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Review Article

Digital transformation in wireless networks: A comprehensive analysis of mobile data offloading techniques, challenges, and future prospects

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ABSTRACT

Mobile data offloading is a highly promising approach in mobile networks that tackles network congestion at Base Stations (BSs) and greatly improves both the Quality of Service (QoS) and Quality of Experience (QoE) for users. It presents significant business opportunities for operators, particularly in light of the exponential growth in mobile data traffic and the ongoing digital transformation. To effectively uphold the desired levels of QoS and QoE in the elevation of escalating digitalization and the unprecedented surge in data traffic, this paper presents offloading through a diverse range of technologies such as data offloading through Small Cell Networks (SCNs), Wi-Fi offloading, Device-to-Device (D2D) offloading, and data offloading through Vehicular Ad-Hoc Networks (VANETs). The SCNs and Wi-Fi offloading involve migrating data traffic to the alternative infrastructure i.e. the small BS and the Wi-Fi Access Points (AP), respectively while D2D focuses on transferring data through the device without transversing the BSs. VANETs is the process of offloading data in vehicular scenarios that consist of Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X). Additionally, mobile data offloading from cellular BS is categorized into four main factors: energy consumption or energy awareness, economic considerations, user satisfaction, and network congestion. These factors play a crucial role in the ongoing adoption and implementation of mobile data offloading strategies. Different technologies utilize diverse techniques to tackle the challenge of offloading, aligning with their specific research objectives. This paper delves into the challenges and outlines future research directions in the field of mobile traffic offloading.

1. Introduction

The advancement of modernization in recent times has resulted in a growing reliance on technology, which has made everyday tasks more convenient for the community. The utilization of the Internet and smartphones is a prominent actor contributing to this surge in technological usage (Abrar et al., 2022). Smartphones and the Internet have been crucial since they are able to deliver data to your fingertips without hassle. Easily accessible sources of multimedia services such as downloading files, video conferencing, and Voice over Internet Protocol (VoIP) have led to an explosion of data traffic (Wang et al., 2022).

Analysts from Cisco have stated that, by 2023, more than 70 % of the world's population will have mobile access. The total number of global mobile subscribers will grow from 5.1 billion in 2018, which is equivalent to 66 % of the population, to 5.7 billion by 2023, which is 71 % of the population (Cisco, 2020). This offers substantial business prospects for operators, especially considering the rapid increase in mobile data usage and the continuous process of digital transformation. Indeed, the progression of technologies like the Internet of Things (IoT), Internet of Everything (IoE), and Internet of Medical Things (IoMT) is leading the charge in digital transformation (Abrar et al., 2024; Chakraborty and Kar, 2022; Lin and Wu, 2022; Tran-Dang and Kim, 2021). "Digital transformation" refers to the extensive incorporation of digital technologies, such as the Internet, computers, mobile phones, and other digital devices, into an organization's operations. As a result of this shift, it smartly able to communicate more efficiently, access and analyse information more rapidly, execute business transactions smoothly, and participate more actively in social and civic activities (Tran-Dang and Kim, 2021).

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With the growth of digital technology usage in the community, data traffic offloading techniques have become crucial to alleviate the increasing demands on network infrastructure and optimize the utilization of network resources. "Data traffic offloading," also known as network offloading, is the process of transferring data traffic to an alternative network. Besides decreasing Base Stations (BS's) load, the process is also able to optimize performance, and improve efficiency, reduce Capital Expenditure (CapEx) and Operating Expenses (OpEx) (Tan and Zeydan, 2018). Data traffic may be offloaded through other corresponding technologiess such as Small Cell Networks (SCNs), WiFi Offloading, Device-to-Device (D2D) and Vehicular Ad-Hoc Networks (VANETs) (Wang et al., 2019; Zhou et al., 2018a).

In mobile data traffic offloading, a variety of factors could be used to make offloading decisions. Some of the criteria are as follows:

Network load: It represents the amount of data traffic being carried by the network.

Bandwidth: It represents the amount of data that may be transmitted from one point to another in a given length of time. Bandwidth is measured in bits per second (bps) and represented as a bitrate (Yan et al., 2010).

Data demand: It represents the amount of data that is being requested by the users on the network.

Mobility: It represents the movement of the user entering and leaving the cellular coverage and the AP coverage. The velocity of the users is crucial in decision-making because it could determine the user flow rate (Liu et al., 2018b).

Cost/Price: Different networks specify and implement various billing rules (Yan et al., 2010). The cost is incurred because of the various policies of the service. As a result, cost/price becomes a major consideration in the offloading choice.

Delay: It defines the time it takes for a packet to travel across a network from a source to a destination.

Power consumption: It indicates the energy usage of a device or the network infrastructure. Switching to another network that consumes less energy would reduce the energy consumption.

Type of application: Different applications have different requirements for data traffic. Offloading part of the traffic according to the application's usage could be beneficial to the network itself.

1.1. Motivation

The increase in traffic demand is overburdening cellular networks, requiring them to operate near (and sometimes above) their capacity limitations (Mehmeti and Spyropoulos, 2014). Thus, to solve the outbreak of mobile network traffic, mobile data offloading has become a promising technique to resolve this challenge with its complementary network communication.

According to (Agamy and Mohamed, 2021), offloading reduces the load on mobile networks, which frees up the band for other users and therefore enhances the Quality of Service (QoS) and Quality of Experience (QoE). Data offloading also lowers the cost of downloading information.

Nevertheless, executing adequate data traffic offloading is intertwined with some concerns such as the users' mobility pattern, privacy, and risks of the data are among the main issues that should be resolved. On top of that, the technology of traffic offloading such as SCN, Wi-Fi Offloading, D2D, VANETs also need to be wisely chosen by the developer. These limitations highlighted the purpose of review paper and find out the key issues with different prospective.

1.2. Contribution

This review paper provides several unique contributions to the existing literature that primarily advance the understanding of mobile data traffic offloading technology and approach. Previous reviews have largely focused on the architectural perspective (Elhami et al., 2015; Zhou et al., 2018b) (Wang et al., 2019), or based on performance metrics such as delay and non-delay offloading (Aijaz et al., 2013; Rebecchi et al., 2014).

Thus, the contributions of this paper are as follows:

- A comprehensive analysis of network offloading technologies including their advantages and disadvantages, will thus enlighten future researchers when exploring these technologies.
- Classifies the network offloading technique based on research-based factors such as energy awareness, economic consideration, user satisfaction, and network congestion. Through this evaluation, we identify the strengths and limitations of different approaches, shedding light on the trade-offs involved in network offloading decisions.
- Identified the targeted candidates and decision criteria for offloading decision-making that could potentially maximize the QoS and QoE of users.
- Identified the challenges and future research trends in mobile data offloading, offering some insights for future researchers.

1.3. Organization

This paper is structured into multiple sections that start with Section 1, Introduction, which provides an overview of the study and key concerns within the existing Internet architecture. Building upon this context, the research motivation is discussed in Section 1.1 emphasizing the significance of mobile data traffic offloading, including the gaps and limitations that need to be addressed followed by Section 1.2, highlights the contributions indicating the uniqueness of the paper, and Section 1.3. presents the organization of the paper as refer to Fig. 1. Section 2 describes the differences between traffic offloading and handover, providing clarity and distinctness of the techniques.

Section 3 describes the network technologies enabling mobile data offloading, presenting the characteristics and deployment scenario of the technologies. Section 4 then, provides a thorough review and analysis of existing literature according to different research approaches. Subsequently, Section 5 discovers the challenges and future trends relevant to the research scope, suggesting potential areas for future research and advancement. Finally, Section 6 summarises the approach of offloading techniques and outlines the opportunities for further exploration.

2. Offloading vs handover

In general, traffic offloading and handover could be defined as the process of changing the point of attachment or interface to another interface within the same network technologies (two neighbouring cellular base stations) or different network technologies (Wi-Fi AP and cellular base station).

To differentiate between offloading and handover, we may examine the underlying reasons for each process. Offloading is typically employed to reduce the burden on the network, resulting in improved utilization of network resources and a better user experience. In contrast, handover is utilized to ensure the uninterrupted quality and continuity of an ongoing session (Ferretti et al., 2016; Zhou and Ai, 2014). The phases of offloading and handover may be described as follows:

Initiation: Traffic offloading is initiated in two situations. Firstly, the traffic offloading scheme is triggered when the capacity at the main base station is insufficient. This situation is known as network-initiated mode. Secondly, offloading happens when users in a coverage area have the option of networks and need a better QoS, which is known as user-initiated mode.

Handover is initiated when the user moves from one coverage area to another. While moving out of a certain area, the signal strength of the BS/AP will change from poor to strong, and User Equipment (UE) will start scanning the channel qualities of different BSs. Both situations, i.e.,

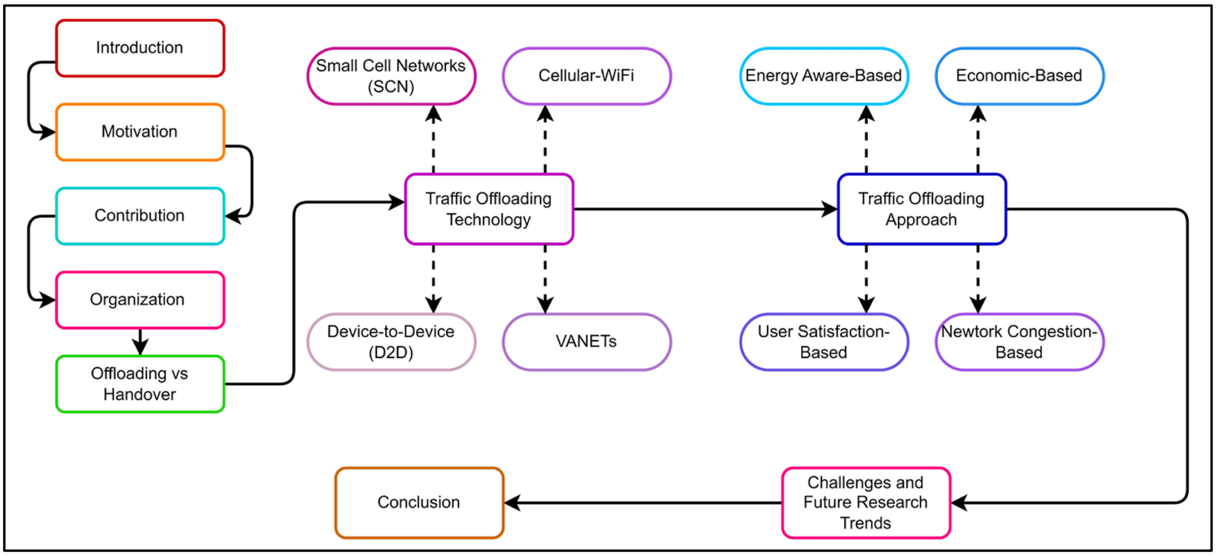

Fig. 1. Organization of the paper.

the initiation of offloading and handover, are illustrated in Fig. 2 and Fig. 3, respectively.

By referring to Fig. 2 the arrow represents the number of users connected to the infrastructure. The red-dotted arrow represents the initial connection of MU1 to cellular BS. The green-dotted arrow indicates the new connection of MU1 after being offloaded to the alternative network. The grey-shaded circle signifies the coverage area of the BS, while the blue-shaded circle shows the coverage area of the AP. Offloading happens when there is a new user (MU2) who wishes to enter the BS coverage area; thus, MU1, who is in the overlapping area, i.e., the cellular coverage area and the alternative network coverage area, will then have to decide to offload from the BS since user or consumer

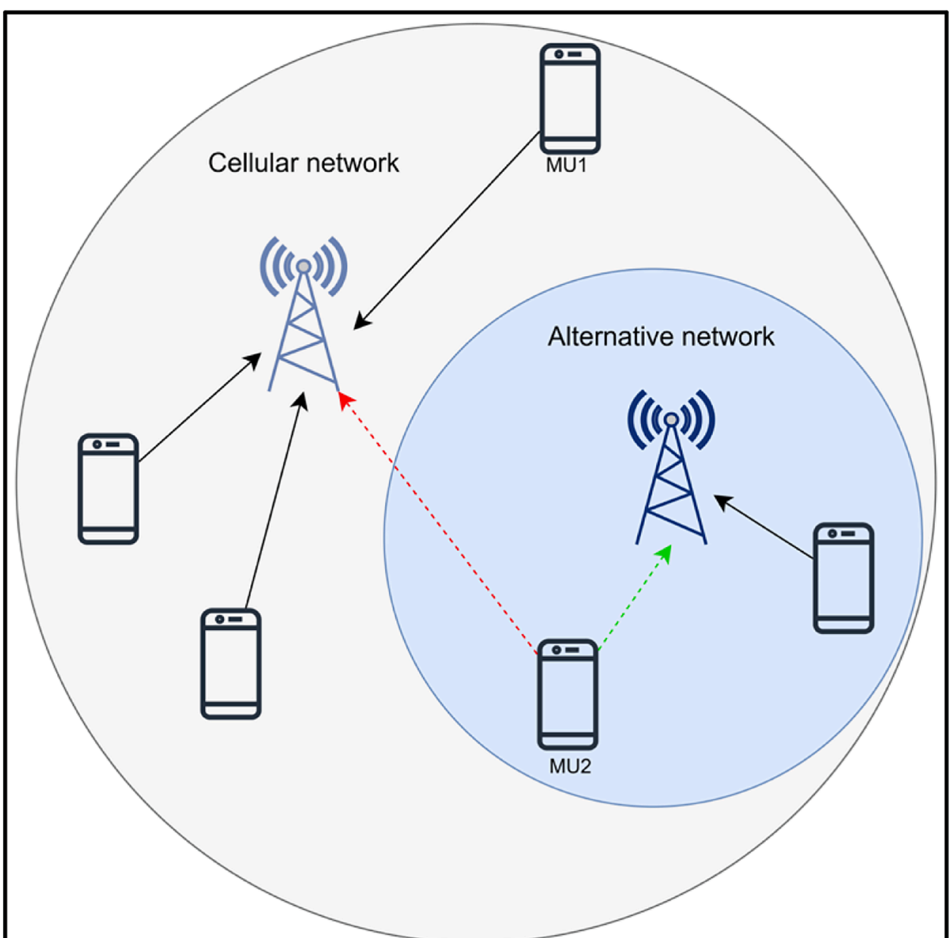

Fig. 2. Traffic offloading scenario.

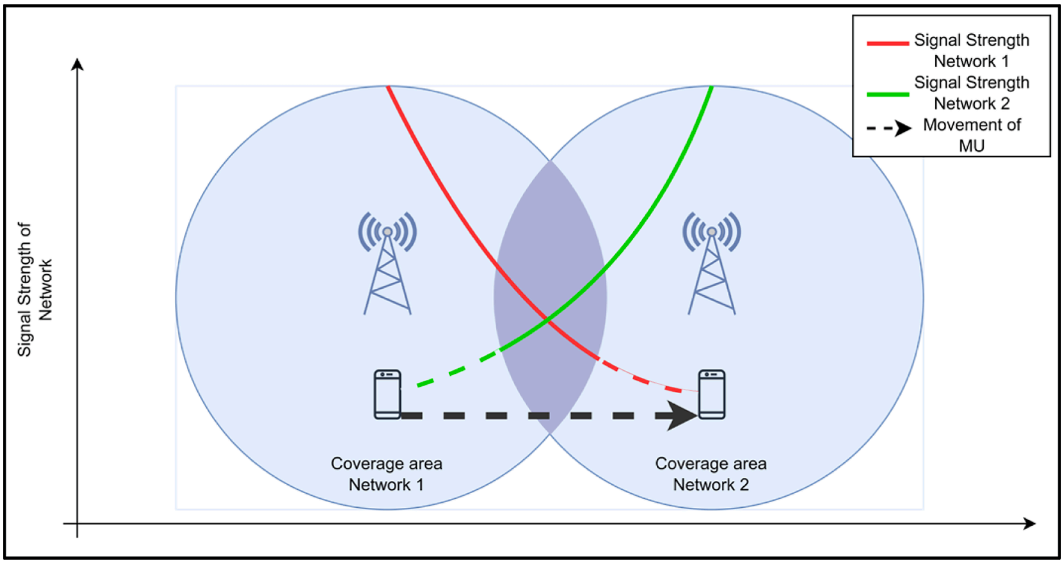

Fig. 3. Traffic handover scenario.

has another option of connection. Therefore, in order to reduce the network load of the BS, MU1 transferred control to the AP that has the less network load.

By referring to Fig. 3 shows the handover process. Here, a user moves from Network 1′s coverage area to Network 2′s. The red line shows Network 1′s signal strength dropping as the user leaves its coverage area. Conversely, Network 2′s signal strength, connected to the user, rises as the user enters its coverage area. The dotted green line indicates no connection in Network 1′s coverage area, while the dotted red line denotes no connection in Network 2′s coverage area.

Network/User Selection: In offloading, there are two types of selections, i.e., user selection and network selection, depending on whether it is a network-initiated mode or user-initiated mode. In network-initiated mode, the network operator needs to select a suitable user to offload based on certain criteria. As for user-initiated mode, users are freely to choose the best network based on their policies. In handover, UE identifies which BS is the best to maintain the connection. To choose the suitable BS, UE will take into consideration the resources and the network load. If offloading or handover is required, the target BS prepares a connection, and the source BS ready to offload or handoff.

Execution: This phase is the same as the offloading and handover. By using the additional operation resources, the UE starts to set up a connection with the target BS. Finally, the UE sends a signal to the target BS indicating the completion of the offloading or handover.

3. Key network technologies enabling traffic offloading

In this section, we classified mobile data offloading technologies into four categories: data offloading through SCNs, data offloading through Wi-Fi networks, data offloading through opportunistic mobile networks, and data offloading through VANETs. The following is a brief introduction, along with the advantages and disadvantages of these four technologies.

3.1. Small cell networks (SCNs)

Small Cell Networks (SCNs) are a complementary macro network consisting of various types of operator-controlled, low-powered Small Base Stations (SBSs) that facilitate offloading. These SBSs include femtocells, picocells, and microcells, with coverage ranges spanning from 10 m to 10 km (Zhou et al., 2018b). Specifically, according to (De and Mukherjee, 2017; Kumari and Singh, 2017), femtocells cover 10 m–30 m, picocells cover 100 m–300 m, microcells cover 250 m–1 km, and macro cells cover 1 km–10 km. SCNs could be deployed indoors or outdoors, operating on licensed, shared, or unlicensed spectrum. In communications, femtocell is designed for homes and small businesses where its connection is via broadband (DSL or cable) to deliver connectivity to mobile devices (Chandrasekhar et al., 2008). The data rate capabilities of femtocells typically range from 7.2 Mbps to 14.4 Mbps, while their power output operates within the frequency range of 1.9 GHz to 2.6 GHz. (Al-Turjman et al., 2018). When a two-tier network system (femtocells and macrocells) operates on the same frequency channel, it is called a Heterogeneous Network (HetNet) (Khan et al., 2019).

As depicted in Fig. 4, the process of offloading is initiated for Mobile User 2 (MU2). This transition occurs when MU2 moves from the BS to the SBS. This shift is triggered when MU2 enters the coverage area of the SBS, consequently leading to a reduction in traffic at the BS. This observation underscores the efficiency of offloading in optimizing network traffic management. The implementation of data offloading via a small-cell technology yields substantial advantages for both network operators and end users. These benefits encompass economical deployment costs, extensive coverage for mobile devices, with a particular emphasis on indoor environments, and an extension in battery longevity (Aijaz et al., 2013; Wang et al., 2019). This highlights the efficacy of small-cell technology in enhancing network performance and the user experience. However, these SCNs may have some limitations in terms of the quantity of service due to the frequency's interference between the small cells and macrocells as well as the scarcity of licensed spectrum bandwidths (Wang et al., 2019; Zhang et al., 2017).

3.2. *Wi-Fi* networks

Wi-Fi, short for Wireless Fidelity, is a wireless networking protocol that adheres to the IEEE 802.11 standards. It operates within the unlicensed frequency bands of 2.5 GHz Ultra High Frequency (UHF) and 5 GHz Super High Frequency (SHF), offering a cost-free solution that does not interrupt the operations of the cellular network (Wang et al., 2019). Wi-Fi offers a compatible and non-intrusive alternative to existing network infrastructures. Wi-Fi could be categorized into third-party and operator-owned networks. The third-party Wi-Fi infrastructure is operated by the Wi-Fi providers with the cellular operator paying them for data usage. Meanwhile, the operator-owned Wi-Fi is deployed and managed by the carriers themselves (Zhao et al., 2020). Currently, Wi-Fi services are available in diverse settings from homes and restaurants to public locations such as airports and libraries (Kaushik, 2012). Besides, most modern devices, especially mobile devices, have built-in Wi-Fi

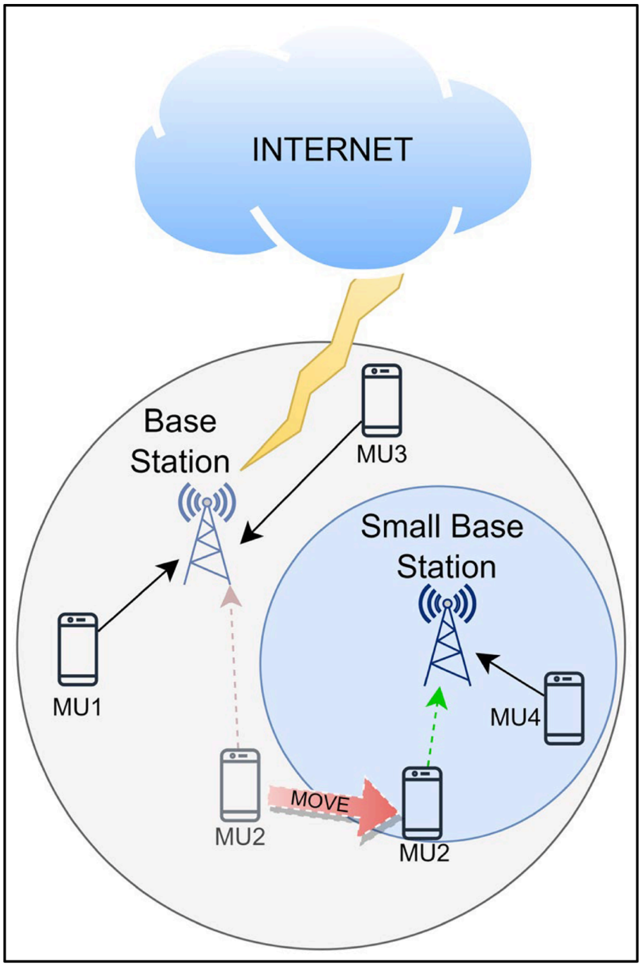

Fig. 4. Small cell networks scenario.

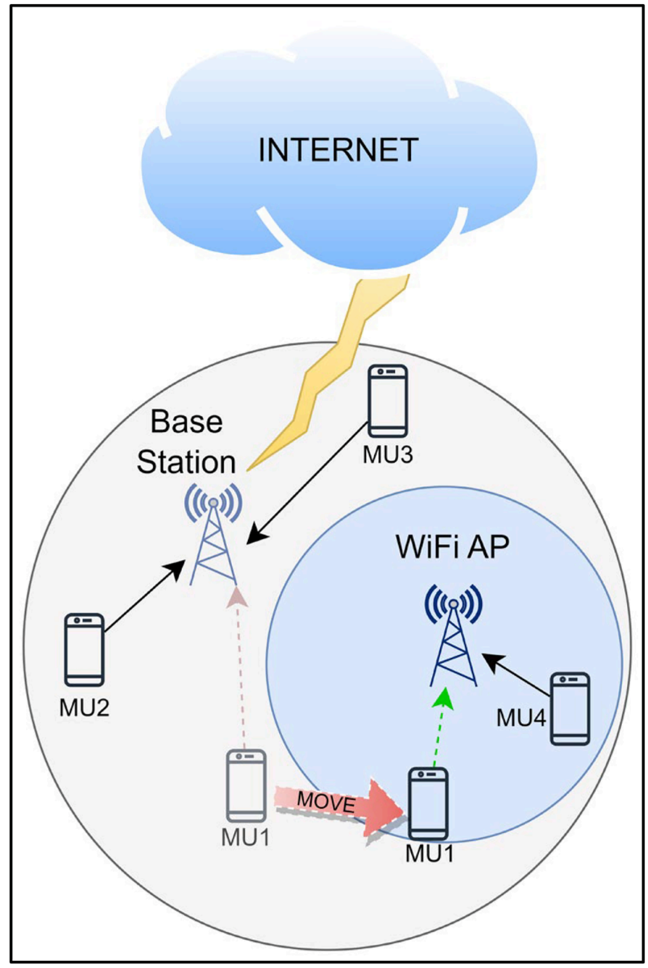

Fig. 5. Wi-Fi offloading scenario.

technology as an alternative to the cellular network. Data offloading through the Wi-Fi network offloads data traffic from the cellular network to the Wi-Fi network through the Wi-Fi AP.

As illustrated in Fig. 5, MU1, initially tethered to the BS, transitions into the coverage area of the Wi-Fi network. This shift enables MU1 to offload to the Wi-Fi network, thereby freeing up a connection at the BS. This underscores the role of Wi-Fi networks in optimizing connectivity and managing network traffic. Data offloading through Wi-Fi aims to solve the congestion in licensed bands, achieve load balancing, and fully utilize unlicensed spectrum resources (Sun and Zhu, 2019).

From the user perspective, data offloading through Wi-Fi also offers several advantages. Users may lower their billing or data subscription (Lee et al., 2014) and have a higher transmission rate than when using the cellular network. Additionally, the device battery's lifetime can be sustained by conserving energy when using the Wi-Fi network (Tang et al., 2021). Meanwhile, from a Mobile Network Operator (MNO) perspective, this technology assists to reduce the network congestion and improves the network capacity management (Zhou et al., 2018b). Thus, data offloading through a Wi-Fi network has become another option in mobile data traffic offloading, with a win–win situation between MNO and users. However, data offloading through the Wi-Fi network is unable to assure the QoS of the users and could reduce the user's device battery lifetime since the devices need to operate on two different technologies (Zhang et al., 2017).

3.3. *Device-**to-Device** (D2D)*

Data offloading from a traditional cellular network to a neighbouring mobile device known as D2D communication is one of the promising technique for offloading (Nitti et al., 2019). According to Kar and Sanyal (2020) D2D communication operates both using licensed cellular spectrum (in-band) and unlicensed spectrum (out-band).

In the case of in-band D2D, the communication be able to directly communicate between two cellular users by reusing the cellular spectrum without traversing the main network, known as underlay D2D communication mode. Feng et al., 2019). However, this mode of communication may cause D2D users and cellular users to interfere. A new approach i.e., overlay mode has been proposed to overcome this concern. This approach allows D2D users to use a certain fraction of cellular resources that are not assigned to normal cellular users (Kar and Sanyal, 2020).

Conversely, the out-band D2D requires hardware compatibility between the communicating devices. Even though there is no interference between cellular users and D2D users, however, interference between devices does happen (Ansari et al., 2017). This dual-mode capability of D2D communication provides network operators with flexible options to optimize network performance and manage traffic efficiently.

As illustrated in Fig. 6 instead of all MU2, MU3, and MU4 connecting to the base station, MU2 serves as a leader (initial seed) to the MU3 and MU4. This situation demoted two connections to the base station and made MU3 and MU4 offload from BS to MU2. In this aspect, the initial seed becomes the receiver from the content service provider and then transmits the input to the other users via their built-in Wi-Fi or Bluetooth. Then, to complete the cycle, MU3 and MU4 transmits back the data to MU2 so that MU2 may report to BS.

Data offloading through a D2D network also has its advantages, such

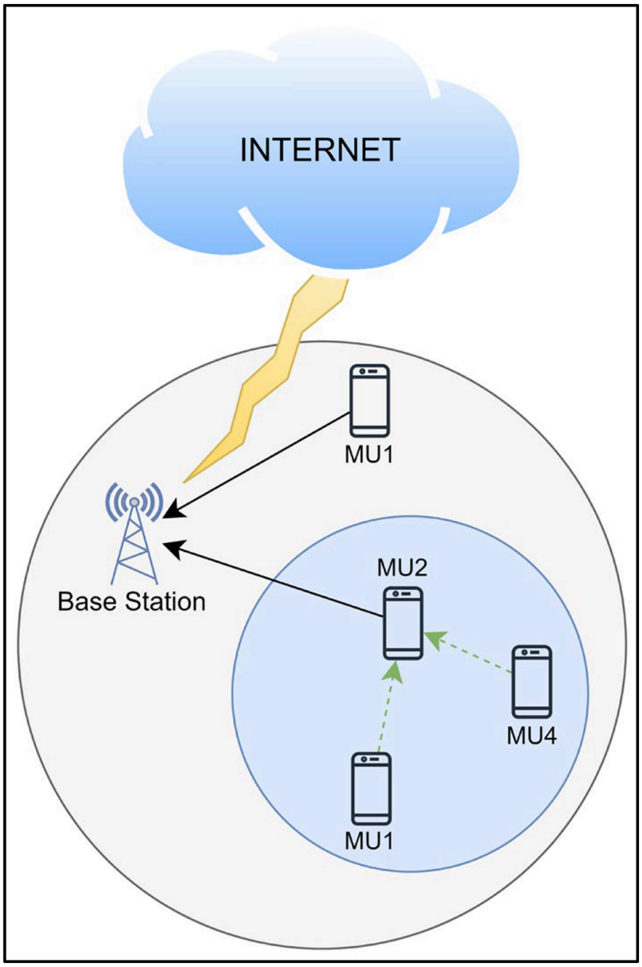

Fig. 6. Device-to-device offloading scenario.

as increasing the network capacity and lowering the monetary cost (Thien et al., 2020; Zhou et al., 2018b). Despite these, it also has limitations such as low battery life, needing to bargain the initial seed, and interference between cellular and D2D users (Feng et al., 2019; Kar and Sanyal, 2020).

3.4. *Vehicular Ad-Hoc* networks *(VANETs)*

With the emergence of mobile Internet, people are expected to connect to the Internet anytime and anywhere, even in their moving vehicles. With that, the development of VANETs has become one of the potential approaches for enhancing the connectivity within vehicles to create services that are particularly relevant to a vehicular environment (Lee and Atkison, 2021). To achieve this, several vehicular offloading techniques have been developed: Vehicle-to-Vehicle (V2V) communications allow direct data exchange between vehicles, Vehicle-to-Infrastructure (V2I) communications enable vehicles to offload data to roadside infrastructure, and Vehicle-to-Everything (V2X) communications encompass a broader ecosystem of vehicle connectivity with other entities, such as pedestrians and smart city infrastructure (Huang et al., 2018).

As illustrated in Fig. 7, in V2V communication, two vehicles share data directly without needing a fixed infrastructure. In case, if the vehicles are close enough, a cellular BS assist to control their communication. Therefore, it has drawbacks such as the turning behaviour and the limitation of encounter time (Matsumoto et al., 2019). For data offloading through V2I, the network service provider strategically places Wi-Fi APs at key roadside infrastructures. These include BSs and Roadside Units (RSUs) (Wang and Wu, 2016; Zhou et al., 2018a). These infrastructures enable data exchange services and applications based on V2I communication. However, this approach also experiences issues like limited coverage and interference between two technologies. The V2X communication was introduced to address the limitations of both V2V and V2I. In this system, vehicles may offload data either through nearby vehicles or the local obtained by using more energy.

4. Mobile traffic offloading approach

In this section, the network traffic offloading approach is classified based on the research objectives. Methods and decision-making approaches are also discussed. The decision-making approaches may be classified into two different groups: network-centric and user-centric.

In network-centric or centralized decision-making, the network

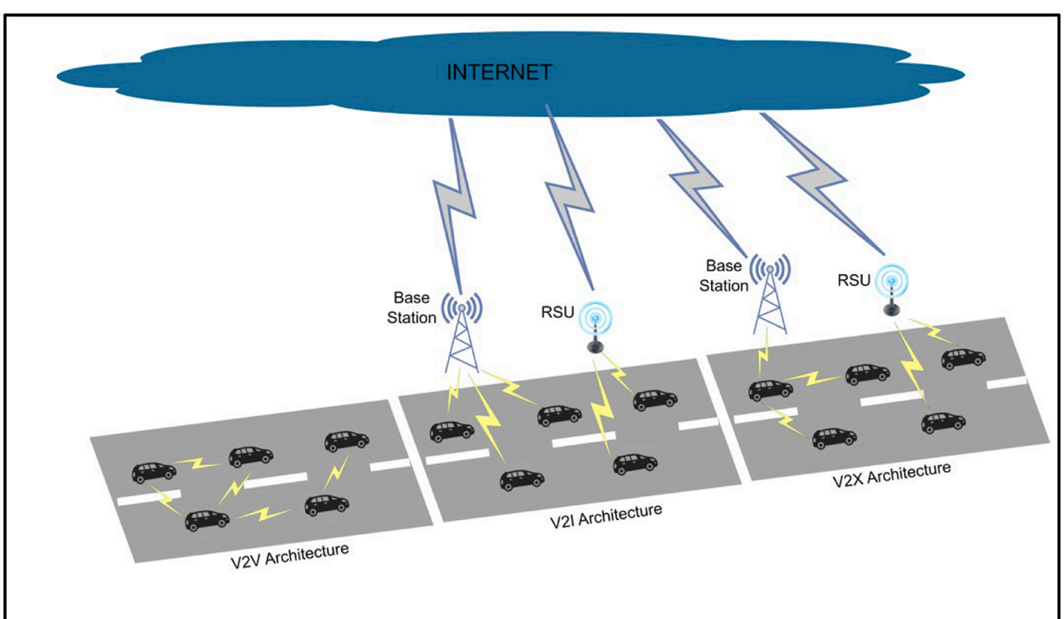

Fig. 7. VANETs scenario.

operator, whether a cellular operator or Wi-Fi AP operator, fully controls the decision while taking into account the user's preferences. Meanwhile, user-centric decision-making is where the decision on offloading is at the user's side to maximize their benefits.

4.1. Energy aware

Energy consumption of communication technology had been forecast to contribute up to 51 % of global electricity in 2030 (Andrae and Edler, 2015). According to Björnson and Larsson (2018), higher data rates could only be obtained by using more energy. In (Li et al., 2017), it is stated that the energy consumption of APs differs when they run in different states. Therefore, it is crucial to minimize the energy consumption for cellular networks (Tao et al., 2019). There have been several studies on data offloading technologies focusing on energy awareness, power consumption, and energy efficiency.

Song et al. (2015) study how SCNs might be used to reduce energy use? The study focusses on two-tier networks that handles two types of data packets, each with different delay needs. In this work, tier-1 represents the macrocell, while tier-2 denotes the femtocell. It is stated that a Class- 1 packet is more sensitive to delay than a Class-2 packet. The study also proposed a traffic offloading method by adjusting BS association biases, which may trigger traffic offloading by transmitting part of the users to nearby lower-power small BSs despite a lower signal strength from the MUs. Additionally, it derived a scheme to identify the optimal BS association biases, $B^*(\lambda)$, that minimizes the packet delay given energy consumption.

$$B^*(\lambda) = \arg\min_B \left\{ \sum_{i=1}^{2} D_i(\lambda, B) \right\}$$

λ is defined as sets of density and $\sum_{i=1}^{2} D_i(\lambda, B)$ denoted the mean packet delay for class *i*.

By exploiting the scheme, the results show that the network-wide mean packet delay is improved by 20 % at the optimal point $B^*(\lambda) = [1, 2.2]$ compared to the case where the BS association bias, $B = 1$. The numerical results showed that the proposed method achieved a lower network energy consumption compared to traffic offloading without controlling BS association biases. The packet delay influences energy consumption. However, this system does not consider the type of user to be offloaded, which affects the user's QoE and the network's QoS.

Huang and Chen (2020) also explored the energy consumption through SCNs to reduce energy consumption at the macro-BS for better system efficiency. The authors applied deep Q network (DQN) decision-making and traffic demand forecasting to the proposed mechanisms. The suggested model forecasts mobile data traffic and determines the number of active SBSs based on energy efficiency. To make it more suitable for this application, DQN parameterizes the Q- function and approximates it with a neural network. In the DQN model, all macrocells share two neural networks: the Q network takes actions, and the target Q network is active only during the training stage. The offloading decision is based on the forecasted states, where the traffic load statistic is predicted through the raw data collected from the environment, according to the DQN. Every decision time t, the offloading is initiated. Consequently, the Markov Decision Process tuple is formed:

$$(\psi(s_t), a_t, r_t, s_t + 1),$$

where $\psi(s_t)$ represents the pre-processed current state of a macrocell. Subsequently, the action, a_t, (the number of active small BSs in the macrocell,) is determined to improve the reward,r_t. The reward is considering both the energy consumptions and the traffic loading, thus is granted based on the action taken. r_t^c is the reward at time t of macrocell c and is calculated as

$$r_t^c = \beta \cdot r_{E,t}^c + \gamma \cdot r_{\rho,t}^c$$

where $r_{E,t}^c$ and $r_{\rho,t}^c$ are the reward component of energy efficiency and BS loading rates, respectively, while β, γ are the scaling factors.

The proposed model is evaluated against four other schemes: macrocell only, static offloading,

Q-learning offloading (Chen et al., 2015), and DQN offloading without forecasting. The simulation results show that the proposed model outperformed the other four schemes by 88 %, 16 %, 8.5 %, and 7 % respectively, in energy efficiency. The system provided a more accurate traffic prediction, which is more significant under higher traffic loads. However, training this model leads to time-consuming and energy-intensive (Ozturk et al., 2021).

Wu et al. (2018) examined the traffic offloading based on energy from both femtocell and Wi-Fi technology perspectives. The study defined the SCN as a Wi-Fi access point and a femtocell. Additionally, it addresses the resource selection for data offloading through dual connections, intending to minimize overall system costs, which include both BS bandwidth utilization and MU total energy consumption. With dual connectivity, users schedule their traffic to transmit delay-sensitive data traffic to the

BS while simultaneously, offloading delay-tolerant, large-volume traffic to the AP. Further, when users offload the data to the small AP aggressively, it experiences an increase in power consumption as the AP and BS are working under different interference. Consequently, it must be carefully plan the transmission of power and traffic to the BS and AP. Thus, it developed a combined optimization approach for BS bandwidth allocation as well as MU traffic scheduling and power allocation. The formulation of the joint optimization problem was as follows:

$$\min \alpha \sum_{i \in I} x_{iB} + (1 - \alpha) \sum_{i \in I} (p_{iA} = p_{iB})$$

st: Eq (1), (2), (4)- (7) in (Yuan Wu et al. (2018)

where α denotes the weight for the BS' bandwidth usage while $(1 - \alpha)$ denotes the weight of the MUs' total power consumption. According to the simulation results, the suggested method saves more than 60 % of the system cost when compared to the fixed bandwidth allocation scheme and more than 75 % of the cost when compared to the fixed traffic scheduling scheme. As a result, when compared to previous systems, the suggested algorithm has considerably decreased the overall system cost. However, it assumes that the macro and small cells belong to the same operator (i.e., they are willing to collaborate), which could deny their respective benefits when accommodating the MUs' traffic via dual connectivity.

Apostolaras et al. (2016) investigated network economics through cellular Wi-Fi offloading. The goal is to reduce the servicing cost of the mobile network operator by offloading a portion of the mobile users to third-party wireless mesh networks, which residential users deploy and manage. They first design a mechanism that aims to reduce the cost of MNO by reducing the BS's energy consumption. The study proposed a scheduling policy that allows the MNO an authority to decide which user needs to be offloaded based on the energy impact and the demand of the MUs. The mesh network's Internet access availability constrains the decision. Additionally, it proposed a multi-commodity minimum cost flow optimization problem in which the mesh network determines how the offloaded traffic will be further routed to and from the Internet gateway by considering the mesh network's available resources and servicing costs. To ensure the cooperation of the mesh nodes, the study proposed the joint offloading task of the mesh nodes based on the concept of Shapley value as a coalitional game and showed that it has a non-empty core. The extensive simulation results show that by offloading 25 % of BS's users, the power saving for an eNB that consumes 19.3308 Watt (in one slot) ranges from 0.88 Watt (4.56 %) up to 10.39 Watt (53.75 %) based on its load. It also found a large amount of cellular traffic during offloading, the delay increment under heavy local load might reach 19.86 % and the corresponding energy consumption 8.13 %. The result shows that the proposed mechanism has reduced the energy consumption of the BS. The offloading mechanism benefits from being customized for the LTE network. It could adapt to various criteria, like prioritizing high-demand users, or different objectives, like maximizing throughput. However, the drawback of the model is that it only considers the static or slowly moving users, while other types of users' mobility should be considered as an important part.

Meanwhile, Saliba et al. (2019) views traffic offloading through cellular to Wi-Fi, aiming to minimize energy consumption at the cellular/Long-term Evolution (LTE). Offloading happens when there is a heavy traffic load on the cellular network, which requires several users with heavy data consumption to be offloaded to the Wi-Fi AP depending on the request throughput and transmit power. Firstly, identify the heavy-load user by determining the resource allocation policy in terms of Resource Block (RBs) assignment and transmission power, as stated in (Apostolaras et al., 2014). Accordingly, there are 'M' available RBs in the BS that may be assigned to users in each subframe $(t = 1, 2, \cdots, T)$. The available spectrum determines the value of 'M' As a result, there are $(M*T)$ RBs in total. The eNB creates the RB assignment and power allocation policy at the start of the period to serve its users. By referring to the calculation in (Apostolaras et al., 2014), the instant rate for each user n is:

$$r_n(t) = \sum\nolimits_{m=1}^{M} x_{nm}(t)\cdot W_b \cdot \log\left(1 + \frac{h_{nm}\cdot x_{nm}(t)\cdot P_{nm}(t)}{\sigma^2}\right)$$

where $x_{nm}(t) \in \{0, 1\}$ indicate if RB $m \in M$ is allocated to user $n \in N_c$ during subframe $(t = 1, 2, \cdots T)$ and $P_{nm}(t)$ indicates the transmission power where $P_{nm}(t) \leq P_{max}$(Watt), the maximum level of aggregated transmission power. The Wi-Fi network's remaining capacity or throughput is then determined by measuring the network load or occupancy level of the Wi-Fi channel i where $i = 1, \cdots, 12$. They define the throughput of Wi-Fi AP $L(L = 1, \cdots, K)$ as R_L and R_{tot} is the total throughput of the Wi-Fi network. Thus, the calculation is as follows:

$$R_L = R_{W_{max}} \cdot \frac{(1 - \alpha_i)}{t_i} R_{tot} = \sum\nolimits_{i=1}^{K} R_L$$

The $1 - \alpha_i$ is the Wi-Fi channel's available idle capacity, and t_i denotes the number of APs operating simultaneously under the different frequencies of the WiFi channel. The calculation determines the minimum number of Wi-Fi APs, K, needed to meet the target average WiFi throughput per user, S_w^{user}. It takes into account a maximum threshold in the LTE network. Any user exceeding this threshold is transferred to WiFi. This threshold also sets the minimum capacity per user that the WiFi network must ensure. Thus, K express as

$$K = \underset{K}{\operatorname{argmin}}\ S_w^{user}$$

By employing the method, the results show that the user experience will be enhanced instead of experiencing possible congestion or throughput deterioration with a limited number of LTE eNBs. Besides, the total consumed power in eNB showed an average of 40 % of savings. Therefore, this method provides some advantages, such as saving the cost of eNB deployment and the power consumption of eNB along with enhancing the user's QoE. However, this model does not consider the mobility criteria of the user, which degrades the network's QoS since the distance of the user from one place to another is different.

Zhang et al. (2019) studied energy efficiency by deploying data offloading through D2D. The authors aim to achieve energy efficiency on the user side while adapting to their increasing demand. The offloading is triggered when some users request the same content from the service provider. Either cellular or D2D communication shares the requested content. The study proposed a social-aware energy-efficient data offloading approach by formulating an offline finite-queue-aware energy minimization problem, which is a time-coupling stochastic mixed-integer non-linear programming (MINLP) problem. The formulated problem involves the consideration of storage capacity allocation, queuing, and transmission scheduling. The following is the formulation for the offline energy consumption minimization problem:

$$P1\ : \min \lim_{T\to\infty} \frac{1}{T} \sum\nolimits_{t=0}^{T-1} \sum\nolimits_{i\in U} E[E_i(t)]$$

$$st : (8), (11), (13) - (16)$$

However, the study reformulated the problem into an online finite-queue-aware energy consumption problem by practicing the Lyapunov drift-plus-penalty theory to break down the time-coupling former problem. The problem further be broken down into separate subproblems in each time slot. Subproblem 1 represented link scheduling and power allocation; Subproblem 2 denoted content allocation; and Sub-problem 3 denoted routing. The study demonstrates the viability and efficiency of their approximation technique based on the simulation results for the content queue performance and the energy cost performance. Based on the simulation results, it could be stated that the user's social preferences affect the energy cost, where the higher the user preference, the lower the time-average energy cost.

W. Wang, Li, Zhang, and Wei (2020) also focus on energy efficiency, which aims to find the maximum energy efficiency of the D2D caching network through the joint optimization of the cache policy and content transmit power. When users request content, known as content sensing, from the surrounding cache users, it immediately triggers the content transfer process (offloading) if the cache users could sense the requested information. Also, calculates the data offloading rate. It took into account the likelihood of successful sensing and transmission using stochastic geometry theory while considering the data transmission rate and the D2D establishment constraint in determining the probability of successful data transmission. Moreover, a joint optimization algorithm is proposed that based on transmit power and cache policies, respectively, to maximize energy efficiency. The optimal cache policy problem is formulated as:

$$P1 : \max_{q} \rho = \sum\nolimits_{f=1}^{F} p_f \pi q_f \lambda_p \left(\frac{1 - e^{\varphi f r^2}}{\varphi_f}\right)$$

$$s.t :\ 0 \leq \sum\nolimits_{f=1}^{F} q_f \leq 1$$

while the formula for the transmit power problem is presented as follows:

$$P2 : I(y) = \max_{P_t} \sum\nolimits_{f=1} F \psi_f \cdot \left(\frac{1 - e^{-y}}{y\theta + t}\right)$$

$$s.t. : 0 < P_t \leq P_{max}$$

According to the findings, the suggested joint optimization algorithms outperformed all previous joint-independent schemes in terms of energy efficiency. However, in both (W. Wang et al., 2020; Zhang et al., 2019), both studies does not consider the privacy risk of the initial seed, and in the D2D region the privacy issues or security issues become one of the important criteria to be considered to encourage users to participate in offloading (Qiao, Li, and Li, 2020).

The Table 1 provides a summary of the offloading decision criteria and the target users while Table 2 presents the performance metrics of each literature.

4.2. Economic/Incentive based

Different operators have different policies for planning the price unit for data traffic. Some plans are based on their profit gain, and some are based on user satisfaction. Furthermore, users desire high network quality and coverage but are unwilling to pay for the necessary technology (Zheng et al., 2017). To get cooperation between different parties, different incentive schemes have been studied.

Feng et al. (2018b) studied incentive cooperation between MNOs and different Wi-Fi operators, where they set alternative price plans based on their needs. The aim is to simultaneously maximize user

Table 1
Offloading decision criteria and target candidates: Energy based.

Ref	When to Offload	Target Candidates	Decision Maker	Decision Criteria
(Song et al., 2015)	When the traffic load reaches its optimal capacity.	Random Candidates.	Network	Network load
(Huang and Chen, 2020)	Based on forecasted state \newline (traffic load statistic).	According to the cloud controller decision.	Network	Network load
(Wu et al., 2018)	Users schedule the offloading when there is heavy-load or data traffic.	Based on the traffic type: delay-tolerant and large-volume traffic.	User	Traffic type
(Apostolaras et al., 2016)	When user set their device to Wi-Fi mode.	Based on the energy impact and demand of the MUs (MU with highest demand).	Network	Energy impact on BSMU's demand
(Saliba et al., 2019)	When the users' demand exceeds 20Mbps.	Heavy load user (demand > 20 Mbps).	Network	Network load
(Zhang et al., 2019)	When some users request the same content from the content provider.	The user requests the same content as the initial seed, provided in the D2D region.	Network	Content availability
(Wang et al., 2020)	When the initial seed senses the user who requests information.	Users who request the same content as the content cache provided, are in the D2D region.	Network	Content availability

Table 2
Performance metrics: Energy based.

Ref	Technology	Evaluation matric(s)
(Song et al., 2015)	SCN	Delay,Power consumption
(Huang and Chen, 2020)	SCN	Power consumption,Energy efficiency, Transmitted data
(Wu et al., 2018)	SCN/Wi-Fi	Power consumption,Throughput
(Apostolaras et al., 2016)	Wi-Fi	Power consumption,Delay
(Saliba et al., 2019)	Wi-Fi	Offloaded traffic,Throughput,No. of needed Wi-Fi
(Zhang et al., 2019)	D2D	Offloaded traffic,Power consumption
(Wang et al., 2020)	D2D	Energy efficiency

satisfaction and minimize the operator's benefit loss via a pricing strategy where the offloading scheme is represented in a two-stage decision process. Stage I is where the MNO and Wi-Fi AP adjust the unit price and broadcast it to the user in the coverage area. Stage II is where users allocate their data traffic requirements to different operators based on the unit price given. The data offloading problem is formulated as a joint optimization of the min–max problem, where the higher level minimizes the operator's benefit loss (Problem 2) and the lower level maximizes user satisfaction (Problem 1). Therefore, it introduces the S-shaped utility function to measure user satisfaction in mobile data offloading, where the user utility curve changes like the capital letter'S' as the user gets more required sources. The utility functions of cellular networks, $U\,(g_{ij})$, and Wi-Fi networks, $U\,(f_{ij})$ were formulated as follows:

$$U\left(g_{ij}\right) = \frac{1}{1 + e^{-a_i\left(g_{ij}-d_{ij}\right)}},$$

$$U\left(f_{ijk}\right) = \frac{1}{1 + e^{-a_k\left(f_{ijk}-d_{ijk}\right)}}$$

While the cellular benefit loss was formulated as:

$$H_1 = \sum\nolimits_{i=1}^{I}\sum\nolimits_{j=1}^{J}(C_{bs} - v_i)g_{ij}$$

Where c_{bs} and v_i are denoted as the standard unit price and the discounted unit price to cellular network user i, respectively.

The Wi-Fi benefit loss was calculated as follows:

$$H_2 = \sum\nolimits_{i=1}^{I}\sum\nolimits_{j=1}^{J}\sum\nolimits_{k=1}^{K}(C_k - c_{ik})f_{ijk}$$

Where c_k and c_{ik} represented the standard unit price and the discounted unit price of Wi-Fi k respectively.

Thus, the total benefit loss of operators, H(c), is calculated as:

$$H(c) = H_1 + H_2,$$

Further, it transforms the both problems into bi-level optimization problems where the optimal solution could be found by dynamic coordinate search-based method, DYCORS. Besides, it also proposed a distributed algorithm to get a near-optimal solution in which a third-party agent altered the data traffic allocation. Further, its comparisons between the proposed DYCORS algorithm and the proposed distributed algorithm for the operators' benefit loss and user satisfaction. The simulation results demonstrate that there is only a little difference between the two methods, with the DYCORS algorithm approaching the optimal point faster than the distributed algorithm, but the latter achieving a better outcome with more repetitions. Further, it considers mobility as users utilize their mobility after the unit price of data traffic and location information is announced. However, the delay sensitivity of the data traffic is neglected.

Ko et al. (2017) studied examined the delay in Wi-Fi offloading to save the monetary cost to the fullest extent while, considering the outage probability on the download time. It is formulated in an analytical model on the expected saving monetary cost C, where ϕ is the monetary cost for unit traffic volume as:

$$C = \phi T_P = \phi T_W \frac{\mu_W \lambda_C}{\mu_W \lambda_C + \mu_C \lambda_W}$$

The expected download completion then is formulated as:

$$T_D = E[t_T] + \frac{F - T_W}{\lambda_A}$$

Where λ_A represents the average download rate after the timer expiration, and the remaining time to download the completion time is expressed by $\frac{F-T_W}{\lambda_A}$. The optimal delay timer is derived based on the analytical model to maximize the monetary cost while maintaining the download completion time at a low level. The offloading is triggered when the users set their devices to Wi-Fi mode. Therefore, it is important to set the delay timer to an appropriate value to balance saving monetary costs and the outage probability of the download time. An event driver simulator based on MATLAB R2014b was developed to verify the analytical model. The extensive simulation results on the expected saving monetary cost, C, and expected download completion time, T_D shows that the difference between the analytical model and the simulation result is less than 3 %. Further, it shows that the monetary cost and expected download completion time increase as the application deadline increases. However, the decision on the offloading is user-centric, where the offloading will be processed only when the user sets their device to the Wi-Fi mode which causes the traffic load of the Wi-Fi AP congested.

Zhou et al. (2020a) investigates an incentive mechanism to stimulate the Wi-Fi APs (third-party companies') participation in the data offloading process. The proposed novel Delay-constrained and Reversed Auction-based Incentive Mechanism (DRAIM) as a nonlinear integer problem from the business perspective. Taking into consideration the delay constraints of the different applications in the optimization problem, it aims to maximize the MNO's revenue. The offloading triggered for the MNO to improve its overall network performance, especially when network congestion occurred. The reverse auction model was designed so that the MNO acts as the auctioneer and the APs act as the bidder. The MNO evaluates and purchases the required bandwidth resources that meet the traffic demand and maximize its revenue after the APs lease their bandwidth resources as commodities and submit the bids. Therefore, to maximize the MNO's revenue, the optimization problem is formulated as follows:

$$\max H_K(x_i, a_{ij}) = U\left(\sum_{j\in N} s_j, \sum_{i\in K}\sum_{j\in N} a_{ij} s\right) - \sum_{i\in K}\sum_{j\in N} x_i a_{ij} \epsilon_{ij}$$

$$\text{s.t}\ :\ \sum_{j\in N} (j \in N) a_i j B_i j \le B_i^{max},\ \forall i \in K, \forall j \in N,$$

$$t_i j \le \delta_j, \qquad \forall i \in K, \forall j \in N$$

$$a_i j \le x_i, \qquad \forall i \in K, \forall j \in N$$

$$x_i, a_i j \in 0, 1, \qquad \forall i \in K, \forall j \in N$$

Where $H_K(x_i, a_{ij})$ is the MNO utility, which is the revenue function without considering payment to the winning AP minus the payment of the winning AP. To solve the problem, it introduces the selection method based on a greedy algorithm, namely as the Greedy Winner Selection Method (GWSM), where the APs with the maximum increase in the MNO's utility are chosen. To further improve the selection method, it proposed the Dynamic Programming Winner Selection Method (DPWSM) to select winning APs and allocates the MUs. Furthermore, to guarantee the individual rationality and truthfulness of DPSWM, it proposed an innovative standard Vickrey-Clark-Groves (VCG) scheme. Furthermore, it compares the proposed methods DPSWM and GWSM with the Random Winner Selection Method (RWSM) in terms of MNO's revenue and the MNO's traffic load under different scenarios. The extensive simulation results show that the proposed method, DPWSM performs the best followed by GWSM and RWSM.

Zhao et al. (2020) investigated how to encourage users to reveal their valuation of resources so that the MNO could efficiently utilize both cellular and operator-owned Wi-Fi resources simultaneously, while strictly controlling the decision cost of users. Therefore, it proposed a novel bid-based Heterogeneous Resources Allocation (HRA) framework specifically said HRA-Profit and HRA-Utility. Both mechanisms are designed to achieve the maximal operator's profit and social utility respectively. The following is the formulation for the maximization of MNO goal profit.

$$\max \sum_{B_j\in B}\sum_{T_z\in T} \pi_j^z\ ,$$

$$\text{s.t}:\ \ b_i^z = b_i'^z, \qquad \forall i \in I_j$$

$$s_i^z \ge s_i^z|_{\delta_i^z=1},\ \ \forall i \in I_j$$

$$\widetilde{L}_k^{j,z} \le \widetilde{C}_k^j, \qquad \forall A_k^j \in A^j$$

The offloading is triggered by two HRA policies. The first is a time-driven trigger where the MNO sets a schedule based on a defined time slot and possibly the daily mobile data traffic pattern within each cellular BS. Secondly, it is the event-driver trigger where the demand for data exceeds the corresponding capacity of cellular networks. The offloaded users are determined based on their claimed bid, data traffic price, and their average data rate during a certain time. Therefore, the bidding profile of U_i is formulated as:

$$f_i^z = \widehat{p}_i, b_i'^z, \overline{v}_i'^z, \overline{v}_i'^{z-1}.$$

Here $\overline{v}_i'^z$ is the average data rate of U_i during time slot T_z on the previous day and $\overline{v}_i'^{z-1}$. is the average data rate during the time slot T_{z-1} on the current day. Additionally, it calculates the actual average data rate of users using an estimated data rate equation since it is unknown for the next time. However, it is less applicable to the real-world scenario. Therefore, it further improves the resource allocation problem by modelling it based on the Stochastic Multi-Armed Bandit (SMAB) problem and designed two near-optimal Upper Confidence Bound (UCB) strategies i.e. The HRA-UCB-Profit and HRA-UCB-Utility to gain near-optimal profit and utility under incomplete user context information. The simulations are classified into two categories such as (i): mechanisms with complete information and, (ii): mechanisms with incomplete information. For part (i) the evaluation involved four resource allocations which are Cell Only (no idle Wi-Fi is available), HRA-Profit, HRA-Utility, and User Choice (users may choose to connect to Wi-Fi only if it gains higher surpluses than connecting to cellular). The results showed that the Operator's Profit under HRA-Profit increased by 25–40 % with benchmarks while social utility under HRA-Utility increased up to 47 %. For part (ii), 100 SMAB problems are selected randomly from all SMAB problems within the 40 valid cells. The results showed that profit gain under HRA-UCB-Profit is close to that gained by optimal choice similar also to the utility gain under HRA-UCB-Utility according to pseudo-regret. The pseudo-regret ratio is strictly under 20 %. The proposed framework should improve the QoS in cellular networks when congestion occurs and also release the overload of the BS.

Liu et al. (2020) study examines that how to effectively allocate AP's bandwidth among multiple MU which is considered a multi-item auction problem. It aims to maximize the gross profit of the MNO and the total number of offloaded MU referred to as mobile subscribers (MS) from the BS. Therefore, it proposes an auction mechanism with an uncertainty set, U_j of item valuations which is constructed based on limit theorems of probability theory since the MUs valuation are hidden from MNO.

The U_j is formulated as

$$U_j = \left\{u_{1j}, \cdots, u_{nj}| - \tau \le \frac{\sum_{i=1}^{n} u_{ij} - n\cdot\mu_j}{\sqrt{n}\cdot\delta_j} \le \tau\right\}$$

The offloading is triggered when there are number of users who sends a bidding price to MNO to get AP's bandwidth. Thus, the MNO chooses and allocate the bandwidth to the winning bidder based on their valuation matrix v. The auction problem is based on a robust optimization approach under the premise of individual rationality, incentive capability, and budget feasibility.

The optimization problem is constructed as follows including the network constraints, AP bandwidth constraints, and MU's demand constraints.

$$\max_{x^v, p^v} R$$

$$\text{s.t}\quad R - \sum_{i\in N} p_i^u \le 0, \qquad \forall u \in U,$$

$$p_i^u \le \sum_{j\in M} u_{ij}\cdot x_{ij}^u, \qquad \forall i \in N, \quad \forall u \in U,$$

Further, it introduced two greedy auction mechanism i.e. Matching AP Scheme and Matching MS Scheme to solve the data offloading problem in polynomial time. The performance of the schemes which are the Optimal scheme, Matching AP scheme, and Matching MS scheme are evaluated with the MDP scheme in (Liu et al., 2017, 2018a) in terms of total revenue, offloaded data traffic, and Winning bidder (MU). The result shows that the Optimal scheme outperformed other schemes in all circumstances while the Matching MS scheme outdid the Matching AP scheme in two scenarios: high AP density and low AP bandwidth.

Li et al. (2020) studied on the user-initiate incentive mechanism through D2D, where the MU offers necessary incentives to the third-party offloading services provider (OSP). The main goal is to maximize the OSP (initial seed) profit as well as the utility of the two types of mobile users which are Mobile Price Takers (MPT) and Mobile Price Setters (MPS). The MPT is a user who is willing to accept the fixed unit payment from OSP and decide the number of requested traffic while the MPS is a user who negotiates the fixed payment with the OSP and the OSP determines the number of traffic that provides to the MPS. The formulation for the OSP total profit is given as

$$V(x,p) = \sum_{n\in N^s} q_n^s(x_n^s) + \sum_{n\in N^t} (q_n^t)(x_n^t) - \phi_1\left(\sum_{n\in N^s} x_n^s\right) - \phi_2\left(\sum_{n\in N^t} x_n^t\right)$$

Where the first term of the equation is the payoff, and the second term is the resource consumption cost. The utility of the two types of MU n is expressed as

$$U_n^t(x_n^t, x_{-n}^t, p^t) = J_n^t(x_n^t, x_{-n}^t) - q_n^t(x_n^t),$$

$$U_n^s(x_n^s, x_{-n}^s, p^s) = J_n^s(x_n^s, x_{-n}^s) - q_n^s(x_n^s)$$

Where U_n^t is the utility function of MPT while U_n^s is for MPS. The offloading is triggered when there are users who request the traffic from the OSP (user failed to download the traffic from BS) if the user is in the range of OSP's D2D communication. To bring balance between the OSP, MPTs, and MPSs, it introduces three-stage social-aware Stackelberg game into the negotiation. The MPS acts as the game leader for the OSP in Stage I of the Stackelberg game, deciding the price strategies, p^s for maximizing their utility. In Stage II, OSP decides the offloading strategy x^s as the follower for MPSs while serving as the leader for MPTs to establish the pricing strategy p^t. In Stage III, the MPTs function as followers for the OSP in determining offloading methods x^t to maximize their utilities. From the simulation, the MPS achieves more positive results as compares the MPT in terms of utility improvement and satisfaction since the MPS set their unit payment to the OSP by themselves. However, in terms of the total profit of the OSP, the MPT contributes more to the profit of the OSP than the MPSs. Regardless, when the MUs participate in the offloading process, the OSP's profit increases.

Qiao et al. (2020) study on a user-initiated incentive mechanism through D2D technology by proposing a two-stage Stackelberg game between the initial seed known as content transmitter (CT) and the end user. The offloading is triggered when the MU failed to download the requested content from the content provider and request the same content to the CT while in the range of CT's offloading area. The proposed mechanism aims to maximize the CT's profit as well as the MUs' satisfaction by combining the effects of social awareness and network congestion in the formulation. The MU's utility was defined as

$$u_i(x_i, x_{-i}, p) = a_i x_i - \frac{1}{2} b_i x_i^2 + \sum_{j\neq i} \Phi(w_{ij} x_i x_j) - p x_i - \frac{1}{2} d\left(\sum_{j\in N} x_j\right)^2, \ \forall i \in N$$

The first three terms of the equation denote the user i's satisfaction and the last two terms denotes the cost to the user i.

The CT's profit is formulated as:

$$R(x,p) = \sum_{i\in N} p x_i + \sum_{i\in N} \left(-u(x_i - v)^2 + uv^2\right) - c\sum_{i\in N} \frac{x_i}{m}$$

It is constructed as a gain minus the cost model. The two-stage Stackelberg game is constructed to create the interaction between the CT and the MU where the CT acts as a leader and the MU acts as the follower. At each stage, CT and MU make the best decision to achieve their respective benefit maximization. In the simulation, it evaluates the model in two different cases which are the socially aware method and the socially unaware method in terms of CT's profit and MU's average utility. The results show that the socially aware method has a positive impact on the offloading.

The Table 3 provides the summary of offloading decision criteria and the target candidates while Table 4 presents the performance metrics of each literature for economic based.

4.3. User satisfaction

User satisfaction is one of the important goals of the data offloading scheme. Different MU have their own requirements for data offloading such as low delay during data transmission and the price offered for using data traffic. Therefore, there have been several studies on maximization of user satisfaction in mobile data offloading technology.

Cheon and Kim (2019) explored the mobile data offloading through small cell backhaul networks in terms of social context, considering a direct influence by each user and an indirect influence by other users. It aims to maximize the QoS of a user and, at the same time, reduce the core network load of an MNO to the greatest extent possible. Therefore, it proposed a social-aware mobile data offloading algorithm that determines the offloading ratio for each application of each user by estimating the application selection probability. The offloading is determined by the MEC (Mobile Edge Computing) server, which collects data to exploit the social context and QoS values of the network and calculate the offloading ratio for each user's application. The formulation of social context-based application selection probability is defined as:

$$P_{ij} = \theta_D \cdot P_{ij}^D + \theta_O \cdot P_{ij}^O$$

where P_{ij} denotes the application selection probability for the application j of user i, P_{ij}^D and P_{ij}^O defines the application selection probabilities for the application j of user i, influenced by users' preferences and by other users, respectively, and θ_D, θ_O denotes the weighting factors influenced by each user's self and by other users, respectively such that $\theta_D, +\theta_O = 1$. The offloading traffic volume for each application of each user is formulated as

$$TL_{ij}^{OL} = r_{ij}^{opt} \cdot TL_{ij}$$

where r_{ij}^{opt} is the final optimal offloading ratio and TL_{ij}, is the traffic volume of each application j of each user i, respectively. For the performance evaluation, it compares the proposed algorithm to that of an algorithm that does not employ the social context model. The findings show that the suggested algorithm outperformed the algorithm that did not take social context into account, particularly in terms of QoS values. Furthermore, the results show that the social context weighting factors had the greatest effect on the suggested algorithm's performance.

Kim et al. (2017) presented a rate control technique based on dynamic programming to maximize user satisfaction. The user satisfaction is defined in this study as offloading efficiency (total data volume transmitted over Wi-Fi) minus the disutility caused by the deadline violation. The formulation for maximization of user satisfaction was constructed as follows:

$$\max_{\pi\in\Pi} E_s^\pi \left[\sum_{t=1}^{T^m} g_t\left(l_t, \delta_t^\pi(s_t^\pi)\right) - c\left(s_{T^m+1}^\pi\right)\right]$$

Where π denotes the user's policy. The first term denotes the total data volume transferred through Wi-Fi during $T = [1, T^m]$ and the second term stands for the disutility caused by the deadline violation at $t = T^m + 1$. The offloading is said to be triggered when there is the availability of Wi-Fi near the user's position. The proposed algorithm was derived from the Dynamic Programming (DP) framework. Further, it proposes a simple threshold-based rate control algorithm to reduce the computation and memory. Further, it addresses the network resource congestion among various flows as well as network transitions between cellular and Wi-Fi networks in the model. In the simulations, it compares the proposed algorithms (DP-based and threshold-based) with another four existing algorithms, which were, on-the-spot-Earliest Deadline First (EDF), Wi-Fi-only, Wi-Fi-only-EDF, and Optimal Delayed Wi-Fi Offloading (Cheung and Huang, 2015) in terms of user satisfaction. The

Table 3
Offloading Decision Criteria and Target Candidates: Economic Based.

Ref	When to Offload	Target Candidates	Decision Maker	Decision Criteria
(Feng et al., 2018b)	When users require a higher transmission bandwidth.When the cellular BS overloaded.	Based on the user's data requirement.	Network	Traffic LoadUser Demand
(Ko et al., 2017)	When users set their devices to the Wi-Fi mode.	Wi-Fi mode user.	User	Type of application
(Zhou et al., 2020a)	When congestion about to happen.	Based on the user's delay tolerance.	Network	Delay ToleranceUser Demand
(Zhao et al., 2020)	When MNO sets a time schedule to offload.When traffic demand exceeds cellular capacity.	Assume that the offloading process is achieved accordingly.	Network	Not Specified
(Liu et al., 2020)	When user requests the bandwidth resources to the cellular network.	User who wins the auction to acquire bandwidth.	Network	User's Budget
(Li et al., 2020)	When the MU requests the traffic to the BS but fails to download provided that the MU is in the OSP's coverage area.	Based on the user satisfaction in terms of the offloading cost.	Network (initial seed)	Data Traffic CostSocial Preference
(Qiao et al., 2020)	When the MU requests the traffic to the BS but fails to download provided that the MU is in the OSP's coverage area.	Based on the user satisfaction in terms of the offloading cost.	Network (initial seed)	Data Traffic CostContent Demand

Table 4
Performance Metrics: Economic Based.

Ref(s)	Technology	Evaluation Metrics
(Feng et al., 2018b)	Wi-Fi	User Satisfaction,Network Benefit Loss
(Ko et al., 2017)	Wi-Fi	Monetary CostExpected Download Completion Time
(Zhou et al., 2020a)	Wi-Fi	MNO Utility,MNO Revenue/Profit,Traffic Load
(Zhao et al., 2020)	Wi-Fi	Social Utility,MNO Profit
(Liu et al., 2020)	Wi-Fi	Total Revenue,No. of Winning Bidder,Offloaded Data Traffic Size
(Li et al., 2020)	D2D	Initial Seed's Total ProfitUser Average Utility
(Qiao et al., 2020)	D2D	Initial Seed's Total Profit,User Average Utility

results show that both DP-based and threshold-based perform closely equivalent with minimum complexity while considering the network resource contention among flows. When it compared to other current algorithms, the suggested algorithms have the potential to enhance user satisfaction as the number of coexisting flows increases.

Song et al. (2020) presented a three-stage Stackelberg game for MNO, Wi-Fi AP, and offloaded users' collaboration. It aims to ensure user satisfaction without jeopardizing MNO revenues. Offloading is said to be triggered when the MNO needs to release the BS's load or when the user in the AP's region means to be served by the AP. The main steps in the three-stage game are presented as follows:

- Stage I: Player: MNO; Strategy: Charge vector z_1, z_2 and compensation vector β_1, β_2; Payoff: $U_{M(z_1,z_2,\beta_1,\beta_2)}$ where U_M is the profit of MNO (the payment from subscribers minus the compensation paid to APs and the cost of serving remaining users)
- Stage II: Players: offloaded users $n \in N$; Strategy: quality sensitive, a_n; Payoff: $U_n(a_n)$ denotes satisfaction function for the user n
- Stage III: Players: APs $i \in I$; Strategy: Contribution amount, λ_i^1, λ_i^2; Payoff: $U_i(\lambda_i^1, \lambda_i^2)$ denotes the utility function of the AP holder (the incomes from its users and the compensation from the MNO.

To find the optimal solution, the suggested framework applies a backward induction approach. The AP determines their contribution amount for the first stage to maximize their reward. The offloaded user calculates their best acceptable pricing relative to access quality in the second step, while the MNO evaluates whether to accept the user's proposed price while taking into account the projected cost of paying APs in the third stage. When the number of AP is set to 8, the simulation results reveal that the suggested scheme outperforms the two-stage system by 16 % of MNO's profit and 18.18 % in terms of user satisfaction. It could be concluded that the proposed scheme had achieved its aim, which was to maximize user satisfaction without risking the MNO's profit.

Feng et al. (2018a) studied the non-cooperative game approach between users and operators in mobile data offloading. It aims to maximize each user's satisfaction and also the network's profit without their cooperation. In the meantime, it also considers the traffic price and user localization. Therefore, it proposed an algorithm to arrange users' traffic in a distributed manner, which is a Marginal Utility-Based Traffic Allocation (MUBTA). To fully satisfy the users' claims in terms of lower traffic prices and higher QoS, and at the same time, avert network congestion, the non-cooperation game theory, which is the bidding approach, is used in the model. Accordingly, the offloading is triggered when there are users who submit their sub-demands and bidding prices to the different networks. By then, each network selects the highest bidding price and allocate the traffic to the corresponding users. The satisfaction of user i is defined as follows:

$$U_i(\theta_{ij}, d_{ij}) = \alpha\left(\sum_{j=1}^{m}\left(Q(\theta_{ij}) - \theta_{ij}D(d_{ij})\right)\right) + F\left(\sum_{j=1}^{m}\left(Q(\theta_{ij}) - \beta(p_{ij}\theta_{ij})\right)\right)$$

where α and β are the quality sensitivity coefficient and bidding price sensitivity coefficient, respectively. d_{ij} signify and θ_{ij} signify the distance and the sub-demand of traffic concerning the user i and network j respectively. While $Q(\theta_{ij})$ represents the satisfaction of QoS, $D(d_{ij})$ represents the satisfaction of energy consumption and $F\left(\sum_{j=1}^{m}\right)$ defines the satisfaction. The $p_{ij}\theta_{ij}$ express the satisfaction of the bidding price. Hence the maximization of user i satisfaction is formulated as:

$$\max U(\theta_{ij}, d_{ij})$$

$$\text{s.t} \sum_{j=1}^{m} \theta_{ij} \geq G_i, \forall i \in I, \theta_{ij} \geq 0$$

The maximization of the network's profit is constructed as:

$$\max R_j = \sum_{i=1}^{n} y_{ij}\left(p_{ij} - c_j\right)$$

$$\text{s.t.} \sum_{i=1}^{n} y_{ij} \leq B_j, 0 \leq y_{ij} \leq \theta_{ij}$$

Where R_j denotes as the profit of the network j and y_{ij} is the traffic that the network j allocate to user i while c_j is the unit traffic cost of the network j. The B_j represents the traffic capacity of the network j. The proposed algorithm is evaluated by numerical results where the size of users and operators set will not affect their conclusion. Further, it compares the proposed method with a traditional method in (Li et al., 2016) where the method does not consider the competition between users. The results demonstrate that the suggested method achieves a near-optimal solution and has a higher user satisfaction value than the traditional method.

Alagrami et al, (2019) proposed an enhanced access network discovery selection function ANDSF Wi-Fi discovery technique. The aim is to offer mobile user equipment with discovery information as well as a list of accessible Wi-Fi networks for a better QoE. The offloading is said to be triggered when the user discovers the availability of Wi-Fi coverage nearby. The ANDSF server constructs the classification model that detects the User Equipment (UE)'s Wi-Fi coverage status using the Decision Tree (DT) machine learning approach and adopts the Classification and Regression Trees (CART) algorithm in the system. Two concepts are being used in the CART decision tree algorithm:

- Entropy: The degree of unpredictability in the data, and is calculated as follows:

$$E(S) = -\sum_{i}^{c} p_i \log_2 p_i$$

If $E(S) = 0$, it denotes the total homogeneity of the data whereas if $E(S) = 1$, the data is completely uncertain.

- Information Gain: The decrease in entropy and be calculated as follows:

$$IG(Y, X) = E(Y) - E(Y|X)$$

Attributes with higher information gain express a more significant reduction in entropy. This implies that the attribute is more effective in separating the data into particular groups.

The proposed technique is being compared with the SVM model. The results show that the DT model prediction accuracy ranges between 90.13–98.48 % while the SVM model ranges between 76.66–87.51 % when against 20 different testing data sets. It shows that the proposed method is more accurate and stable than the SVM model.

Sun and Zhu (2019) developed a Wi-Fi offloading technique based on Q-learning and Multi-Attribute Decision-Making (MADM), where the Q-learning scheme is utilized for user decision-making. The Analytic Hierarchy Process (AHP) and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) are selected as two MADM algorithms. It aims to maximize user satisfaction by taking into account user throughput (TP), terminal power consumption (PC), user cost (C), and communication delay (D), all of which indicate QoS. The offloading decision is evaluated based on the four attributes, i.e., TP, PC, C, and D.

The throughput of the agent can be calculated as

$$V_i^{TP} = W \times \log_2\left(1 + \frac{P_i^r}{N_0 \times W}\right)$$

Where W denotes the available bandwidth of the agent and P_i^r is the signal power received from the BS or AP. To ensure normal transmission data, the minimum transmit power of the BS or AP is P_{min}^t is calculated as

$$P_{min}^t = P_{min}^r + L,$$

and the agent consumption power is calculated as

$$V_i^{PC} = P_0 + P_i^t$$

Further, the study highlights the V_i^C and V_i^D as the unit price charged per second and the transmission delay after the agent accesses the network at i_{th} position respectively. The simulation results show that the proposed algorithm is better in terms of user satisfaction under both stream and conversation services, respectively compared to the RSS scheme and Fakhfakh and Hamouda's algorithm in (Fakhfakh and Hamouda, 2017). The difference between the proposed algorithm and others is the reward function where reference (Fakhfakh and Hamouda, 2017) only considers the SINR, handover delay, and AP load while RSS takes into consideration the received signal strength of the terminal. Despite that in terms of average delay, under stream services, the proposed algorithm underperformed, but was almost on par with RSS (the best) under the conversation service because of the difference in the delay attribute weightage.

Bhooanusas et al. (2021) proposed a Satisfaction-based Dynamic Bandwidth Reallocation (SDBR) technique for multi-path offloading of mobile data in Wi-Fi networks and cellular. The aim to optimize user satisfaction with user payment and blocking probability in the data offloading environment, as well as MNO income. The satisfaction function is given by:

$$S(t_1) = \begin{cases} P_{max} - at_1^b, & \text{if } t_1 < t_d \\ 0, & \text{otherwise} \end{cases}$$

and

$$p = P(S(t_1))$$

Where P_{max} is the maximum downloading price for t. The offloading is triggered when the cellular resources are full or when the traffic load increases. This technique motivates BS to permit more download sessions by considering the Wi-Fi connection state of current connected customers in line with a price-based satisfaction function to balance download latency and serving cellular bandwidth. The SDBR is being compared to the DBR scheme in two scenarios. In the time-based file download scenario, the SDBR technique improves overall revenues and average user expenditures by 11.36 % and 17.02 %, respectively, while lowering blocking probability rates by 30 %. In volume-based file downloading scenarios, the SDBR scheme increases the overall revenue and average use expenses and reduces blocking probability by 47.5 %, 13.33 %, and 12.5 %.

The Table 5 provides a summary of offloading decision criteria and its target candidates while Table 6 presents the performance metrics of each literature for user satisfaction based.

4.4. Congestion based

Congestion arises when a network is unable to manage the volume of traffic flowing across it or reach maximum capacity. While network congestion is generally a transient state rather than a permanent aspect of a network, there are some instances when a network is constantly crowded, indicating a deeper problem. In this section, there are several research studies on ways to minimize network congestion at the BS.

Liu et al. (2018b) explored Wi-Fi offloading in smart communication by considering network congestion and user mobility management. The aim is to maximize the network throughput and minimize network congestion by optimizing the ratio of users performing offloading when user enters the Wi-Fi network coverage. The offloading is triggered when the user enters the Wi-Fi network coverage, where the offloaded users are chosen based on the offloading ratio p_i. The throughput is measure as the sum of all networks, i.e., the cellular network c and the Wi-Fi network i.

$$T\vec{p} = \sum_{i}^{M} T_i(p_i) + T_c\,\vec{p}$$

Further, the network congestion is denoted as the blocking probability, which acts as the penalty when congestion happens and is formulated as

$$B\vec{p} = \sum_{i}^{M} P_i^b + P_c^b$$

The proposed Congestion-Optimal Wi-Fi Offloading (COWO) based on the sub-gradient method in (Matei and Baras, 2011) to determine the offloading ratio for each AP. Due to the computational complexity of the COWO algorithm, it further improves by introducing Virtualized Congestion-Optimal Wi-Fi Offloading (VCOWO). This method treats all the AP as one virtual Wi-Fi network, with all the channels and other resources in the Wi-Fi network being jointly scheduled. The virtual Wi-Fi network meets the corresponding criteria as follows:

Table 5
Offloading Decision Criteria and Target Candidates: User Satisfaction Based.

Ref	When to Offload	Who to be Offloaded	Decision Maker	Decision Criteria
(Cheon and Kim, 2019)	Based on MEC server data collection.	Based on user's application traffic demand.	Network	Social Context, Network QoS, Device Application
(Kim et al., 2017)	When device connect with Wi-Fi network, when it is available.	Does not indicate the type of user who will be offloaded.	User	Traffic Flow,Total Data Size
(Song et al., 2020)	When MNO want to release traffic burden at the cellular BS. When user in the range of AP's region and needs to be served by the AP.	Not specified	Network	Not specified
(Feng et al., 2018a)	When the user submits a bidding price for required data traffic to the MNO.	Users who submit a higher bidding price than the network base price.	Network	Traffic PriceNetwork QoSTraffic Demand
(Alagrami et al., 2019)	When users discover the availability of a Wi-Fi network.	Users who wish to get better QoE.	User	Not Specified
(Sun and Zhu, 2019)	Based on the Q-learning and MADM algorithm.	Based on user satisfaction level.	User	User QoS
(Bhooanusas et al., 2021)	When cellular BS is full, or the load is increasing.	Based on the user location whether in the Wi-Fi network region or not.	User	Traffic LoadBandwidthWi-Fi Availability

Table 6
Performance Metrics: User Satisfaction Based.

Ref(s)	Technology	Evaluation Metrics
(Cheon and Kim, 2019)	SCN	Transmission Delay,Packet Error Loss RateData Rate
(Kim et al., 2017)	Wi-Fi	User Satisfaction
(Song et al., 2020)	Wi-Fi	Offloaded Traffic, MNO Profit,Motivations for APs,Social Welfare
(Feng et al., 2018a)	Wi-Fi	User Satisfaction
(Alagrami et al., 2019)	Wi-Fi	Receiving Operating CharacteristicsValidation AccuracyTesting Accuracy
(Sun and Zhu, 2019)	Wi-Fi	Throughput, Terminal Power ConsumptionUser CostCommunication Delay
(Bhooanusas et al., 2021)	Wi-Fi	MNO Overall ProfitAverage User Expenses, Blocking Probability

1. The user flow rate of the virtual Wi-Fi network γ_a is the sum of the user flow rate for each AP.
2. The active users' arrival rate of virtual Wi-Fi.

From the observation, the VCOWO algorithm reduced the COWO computational complexity, i.e., $O(U+M)$ to $O(U+1)$ where U is the number of MBS and be assumed as $U = 1$. The proposed algorithms are assessed using the OTSO scheme. The performance comparison between COWO and OTSO is supervised under user arrival rates ranging from 0 to 0.5. Simulation findings show that the suggested strategy may provide higher throughput while decreasing network congestion when compared to other current offloading approaches. Further, it considers the user's mobility in their scheme.

Mochizuki et al. (2019) presented and assessed a delay-tolerance-based mobile data offloading approach based on deep reinforcement learning, specifically known as Double Deep Q-Network (DDQN). The purpose to accomplish load balancing, enhance the bandwidth usage efficiency of cellular infrastructure, and address traffic demand locally. To solve the traffic's temporal locality, deep reinforcement learning is applied to the mobile data offloading protocol (MDOP). The offloading is triggered in three scenarios based on the MDOP policy i.e.,

1. When the user moves from high-load eNB to low-load
2. eNB.
3. When the BS has a high load traffic.
4. When the user moves from BS to the Wi-Fi network region.

The evaluation of the proposed algorithm benchmarking with the MDOP's time-wise offloading and the no-control algorithm, focusing on how efficiently each utilizes cellular infrastructure. According to the results, the suggested technique reduced traffic over the control goal by 35 % when compared to time-wise offloading of MDOP.

Pan et al. (2017) developed a model to solve the optimization problem, taking into account the best strategy for pushing content. The model takes into consideration both the content preferences and the sharing willingness of the users. In this context, a MU's demand for content is referred to as a content preference, and the content that another MU shares via D2D are known as sharing willingness. The goal of their model is to maximize the offloading gain, which measure by the amount of traffic offloaded via D2D communications. In the pushing stage, the MUs are categorized into four types:

1. The MUs who accept the request and download the content from BS (User Equipment, UE-A).
2. The MUs who refuse the pushing request (UE-R).
3. The MUs who did not receive the pushing request while they were interested in the content (UE-T).
4. The MUs who did not relate to the content distribution process (UE-N).

Moreover, it presents an Alternate Group Offloading (AGO) approach to tackle the optimization problem in general. The offloading is triggered when there are users who request content to the cellular BS and users who have the same interest as the initial seed is selected to be offloaded. The D2D link conducted by the content transmitters (known as pushed UE in the paper) is assumed to be scheduled by the BS. The optimization problem to maximize the offloading gain is formulated as

$$P1 : \max_{c} G(c) = \sum\nolimits_{m\in M} n_m P_m,$$

$$\text{s.t.} \quad 0 \le c_m \le 1, \quad \forall m \in M$$

From the performance evaluation, they conclude that it is more important to equip MU with a strong sharing willingness and a high pushing likelihood.

Zhou et al. (2020b) investigate a unique freshness-aware seed selection issue described as a utility optimization problem that considers both the material's freshness and the cost transmission from cellular networks to the initial seed. To tackle the optimization problem, it offers two seed selection methods: greedy seed selection and decay-based seed selection. The findings are intended to reduce network load at the BS and to determine the appropriate quantity of initial seed. Thus, it states the freshness-aware seed selection problem is expressed as follows:

$$\text{Max } U(S) = |S|(F_0 - c) + \sum_{j \notin S, \in V} F(j)$$

$$\text{s.t. } |S| \leq K$$

The offloading is triggered when there is a user who requests the same content as the initial seed from the MNO. It compares the proposed method with a random seed selection technique. The results indicated that Decay outperformed both Greedy and Random methods in the Infocom 06 trace and the MIT Reality trace, as expected. This work guarantees the freshness of the content as the content will decay over time and it also considered the benefit of the initial seeds. However, it impotent to consider the energy consumption of the initial nodes, as it need to always update the freshness of the content.

Feng et al. (2019) presented a D2D communication-assisted traffic offloading (DAO) method that takes the use of D2D communications in permitted cellular bands. In integrated cellular and Wi-Fi networks, it seeks to maximize the amount of traffic offloaded from cellular to Wi-Fi while ensuring customers' long-term data rates. The DAO is defined as an optimization problem that takes into consideration the active nodes and their connections to arrive at the optimal scheme. As the problem is NP-hard, they addressed the joint optimization issue by taking advantage of its layered nature and breaking it down into sub-problems based on time-scale separation. From the simulation results, it discovered that DAO could accommodate considerably more offloaded traffic than traditional offloading, particularly in high-traffic load circumstances.

Raja et al. (2020) introduced a technique called IR-DON for next-generation vehicular networks. This technique uses a module called I-ANDSF along with an SDN controller. Its design allows it to choose the most suitable RSU from available options based on a reward calculated by a Q-learning module. The aim to reduce the cellular network congestion and overcome the issues of RAT selection. The elements of the Q-learning algorithm are as follows:

- **State:** $s' \in S$ which represents the position of the user.
- **Action**: $a' \in A(s)$ which denotes the set of RSU detected by the users.
- **Agent**: Vehicular user follows a feasible path at a certain position.
- **Reward:** The user makes the offloading decision based on the reward calculation, where the reward is splitting into two, i.e the RSU reward, R_{RSU}, and the cellular reward R_C.

It decides to choose a user with a higher bandwidth-consuming application to be offloaded to a nearby AP. The proposed technique provides guaranteed QoS to the users. According to the simulation findings, the IR-DON improves the total throughput of the system by 17 % and reduces the latency by 15 % which could be concluded that the IR-DON guarantees the QoS and also has a better achievement in offloading even when the number of users is increasing.

Fan et al. (2020) presented a C-V2X network framework defined by intelligent software by splitting the network into a data plane and a control plane. The data plane is primarily responsible for traffic offloading. The cellular traffic offloading and vehicle-assisted traffic offloading is carried out in combination. The control plane is in charge of developing traffic offloading techniques and decreasing control complexity.

They intend to alleviate network congestion and enhance traffic load balancing. The offloading is triggered when the AP has reached the limit in terms of the number of users or, more likely, when congestion happens. Further, it utilized the multi-objective optimization problem for traffic offloading, where it formulated into two different optimizations objectives and decision variables for two parts of traffic offloading. The first optimization objective is the throughput of AP with consideration of the load balance. The formulation is as follows:

$$O_1 = \sum_{q \in Q} \sum_{m \in M} L \cdot R_{q,m}$$

Where L represents the system load. The second optimization objective is the throughput of vehicles with consideration of vehicle mobility and is formulated as follows:

$$O_2 = \sum_{v \in V} \sum_{m \in M_2} H_{v,m} \cdot R_{v,m}$$

Where the $H_{v,m}$ represents the vehicle mobility. The proposed scheme is being compared with 1) the Conventional Traffic Offloading (CTO) scheme 2) the SDN-enabled Traffic Offloading (STO) scheme and 3) the Vehicle Traffic Offloading (VTO) scheme. When compared to the other techniques described, simulation results demonstrate that the suggested traffic offloading methodology may significantly improve network performance, load balance, and user service ratio.

The Table 7 summarizes the offloading decision criteria and its targeted candidates, while Table 8 provides performance metrics for congestion based.

5. Challenge and future research trends

Mobile data offloading is still a hot research topic in the networking area. Despite the extensive existing research in this field, there are still many unanswered questions, restricting the full potential of this field. Thus, this section aims to provide insights into the current issues and suggest potential approaches for future research.

5.1. Challenges

Mobility: One of the challenges is the mobility of the user, which the network operator is unable to control and predicts in some scenarios. In mobile networks, mobility covers the mobile users' movement patterns as well as how their position, velocity, and acceleration vary over time

Table 7
Offloading Decision Criteria and Target Candidates: Congestion Based.

Ref	When to Offload	Targeted Candidate	Decision Maker	Decision Criteria
(Liu et al., 2018b)	When user entered the Wi-Fi network region.	Based on the offloading ratio.	Network	Traffic loadUser's Mobility
(Mochizuki et al., 2019)	Based on three conditions: When the user moves from high load eNB to low load eNB.When BS achieves a higher load. When the user moves to the Wi-Fi network region.	Based on the RL server decision.	Network	Content Delay ToleranceBS loadUser's Mobility
(Zhou et al., 2020b)	When a user requests the same content as the initial seed from the MNO.	Users who are in the same region as D2D initial seed and request the same content.	Network	Traffic Cost, Requested Content
(Raja et al., 2020)	When the user achieves a higher load traffic.When a user is in the RSU region.	User with higher bandwidth-consuming application.Use the RSU region.	Network, User	Bandwidth Network Load, Device's Battery,SINR
(Fan et al., 2020)	When congestion happens.	According to the type of user	Network	Traffic LoadUser Delay Tolerance

Table 8
Performance Metrics: Congestion Based.

Ref(s)	Technology	Evaluation Metrics
(Liu et al., 2018b)	Wi-Fi	Throughput,Blocking ProbabilitySystem Utility
(Mochizuki et al., 2019)	SCN/Wi-Fi	Cellular Infrastructure Utilization Efficiency
(Zhou et al., 2020b)	D2D	Content Utility
(Raja et al., 2020)	VANET (V2X)	LatencyThroughput
(Fan et al., 2020)	VANET (V2I)	Throughput,Load Balance,User Service Ratio

(Bai and Helmy, 2004). According to Tabassum, Salehi, and Hossain (2019), the mobility model may be described as a purely random model, as well as spatially correlated and temporally correlated models. It is important to include the mobility of the user in the offloading mechanisms, as the user's mobility that may affect

the data offloading efficiency in terms of degradation in QoS and QoE.

Security and Privacy Risks: Besides that, in D2D offloading, other issues need to be further studied, among which the security and privacy risks of mobile users are uncertain. Since D2D technology is a kind of content sharing between users in a certain region, the leak or risk in privacy terms could be high. According to Jayakumar (2021) D2D communication still has many concerns and challenges that need to be further studied.

5.2. Future research trends

Hybrid Decision-Making: One of the trends is the consideration of user-centric and network-centric parameters in offloading decision-making. Most of the existing literature has studied either user-centric decision-making or network-centric decision-making. There is still open research in terms of hybrid decision-making, i.e., the combination of user-centric and network-centric decision-making. Both the network and user have their decision criteria in the offloading process, and each of them wants to maximize their benefit. By considering hybrid decision-making, the network performance, and the quality of experience of users have the potential to be improved simultaneously.

Integration of Smart Network: Smart networks refer to the involvement of Artificial Intelligence (AI), IoT, and IoE (Yulei Wu, Dai, Wang, Xiong, and Guo, 2022) in the development of the heterogeneous network architecture. AI could dynamically learn and forecast (Gregory, Henfridsson, Kaganer, and Kyriakou, 2021) the network pattern, thus assisting in resource allocation. These advanced technologies also will efficiently enhance the QoS of the network in terms of latency, jitter control, packet loss, and bandwidth management for data flows.

6. Conclusion

Mobile data offloading serves as a method to reduce the load on cellular base stations by transferring a portion of the data traffic from the base station to another network. The surge in mobile data traffic, especially in the ongoing digital transformation, underscores the importance of studying mobile data offloading techniques. Offloading is able to reduce the load on mobile networks, enhances the Quality of Service (QoS) and Quality of Experience (QoE), improving energy efficiency and also lowers the cost of downloading information. The review paper aimed to provide a comprehensive overview of various technologies and techniques for mobile data traffic offloading.

This paper examines offloading technologies into four groups: SCNs, cellular-Wi-Fi, D2D, and VANETs. The SCNs and Wi-Fi offloading involve migrating data traffic to the alternative infrastructure i.e. the small BS and the Wi-Fi AP, respectively while D2D focuses on transferring data through the device without transversing the BSs. VANETs are the process of offloading data in vehicular scenarios that consist of Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X). The decision to offload users from the cellular base station typically hinges on four factors: energy consumption, economic considerations, user satisfaction, and network congestion. From the observations, in Wi-Fi and V2I technologies, offloading usually occurs when an AP is available near the user's location. In addition, different technologies employ various techniques to address the offloading issue, depending on the research objective. However, it's worth noting that the most used techniques are the Stackelberg Game (either the three-stage or two-stage game) and optimization techniques. In the D2D technology, the content requests made by the users to either the cellular base station or the initial seeds primarily influenced the offloading process.

It has been observed that while offloading can significantly improve network performance and energy efficiency, some issues related to mobility, privacy, and security risks should also be addressed. Thus, to overcome these challenges, it is suggested to adapt the hybrid decision-making and integration of smart cities into heterogeneous network architectures.

CRediT authorship contribution statement

Noryusra Rosele: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Khuzairi Mohd Zaini:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Nurakmal Ahmad Mustaffa:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing. **Ahmad Abrar:** Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing, Funding acquisition. **Suzi Iryanti Fadilah:** . **Mohammed Madi:** Project administration.

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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References

Abrar, A., Arif, A.S.C.M., Zaini, K.M., 2022. A mobility mechanism to manage producer mobility in named data networking. Paper Presented at the 2022 IEEE Region 10 Symposium (TENSYMP).
Abrar, A., Arif, A. S. C. M., Zaini, K. M., bin Omar, M. T. M. H., & Meng, Y. (2024). Advancing producer mobility management in Named Data Networking: A comprehensive analytical model. J. King Saud Univ.-Comput. Informat. Sci., 102045.
Agamy, A., Mohamed, A.M., 2021. Impact of offloading on the efficiency of wireless access networks. Int. J. Wireless Inf. Networks 28 (1), 134–146.
Aijaz, A., Aghvami, H., Amani, M., 2013. A survey on mobile data offloading: technical and business perspectives. IEEE Wirel. Commun. 20 (2), 104–112.
Alagrami, A., Elmesalawy, M.M., Abd El-Haleem, A.M., 2019. Enhanced ANDSF WiFi Discovery Mechanism Using Machine Learning for Mobile Data Offloading. Paper Presented at the 2019 15th International Computer Engineering Conference (ICENCO).
Al-Turjman, F., Ever, E., Zahmatkesh, H., 2018. Small cells in the forthcoming 5G/IoT: Traffic modelling and deployment overview. IEEE Commun. Surv. Tutorials 21 (1), 28–65.

Andrae, A.S., Edler, T., 2015. On global electricity usage of communication technology: trends to 2030. Challenges 6 (1), 117–157.
Ansari, R.I., Chrysostomou, C., Hassan, S.A., Guizani, M., Mumtaz, S., Rodriguez, J., Rodrigues, J.J., 2017. 5G D2D networks: Techniques, challenges, and future prospects. IEEE Syst. J. 12 (4), 3970–3984.
Apostolaras, A., Iosifidis, G., Chounos, K., Korakis, T., Tassiulas, L., 2014. C2M: Mobile data offloading to mesh networks. Paper Presented at the 2014 IEEE Global Communications Conference.
Apostolaras, A., Iosifidis, G., Chounos, K., Korakis, T., Tassiulas, L., 2016. A mechanism for mobile data offloading to wireless mesh networks. IEEE Trans. Wirel. Commun. 15 (9), 5984–5997.
Bai, F., Helmy, A., 2004. A survey of mobility models in wireless adhoc networks. Wireless Ad Hoc and Sensor Networks 1–30.
Bhooanusas, N., Sou, S.-I., Cheng, K.-C., 2021. Satisfaction-based Dynamic Bandwidth Reallocation for multipath mobile data offloading. Comput. Netw. 185, 107594.
Björnson, E., Larsson, E.G., 2018. How energy-efficient can a wireless communication system become? Paper Presented at the 2018 52nd Asilomar Conference on Signals, Systems, and Computers.
Chakraborty, A., Kar, A.K., 2022. How does internet of everything enable digital transformation: A review and a research agenda from an editorial perspective. Manag. Dyn. 22 (2), 9.
Chandrasekhar, V., Andrews, J.G., Gatherer, A., 2008. Femtocell networks: a survey. IEEE Commun. Mag. 46 (9), 59–67.
Chen, X., Wu, J., Cai, Y., Zhang, H., Chen, T., 2015. Energy-efficiency oriented traffic offloading in wireless networks: A brief survey and a learning approach for heterogeneous cellular networks. IEEE J. Sel. Areas Commun. 33 (4), 627–640.
Cheon, H.-R., Kim, J.-H., 2019. Social-aware mobile data offloading algorithm through small cell backhaul network: Direct and indirect user influence perspectives. Comput. Netw. 165, 106951.
Cheung, M.H., Huang, J., 2015. DAWN: Delay-aware Wi-Fi offloading and network selection. IEEE J. Sel. Areas Commun. 33 (6), 1214–1223.
Cisco, U., 2020. Cisco annual internet report (2018–2023) white paper. Cisco: San Jose, CA, USA 10 (1), 1–35.
De, D., Mukherjee, A., 2017. Group handoff management in low power microcell-femtocell network. Digital Commun. Networks 3 (1), 55–65.
Elhami, G., Zehni, M., Pakravan, M.R., 2015. A survey on heterogeneous access networks: Mobile data offloading. Paper Presented at the 2015 23rd Iranian Conference on Electrical Engineering.
Fakhfakh, E., Hamouda, S., 2017. Optimised Q-learning for WiFi offloading in dense cellular networks. IET Commun. 11 (15), 2380–2385.
Fan, B., He, Z., Wu, Y., He, J., Chen, Y., Jiang, L., 2020. Deep learning empowered traffic offloading in intelligent software defined cellular V2X networks. IEEE Trans. Veh. Technol. 69 (11), 13328–13340.
Feng, G., Lv, H., Wang, C., Xia, F., Lv, H., Wang, H., Zhao, Q., 2018a. A non-cooperative game-theoretical approach to mobile data offloading. Paper Presented at the 2018 IEEE Global Communications Conference (GLOBECOM).
Feng, G., Xia, F., Zhang, Y., Su, D., Lv, H., Wang, H., Lv, H., 2018b. Optimal cooperative wireless communication for mobile user data offloading. IEEE Access 6, 16224–16234.
Feng, B., Zhang, C., Liu, J., Fang, Y., 2019. D2D communications-assisted traffic offloading in integrated cellular-WiFi networks. IEEE Internet Things J. 6 (5), 8670–8680.
Ferretti, S., Ghini, V., Panzieri, F., 2016. A survey on handover management in mobility architectures. Comput. Netw. 94, 390–413.
Gregory, R.W., Henfridsson, O., Kaganer, E., Kyriakou, H., 2021. The role of artificial intelligence and data network effects for creating user value. Acad. Manag. Rev. 46 (3), 534–551.
Huang, C.-W., Chen, P.-C., 2020. Joint demand forecasting and DQN-based control for energy-aware mobile traffic offloading. IEEE Access 8, 66588–66597.
Huang, C.-M., Chiang, M.-S., Dao, D.-T., Su, W.-L., Xu, S., Zhou, H., 2018. V2V data offloading for cellular network based on the software defined network (SDN) inside mobile edge computing (MEC) architecture. IEEE Access 6, 17741–17755.
Jayakumar, S., 2021. A review on resource allocation techniques in D2D communication for 5G and B5G technology. Peer-to-Peer Network. Appl. 14, 243–269.
Kar, U.N., Sanyal, D.K., 2020. A critical review of 3GPP standardization of device-to-device communication in cellular networks. SN Computer Science 1 (1), 37.
Kaushik, S. (2012). An overview of technical aspect for WiFi networks technology. Int. J. Electron. Comput. Sci. Eng. (IJECSE, ISSN: 2277-1956), 1(01), 28-34.
Khan, S.A., Kavak, A., Kucuk, K., Asshad, M., 2019. A new fractional frequency reuse method for interference management in LTE-A HetNets. Paper Presented at the 2019 27th Signal Processing and Communications Applications Conference (SIU).
Kim, Y., Lee, J., Jeong, J., Chong, S., 2017. Multi-flow management for mobile data offloading. ICT Express 3 (1), 33–37.
Ko, H., Lee, J., Pack, S., 2017. Performance optimization of delayed WiFi offloading in heterogeneous networks. IEEE Trans. Veh. Technol. 66 (10), 9436–9447.
Kumari, S., Singh, B., 2017. Comparative Study of Power Consumption in Different Small Cell Networks. Information & Communication Technology (RTEICT).
Lee, M., Atkison, T., 2021. VANET applications: Past, present, and future. Veh. Commun. 28, 100310.
Lee, J., Yi, Y., Chong, S., Jin, Y., 2014. Economics of WiFi offloading: Trading delay for cellular capacity. IEEE Trans. Wirel. Commun. 13 (3), 1540–1554.
Li, F., Wang, X., Cao, J., Wang, R., Bi, Y., 2017. A state transition-aware energy-saving mechanism for dense WLANs in buildings. IEEE Access 5, 25671–25681.
Li, Y., Zhang, J., Gan, X., Fu, L., Yu, H., Wang, X., 2016. A contract-based incentive mechanism for delayed traffic offloading in cellular networks. IEEE Trans. Wirel. Commun. 15 (8), 5314–5327.
Li, Y., Li, J., Ahmed, M., 2020. A three-stage incentive formation for optimally pricing social data offloading. J. Netw. Comput. Appl. 172, 102816.
Lin, B., Wu, S., 2022. Digital transformation in personalized medicine with artificial intelligence and the internet of medical things. OMICS 26 (2), 77–81.
Liu, D., Khoukhi, L., Hafid, A., 2017. Data offloading in mobile cloud computing: A Markov decision process approach. Paper Presented at the 2017 IEEE International Conference on Communications (ICC).
Liu, D., Khoukhi, L., Hafid, A., 2018a. Prediction-based mobile data offloading in mobile cloud computing. IEEE Trans. Wirel. Commun. 17 (7), 4660–4673.
Liu, D., Hafid, A., Khoukhi, L., 2020. Multi-item auction based mechanism for mobile data offloading: A robust optimization approach. IEEE Trans. Veh. Technol. 69 (4), 4155–4168.
Liu, B., Zhu, Q., Tan, W., Zhu, H., 2018b. 2018. Congestion-optimal WIFI offloading with user mobility management in smart communications, Wireless Communications and Mobile Computing.
Matei, I., Baras, J.S., 2011. Performance evaluation of the consensus-based distributed subgradient method under random communication topologies. IEEE J. Sel. Top. Signal Process. 5 (4), 754–771.
Matsumoto, H., Gu, B., Mizuno, O., 2019. A V2X task offloading method considering automobiles' behavior in urban area. Paper Presented at the 2019 20th Asia-Pacific Network Operations and Management Symposium (APNOMS).
Mehmeti, F., Spyropoulos, T., 2014. Is it worth to be patient? Analysis and optimization of delayed mobile data offloading. Paper Presented at the IEEE INFOCOM 2014-IEEE Conference on Computer Communications.
Mochizuki, D., Abiko, Y., Saito, T., Ikeda, D., Mineno, H., 2019. Delay-tolerance-based mobile data offloading using deep reinforcement learning. Sensors 19 (7), 1674.
Nitti, M., Stelea, G.A., Popescu, V., Fadda, M., 2019. When social networks meet D2D communications: A survey. Sensors 19 (2), 396.
Ozturk, M., Abubakar, A.I., Nadas, J.P.B., Rais, R.N.B., Hussain, S., Imran, M.A., 2021. Energy optimization in ultra-dense radio access networks via traffic-aware cell switching. IEEE Trans. Green Commun. Network. 5 (2), 832–845.
Pan, Y., Pan, C., Zhu, H., Ahmed, Q.Z., Chen, M., Wang, J., 2017. On consideration of content preference and sharing willingness in D2D assisted offloading. IEEE J. Sel. Areas Commun. 35 (4), 978–993.
Qiao, Y., Li, Y., Li, J., 2020. An economic incentive for D2D assisted offloading using stackelberg game. IEEE Access 8, 136684–136696.
Raja, G., Ganapathisubramaniyan, A., Anbalagan, S., Baskaran, S.B.M., Raja, K., Bashir, A.K., 2020. Intelligent reward-based data offloading in next-generation vehicular networks. IEEE Internet Things J. 7 (5), 3747–3758.
Rebecchi, F., De Amorim, M.D., Conan, V., Passarella, A., Bruno, R., Conti, M., 2014. Data offloading techniques in cellular networks: A survey. IEEE Commun. Surv. Tutorials 17 (2), 580–603.
Saliba, D., Imad, R., Houcke, S., El Hassan, B., 2019. WiFi Dimensioning to offload LTE in 5G Networks. Paper Presented at the 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC).
Song, Y., Kong, P.-Y., Han, Y., 2015. Minimizing energy consumption through traffic offloading in HetNets with two-class traffic. IEEE Commun. Lett. 19 (8), 1394–1397.
Song, X., Qin, L., Qi, H., Li, S., Qian, H., Dong, L., Ni, Y., 2020. Incentive framework for mobile data offloading market under QoE-aware users. IET Commun. 14 (13), 2151–2161.
Sun, L., Zhu, Q., 2019. WiFi offloading algorithm based on Q-learning and MADM in heterogeneous networks. Mob. Inf. Syst. 2019, 1–12.
Tabassum, H., Salehi, M., Hossain, E., 2019. Fundamentals of mobility-aware performance characterization of cellular networks: A tutorial. IEEE Commun. Surv. Tutorials 21 (3), 2288–2308.
Tan, A.S., Zeydan, E., 2018. Performance maximization of network assisted mobile data offloading with opportunistic Device-to-Device communications. Comput. Netw. 141, 31–43.
Tang, W., Wu, C., Qi, L., Zhang, X., Xu, X., Dou, W., 2021. A WiFi-aware method for mobile data offloading with deadline constraints. Concurrency and Computation: Practice and Experience 33 (7), 1.
Tao, R., Liu, W., Chu, X., Zhang, J., 2019. An energy saving small cell sleeping mechanism with cell range expansion in heterogeneous networks. IEEE Trans. Wirel. Commun. 18 (5), 2451–2463.
Thien, H.T., Vu, V.-H., Koo, I., 2020. Game theory-based smart mobile-data offloading scheme in 5G cellular networks. Appl. Sci. 10 (7), 2327.
Tran-Dang, H., Kim, D.-S., 2021. The physical internet in the era of digital transformation: perspectives and open issues. IEEE Access 9, 164613–164631.
Wang, W., Li, H., Zhang, W., Wei, S. (2020). Energy efficiency for data offloading in D2D cooperative caching networks. Wireless Commun. Mobile Comput., 2020.
Wang, T., Li, P., Wang, X., Wang, Y., Guo, T., Cao, Y., 2019. A comprehensive survey on mobile data offloading in heterogeneous network. Wirel. Netw 25, 573–584.
Wang, Q., Sun, H., Hu, R.Q., Bhuyan, A., 2022. When machine learning meets spectrum sharing security: Methodologies and challenges. IEEE Open J. Commun. Soc. 3, 176–208.
Wang, N., Wu, J., 2016. Opportunistic WiFi offloading in a vehicular environment: Waiting or downloading now? Paper Presented at the IEEE INFOCOM 2016-the 35th Annual IEEE International Conference on Computer Communications.
Wu, Y., He, Y., Qian, L.P., Huang, J., Shen, X., 2018. Optimal resource allocations for mobile data offloading via dual-connectivity. IEEE Trans. Mob. Comput. 17 (10), 2349–2365.
Wu, Y., Dai, H.-N., Wang, H., Xiong, Z., Guo, S., 2022. A survey of intelligent network slicing management for industrial IoT: Integrated approaches for smart transportation, smart energy, and smart factory. IEEE Commun. Surv. Tutorials 24 (2), 1175–1211.

Yan, X., Şekercioğlu, Y.A., Narayanan, S., 2010. A survey of vertical handover decision algorithms in Fourth Generation heterogeneous wireless networks. Comput. Netw. 54 (11), 1848–1863.

Zhang, X., Guo, L., Li, M., Fang, Y., 2017. Motivating human-enabled mobile participation for data offloading. IEEE Trans. Mob. Comput. 17 (7), 1624–1637.

Zhang, X., Huang, P., Guo, L., Fang, Y., 2019. Social-aware energy-efficient data offloading with strong stability. IEEE/ACM Trans. Networking 27 (4), 1515–1528.

Zhao, Y., Xu, K., Zhong, Y., Li, X.-Y., Wang, N., Su, H., Li, Z., 2020. Incentive mechanisms for mobile data offloading through operator-owned WiFi access points. Comput. Netw. 174, 107226.

Zheng, L., Chen, J., Joe-Wong, C., Chee, W.T., Chiang, M., 2017. An economic analysis of wireless network infrastructure sharing. Paper Presented at the 2017 15th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt).

Zhou, Y., Ai, B., 2014. Handover schemes and algorithms of high-speed mobile environment: A survey. Comput. Commun. 47, 1–15.

Zhou, H., Wang, H., Chen, X., Li, X., Xu, S., 2018a. Data offloading techniques through vehicular ad hoc networks: A survey. IEEE Access 6, 65250–65259.

Zhou, H., Wang, H., Li, X., Leung, V.C., 2018b. A survey on mobile data offloading technologies. IEEE Access 6, 5101–5111.

Zhou, H., Chen, X., He, S., Chen, J., Wu, J., 2020a. DRAIM: A novel delay-constraint and reverse auction-based incentive mechanism for WiFi offloading. IEEE J. Sel. Areas Commun. 38 (4), 711–722.

Zhou, H., Chen, X., He, S., Zhu, C., Leung, V.C., 2020b. Freshness-aware seed selection for offloading cellular traffic through opportunistic mobile networks. IEEE Trans. Wirel. Commun. 19 (4), 2658–2669.