda^o_{1,nm} + \Delta\lambda^o_{1,nm} \left(\Psi^*_{nm} - \beta_n \right) \\ \lambda^i_{2,nm} &= \lambda^o_{2,nm} + \Delta\lambda^o_{2,nm} \left(\Phi^*_{nm} - \Phi_{max} \right) \\ \lambda^i_{3,nm} &= \lambda^o_{3,nm} + \Delta\lambda^o_{3,nm} \left(\sum_{n=1}^{N} \tau_{nm} - T \right) \\ \lambda^i_{4,nm} &= \lambda^o_{4,nm} + \Delta\lambda^o_{4,nm} \left(\zeta_{nm} - \zeta_{max} \right) \end{aligned} \tag{19}$$

Eq. (19) specifies that $\Delta\lambda^o_{:,nm}$ serves as the step size for the current iteration, with the Lagrange variable being set to zero if it takes on a negative value. Further details on the explanation and working principle can be found in Algorithm 1

Algorithm 1: Maximizing Resource Utilization: A Unified Algorithmic Approach

1 **Initialization:** i^{max} ← maximum number of iterations, p^o_{nm} ← initial transmission power, ζ^o_{nm} ← local resources, η^o_{nm} ← User Association τ^o_{nm} ← time slot, N ← Number of users, M ←number of MEC server, g^o_{nm} ← effective channel gain ϵ ← Threshold Value;
2 **Output:** $\{\zeta^*_{nm}, \eta^*_{nm}, \vartheta^*_{nm}, \tau^*_n, p^*_{nm}, \Gamma^*_{nm}, \lambda^*\}$;
3 **while** *Error* $\leq \epsilon$ & $i \leq i^{max}$ **do**
4 Given the initial value of all system parameter, calculate ζ^i_{nm} and p^i_{nm} using equation (11), (12);
5 Calculate the value of η^i_{nm} using matching Strategy as expressed in section 4.2;
6 calculate the objective function value, τ^i_{nm} using the equation (17);
7 Update the value of Auxiliary and Lagrange Multiplier variables as discussed in section 4.4.;
8 Given all the values of decision variables, Calculate the objective function values using the equation (4a), and store results in X_i ;
9 Calculate Error values, Error = X_i-X_{i-1};
10 **end**
11 **Output:** $\{\zeta^*_{nm}, \eta^*_{nm}, \vartheta^*_{nm}, \tau^*_n, p^*_{nm}\}$;

4.5. Complexity analysis

The given algorithm has a worst-case time complexity of $O(i^{max} N^3 M^3)$. During initialization, various system parameters are initialized, and the time complexity of this step is constant, i.e., O(1). The main loop of the algorithm runs until the error is less than or equal to a threshold value, or the maximum number of iterations, which is i^{max}, is reached. Hence, the time complexity of the loop is $O(i^{max})$. Within the loop, the algorithm performs calculations using Eqs. (11), (12), and (17) and updates the auxiliary and Lagrange multiplier variables. These calculations require $O(NM)$ time complexity, where N and M are the number of users and MEC servers, respectively. The matching strategy used to calculate η^i_{nm} in step 3 has a worst-case time complexity of $O(N^3 M^3)$. Finally, the calculation of the error value in step 7 also has a worst-case time complexity of $O(NM)$. Therefore, the overall worst-case time complexity of the algorithm is $O(i^{max} N^3 M^3)$, which is the maximum of the time complexities of all the steps.

5. Results and discussion

In this section, we demonstrate the effectiveness of our proposed scheme through numerical results obtained from extensive simulations. The simulations were carried out by varying the number of Industry 5.0 smart devices (N) from 5 to 40, the number of MEC servers (M) from 5 to 40, and the data size (β_n) from 2 to 14 K-bits. The simulation parameters were carefully chosen to simulate a practical environment for Industry 5.0 smart devices. We set the time duration to 1 second (T = 1 s) to reflect the real-world use case of short data transmission intervals. The maximum battery capacity of devices is set to 2 joules (Φ_{max} = 2 J) to reflect the typical energy capabilities of Industry 5.0 smart devices. The maximum computational capability of the devices is set to 1 GHz (ζ_{max} = 1 GHz) to reflect the expected network capacity in Industry 5.0 scenarios. The energy consumption coefficient was set to 10^{-34} ($\epsilon_n = 10^{-34}$) to reflect the low power requirements of Industry 5.0 smart devices. These parameters allowed us to obtain reliable and realistic results that demonstrate the effectiveness of our proposed scheme.

To demonstrate the effectiveness of our proposed scheme, we present results obtained through multiple iterations. Our results in Fig. 3 show that the algorithm converges to a stable point over the course of these iterations. The convergence of the algorithm is important as it ensures that the system is functioning optimally and can provide reliable results. However, the convergence time varies depending on the simulation parameters employed. As the number

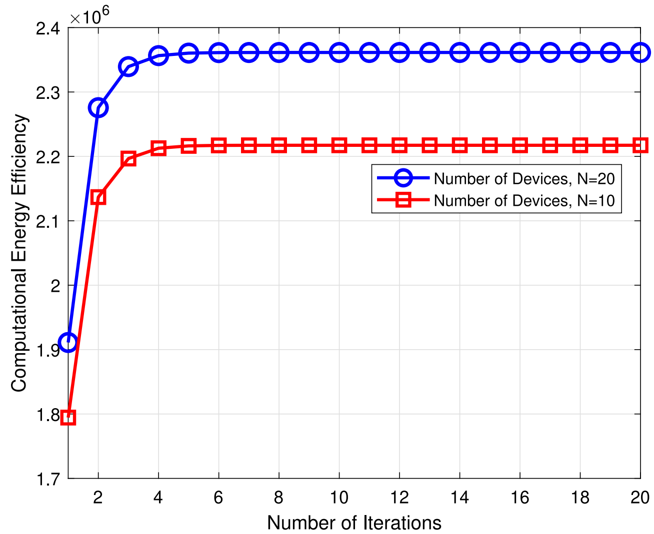

Fig. 3. Convergence analysis.

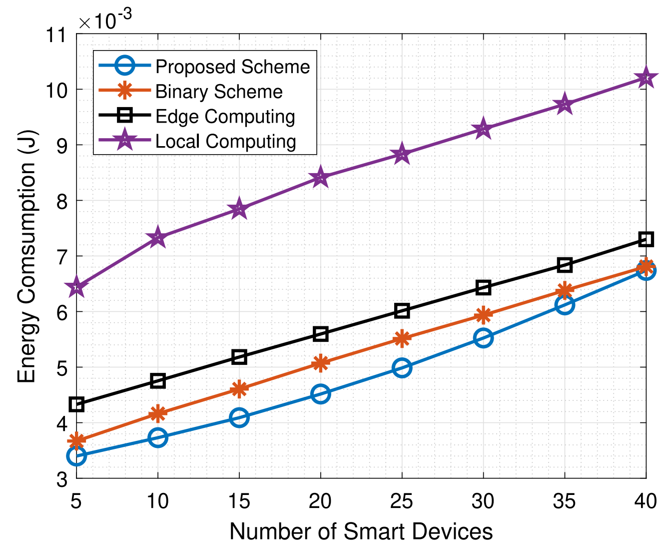

Fig. 6. Energy consumption.

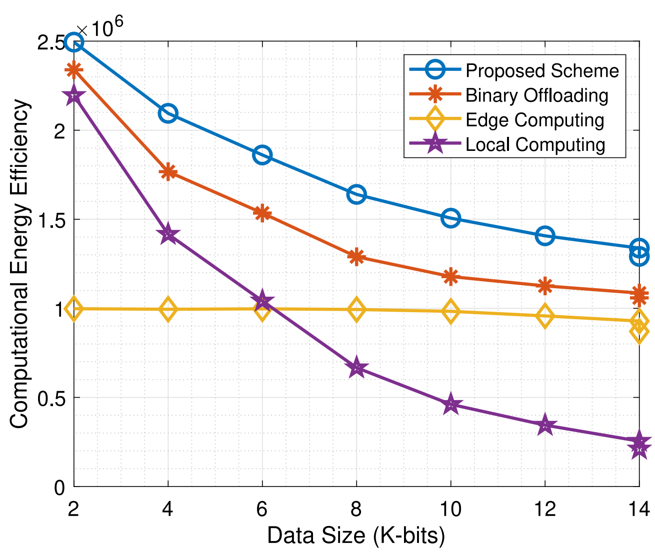

Fig. 4. Computational energy efficiency across data size.

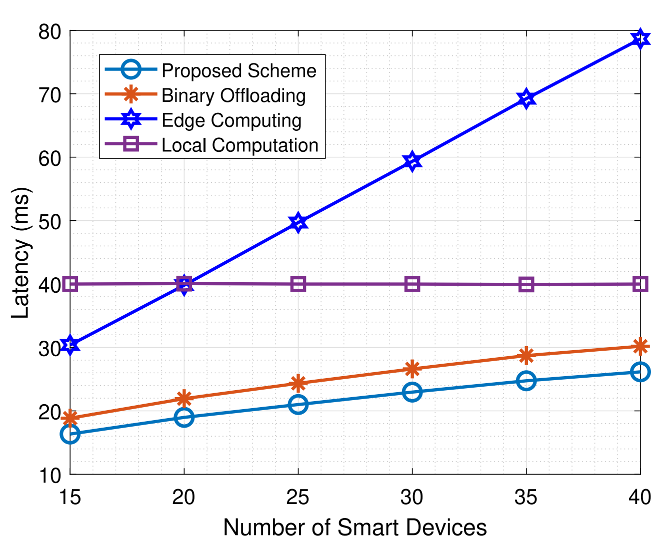

Fig. 5. Latency in Industry 5.0.

of users increases and more simulation parameters are added to the system, more computational power is required for convergence.

Next, we compare the performance of the proposed scheme with the benchmark schemes, including binary offloading, edge, and local computation. The comparison was made based on computational energy efficiency as the performance metric, as shown in Fig. 4. The results demonstrate that for small data size requirements, the performance of our proposed scheme is similar to the other schemes. However, as the data size requirements increase, our proposed scheme starts performing better than the other schemes. This is due to the fact that in our proposed scheme, optimal allocation of computational and communication resources was carried out, resulting in better computational energy efficiency. This also highlights the fundamental tradeoff between the edge computational scheme and our proposed scheme and underscores the importance of computational energy efficiency as a critical performance metric in Industry 5.0 scenarios.

After analyzing the computational energy efficiency for smart devices in Industry 5.0, it is important to address latency as it is also a crucial parameter. Therefore, extensive simulations were carried out, and the results were compared with benchmark schemes as shown in Fig. 5. The results demonstrate that the proposed scheme outperforms the other schemes across the number of smart devices. However, the results also show that the latency of the network increases with an increase in the number of devices. This occurs as a result of the fact that as the number of devices grows, more time is needed to offload the data, increasing the network's latency. In Industry 5.0, it is critical to address latency concerns because they can impair system performance as well as the effectiveness and productivity of industrial processes.

Next, we should look at energy consumption, which is important for every communication network. Fig. 6 findings show that as the number of users rises, so does the energy consumption of smart devices. The suggested strategy still performs better than the other benchmark schemes, though. The reason for this is that as the number of devices rises, shared resources become limited and smart devices begin to execute tasks locally, increasing their energy usage. Minimal energy consumption is essential in the context of Industry 5.0, where smart devices are widely employed, to ensure sustainable and effective operations, cut expenses, and lessen the environmental impact. The proposed scheme's ability to outperform the other benchmark schemes while consuming less energy is a significant advantage that could lead to widespread adoption in Industry 5.0.

The outage probability is another important performance metric to consider when evaluating the effectiveness of the proposed scheme in

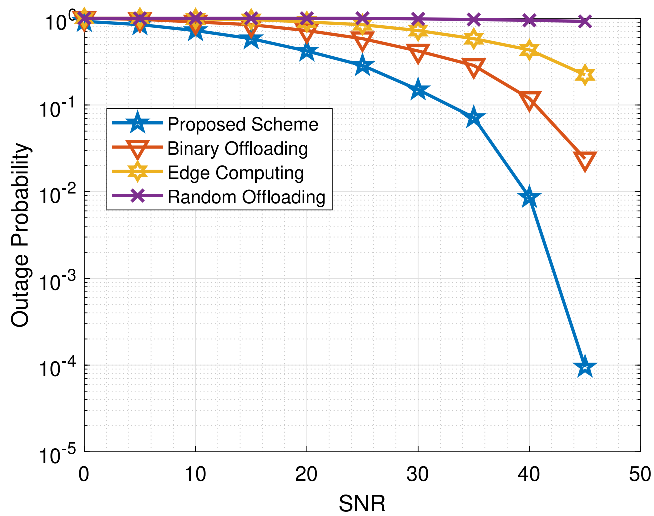

Fig. 7. Analysis of outage probability.

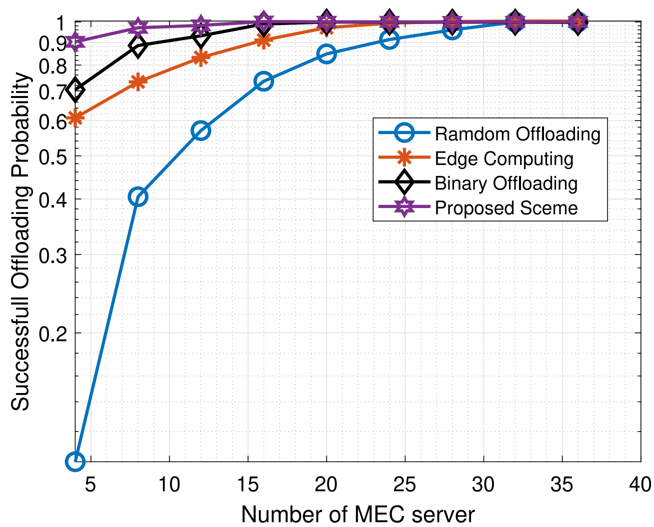

Fig. 8. Analysis of offloading probability.

Industry 5.0. As shown in Fig. 7, this was evaluated and compared to other benchmark schemes. The results show that the proposed scheme outperforms the other schemes with an outage probability of 0 as the signal-to-noise ratio (SNR) value increases. This underlines how crucial it is to consider outage probability when developing and assessing communication systems in Industry 5.0 because it directly affects the dependability and effectiveness of communication between smart devices.

Efficiency and dependability in data processing are essential for achieving peak performance in Industry 5.0. A key element in achieving this goal is the number of MEC servers necessary to enable data offloading. Our suggested scheme illustrates the significance of requiring fewer MEC servers for optimal performance by analyzing the impact of the number of MEC servers on the offloading probability, as shown in Fig. 8. As a result, the network becomes more dependable and energy-efficient while infrastructure costs are decreased. The results also show that our suggested scheme outperforms previous schemes by requiring fewer MEC servers to maximize the network's offloading probability, which is a critical element of attaining efficient and trustworthy data processing in Industry 5.0.

6. Conclusion

An integrated framework for MEC and Industry 5.0 has presented in this study's conclusion with the goal of boosting the productivity, effectiveness, and adaptability of industrial operations. By distributing resources like processing power, computing resources, and device association in the most effective way feasible, our proposed joint optimization problem has reduced computational energy efficiency. We split down the difficult and challenging problem into a number of smaller problems and iteratively resolved them. Our analysis also emphasizes the inherent contradiction between partial offloading and local computation. Results show that our suggested hybrid approach, which includes a partial offloading technique, performs better than others, emphasizing its suitability for tackling the joint optimization problem. This study, which is among the first to look at how MEC servers fit into Industry 5.0, shows how this framework has the capability to completely change the industrial sector. Businesses can achieve real-time data processing and analysis, reducing communication latency, accelerating reaction times, and enhancing system reliability by shifting computation-intensive jobs to MEC servers. The shortcomings of smart devices such as their short battery lives and limited computational power, emphasize the importance of this integration even more. Overall, this study establishes a framework for further investigation into the rapidly evolving topic of MEC and Industry 5.0.

Future research directions in the integration of MEC and Industry 5.0 include optimizing the joint problem, exploring the balance between partial offloading and local computation, and tailoring the framework to specific industrial needs. Further work could focus on scalability considerations and the development of efficient algorithms, building on the foundations laid in this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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