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Dynamic Cellular-Wi-Fi Offloading Strategy Inspired by Cloud Load Balancer Mechanism

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ABSTRACT

The evolution of mobile communication technology has coincided with the rapid growth in mobile applications and Internet of Things (IoT) services. As a result, it is anticipated that data will increase and duplicate rapidly, which may lead to network overload and slowdowns. On the other hand, the radio spectrum is finite, and network service providers have to ensure user satisfaction, including low latency, high access speed, and minimal energy consumption. Offloading technology is a promising technique to mitigate the traffic load problem from cellular networks to other types of networks, such as Wi-Fi. This paper proposes a modified dynamic Access Network Discovery and Selection Function (ANDSF) cellular to Wi-Fi offloading algorithm for dense mobile networks. The modified ANDSF is inspired by the adoption of the concept of dynamic variation of the Cloud Load Balancer (CLB) mechanism. The performance of the cellular network is evaluated by comparing the legacy ANDSF offloading algorithm and its modified version. The obtained results show that the performance of the entire network is improved in terms of data throughput, latency, energy consumption, and packet loss by 59%, 33%, 42%, and 46%, respectively.

1. INTRODUCTION

Wireless access communication scales rapidly due to the widespread adoption of Smart Mobile Devices (SMDs), including smartphones, tablets, personal computers, personal digital assistants (PDAs), smart terminals, wearables, and virtual reality devices [1]. Several new requirements for Internet of Things (IoT) applications have also been brought about by the proliferation of SMDs and the development of 5G networks [2, 3]. Recently, more applications have become needed in advance of higher demand for security, real-time, and intelligence to improve the Quality of Experience (QoE) of SMDs. Applications are becoming more and more dependent on response times [4]. The key problem presented in crowded mobile environments is that users may experience decreased performance due to network overload, especially in cellular networks. Traditional Access Network Discovery and Selection Function (ANDSF)-based offloading methods employ static rules to transfer data from cellular to Wi-Fi networks, without considering the current network state. In other words, it lacks real-time adaptation and inadequate handling of network overcrowding. This often leads to inefficient offloading decisions, increased latency, packet loss, and energy consumption. The disparity between the need to execute complicated applications and SMDs' limited capabilities rapidly becomes more pronounced [5]. Compared to conventional SMD applications, these computing-intensive applications demand more energy and processing capacity [6, 7]. It is generally more difficult to run these mobile apps efficiently on SMDs due to their constrained computing capabilities (such as memory and CPU frequency) and battery life [8].

In order to address these restrictions, in this paper, a dynamic offloading technique that incorporates the Cloud Load Balancer (CLB) mechanism into the ANDSF decision-making is proposed. The system adjusts transmission rates and makes wise, real-time offloading decisions that improve network performance by continuously monitoring throughput, Round-Trip Time (RTT), packet loss, and power consumption. Offloading, as used in 4G and 5G cellular networks, is the process of rerouting data traffic to other networks, such as Wi-Fi and small cells, to reduce overload and improve user experience. Computation offloading, also known as Mobile Cloud Computing (MCC), is envisioned as a potential solution to the difficulty of moving computations from the SMD to the cloud server [9] since the cloud server has better capacity and storage than the SMD. Relocating the cloud computing resource close to SMDs is possible with Mobile Edge Computing (MEC) [10]. Moreover, Ultra Dense Networks (UDNs), in particular, compute all offloading tasks to the MEC server increases interference and leads to unanticipated transmission delays [11]. As a result, some computation tasks should be carried out on SMDs (local computing), as it is not feasible to transfer all of them to the MEC server. Local computing can dramatically reduce execution latency and consume more energy without extra communication or waiting time [12].

Wi-Fi is a wireless networking technology that complies with IEEE 802.11 specifications. It provides a free solution that does not interfere with cellular network operations by operating in the unlicensed frequency bands of 2.5 GHz Ultra High Frequency (UHF) and 5 GHz Super High Frequency (SHF) [13, 14]. Wi-Fi could be categorized into third-party and operator-owned networks. Wi-Fi providers operate the third-party Wi-Fi infrastructure, with the cellular operator paying them for data usage. Meanwhile, the operator-owned Wi-Fi is deployed and managed by the carriers themselves [15]. Wi-Fi services are already offered in a variety of places, including restaurants, houses, and public spaces like airports and libraries. Also, the majority of modern mobile devices are equipped with built-in Wi-Fi technology as an alternative to the cellular network. Mobile devices that support Wi-Fi technology allow offloading data traffic from the cellular network to the Wi-Fi network through the Wi-Fi Access Point (AP). Wi-Fi-based data offloading has many benefits for users as well. In comparison to using the cellular network, users may have a greater transmission rate and reduce their billing or data subscription [16]. Furthermore, energy conservation when utilizing the Wi-Fi network might prolong the battery life of the device [17]. Meanwhile, this technology helps improve network capacity management and lessen network overload from the standpoint of a mobile network operator [18]. As a result, data offloading over a Wi-Fi network has emerged as an additional choice for offloading mobile data traffic. Nevertheless, 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 [19]. To investigate the best trade-off among energy consumption, latency, and throughput, we concentrate on assessing the performance of offloading cellular network traffic algorithms to Wi-Fi networks in this study. This paper's primary contributions are as follows:

- Adopting the CLB mechanism to modify the ANDSF offloading algorithm from a static to a dynamic operation.
- Simulation and evaluation of the point of interest metrics, including consumed energy, correlated latency, and the corresponding data throughput for both the traditional ANDSF and its modified version.

The rest of this paper is organized as follows: Section 2 provides an overview of the relevant works on offloading cellular network traffic to Wi-Fi networks. In Section 3, a concise description of the theoretical research background is introduced. The design of the proposed offloading algorithms is illustrated in Section 4. In Section 5, the evaluation processes are demonstrated. Section 6 includes a simulation and discussion. In Section 7, the conclusion of the paper is presented.

2. RELATED WORK

The offloading technique in cellular networks has received noticeable attention from academia due to its urgent requirement to meet the exponential growth of connections, represented by ordinary human subscribers, along with the communicating machines [20]. Mainly, four key routes have been followed to tackle the challenges of offloading in mobile networks. The first method of offloading is called "offloading to the cloud," out of four. Cellular network to small cells or other networks is the second strategy; device-to-edge computing nodes are the third. The fourth strategy, which represents the point of interest in this work, is the cellular network for Wi-Fi offloading. Hence, a concise review of the research contributions related to cellular networks for Wi-Fi offloading is demonstrated as follows. The reviewed papers can be mainly classified into the following primary groups, including first techniques for static offloading (such as conventional ANDSF-based techniques). Second, network metrics-based dynamic offloading, e.g., latency and throughput. Third, predictive-based offloading and machine learning. Last but not least, network bottleneck-aware techniques. Regarding the static offloading research studies, Hagos [21] proposed a fixed SNR threshold-based handover algorithm, which is straightforward to implement and integrated with an extension to the ANDSF framework for Long-Term Evolution (LTE)-to-Wi-Fi offloading. The simulation results indicate that this method effectively controls offloading onto Wi-Fi, thereby further enhancing network performance.

Corici et al. [22] proposed the ANDSF architecture. It allows for seamless network discovery and optimized selection for various access types such as Wi-Fi and cellular. In doing so, the proposed system helps provide a better user experience in the sense of deciding on handover based on policy and context-awareness. Another challenge arises here when a static offloading policy similar to the ANDSF is used will result as follows: when the offloading is fixed, for instance, a pre-defined number of users (e.g., only 10 are off-loaded to Wi-Fi), while the network can handle more (20 or 30 users or maybe more), this means a static offloading policy is used. The lack of adaptability can lead to excessive load on the cellular network and underuse of the Wi-Fi network capacity. Because the load stays constant, nothing changes whether the number of users rises or usage patterns shift. Some literature tried to enhance the traditional ANDSF algorithm. In 2017, Leu et. al. [23] tried to enhance E-ANDSF, which relies on the filtering of the best asymmetric non-Third Generation Partnership Project (3GPP) and its base station during handover connection, focusing more on heterogeneous or non-aligned networks by the multiple parameters decision-making mechanism. This solution enhances the hand-off efficiency and dictates the optimal choice of receiving network and station.

Other techniques have utilized network metrics for dynamic offloading (e.g., latency, throughput, traffic overload). To increase the bandwidth available in cellular networks, Ajao et al. [24] suggested classifying cellular customers based on usage patterns and rerouting unnecessary data traffic onto Wi-Fi networks (a practice known as Wi-Fi offloading). They suggest a hybrid solution to improve the quality of service and alleviate cellular network overload. The outcomes show observable increases in network performance and decreased usage of cellular capacity. In 2023, Ahmad and Awang [25] tried to find out how effective Wi-Fi offloading is in reducing mobile data usage in an office setting. The results were based on actual measurements of users' reliance on Wi-Fi networks instead of cellular networks while at work. The findings showed that Wi-Fi offloading improves user experience while dramatically lowering cellular network load. A performance model for multipath mobile data offloading in cellular/Wi-Fi networks under bandwidth uncertainty is suggested by

Bhooanusas and Sou [26]. The study optimizes path selection for increased offloading efficiency by analyzing energy and delay trade-offs. Fan et al. [27] focused on mapping the performance of mobile data offloading across cellular and Wi-Fi networks as well as numerous pathways. It calculates the impact of fluctuating bandwidth on performance. Multipath Transmission Control Protocol (TCP) is used in this study to transfer dynamic user access between the two networks. Overall results indicate that it boosts the efficiency of bandwidth use, as well as a decline in data loss and delay. In 2022, Vanitha et al. [28] proposed a multi-criteria prediction mechanism for offloading vehicle data to Wi-Fi networks instead of cellular networks. The mechanism uses parameters such as vehicle speed, density of Wi-Fi hotspots, and type of service needed to make the best offloading decision. The results showed a better reduction in cellular data consumption and stability in connection.

The coexistence of Wi-Fi and heterogeneous small cell networks sharing an unlicensed spectrum is examined by Xiao et. al. [29] to enhance the performance of both networks when they share a frequency band. The study also suggests an interference avoidance technique based on the calculation of the density of nearby access points. The influence of data offloading on wireless access network efficiency is suggested by Zreikat and Alabed [30], with a focus on mixed LTE and Wi-Fi situations. An analytical model that considers various application and their effects on service quality was created. Performance was assessed using the network simulator and measures like throughput, latency, and packet loss under different traffic loads.

Another research approach related to the field of machine learning and predictive mechanisms is discussed as follows. Alawi et al. [31] studied channel allocation in hybrid networks based on Wi-Fi and cellular technology. The study proposes a dynamic channel allocation algorithm under network conditions and user demand. The results prove that this method minimizes interference with consequent improvement in spectrum efficiency and quality of service. Alagrami et al. [32] used the signal strength received from cellular base stations to build Wi-Fi fingerprints and assess their coverage via a decision tree-based machine learning algorithm, thus reducing the reliance on place. This method can increase the accuracy of detecting active Wi-Fi hotspots while not requiring continual location updates. Likewise, Raja et al. [33] proposed an intelligent reward data offloading system using a reinforcement learning algorithm within the intelligent ANDSF module to dynamically shift data traffic to optimal Wi-Fi access points, improving performance and reducing latency.

Furthermore, it is worth stating that users may have significant performance-affecting problems if they are moved to a crowded network (such as crowded Wi-Fi) without first verifying its true condition. The most significant of these are: heavy degradation in QoS, increasing latency, high packet loss, negative effects on the existing users, and new users utilizing network resources, thus causing overload. The research study conducted by Zhao et al. [34] in 2024 developed a joint strategy implementation of offloading and caching services in multi-access edge computing on heterogeneous Wi-Fi and cellular networks. An improved model balancing response time and energy consumption is suggested. Simulation results have shown that the combination of task offloading and service caching extends system performance while effectively conserving network resources. In order to alleviate network overload and improve wireless capacity, Han [35] proposed an offloading technique that dynamically determines whether to use cellular or Wi-Fi depending on throughput capacity and real-time congestion levels. It allows for better offloading efficiency under ambiguous bandwidth constraints by taking into account both bottleneck avoidance and network condition variations. In this paper, a dynamic offloading strategy is proposed using the concepts of the CLB Mechanism to offload the network's users dynamically and adaptively. Table 1 includes a summary of the limitations of the prior works.

Table 1. Summary of research gaps in the existing work

References	Aspects Require Further Investigation
[21]	It considers a fixed SNR threshold for offloading that never adapts to real-time variations without a multi-metric context-aware offloading strategy.
[22]	It depends on static policies that are based on operator properties. Hence, an adaptive decision-making process is required.
[23]	Lacks the flexibility to adjust to changing network performance and is dependent on fixed ANDSF actions.
[24]	Lacks real-time dynamic user association and delay-sensitive decision-making under mobility, but it concentrates on energy harvesting and offloading in ultra-dense MEC.
[25]	A measurement study, but it has no intelligent adaptation or prediction strategies for real-world deployments.
[24]	Addresses multipath offloading but disregards energy trade-offs and real-time bandwidth variations.
[27]	Deals with multipath offloading, but ignores real-time bandwidth fluctuations and energy trade-offs.
[28]	lacked adaptive or predictive channel allocation mechanisms and employed static channel allocation strategies without taking into account real-time traffic variations or user mobility patterns.
[29]	Offers offloading that is guaranteed to be reliable, but it does not have context-aware ANDSF adaptation.
[30]	Lacks adaptive learning-based control strategies but models the coexistence of LTE and Wi-Fi.
[31]	More focus on situations with sparse or inconsistent historical records is required because it depends on historical connectivity and trajectory data.
[32]	Requires more investigation into sophisticated learning models and more comprehensive context, such as user behavior or network load.
[33]	Suggests reward-based offloading in vehicle networks, but it lacks energy modeling and system-wide performance, such as real mobility.
[34]	It restricts the application in extremely dynamic settings and the ability to adjust in real time to erratic workload arrivals.
The proposed approach	A dynamic offloading algorithm makes adaptive, energy-efficient decisions by utilizing real-time network metrics and CLB behavior. Outperforming conventional static ANDSF, it dramatically increases throughput, lowers latency and packet loss, and scales well with growing user load.

3. RESEARCH BACKGROUND

In this section, the basic concepts of key components of this research will be explained, including the features of hybrid offloading algorithms, the details of the ANDSF offloading algorithm, and the mechanism of the CLB is discussed.

3.1 Hybrid cellular/Wi-Fi offloading algorithm

Hybrid access networks represent a reliable and efficient means of meeting the increasing demands for connectivity. Their intelligent combination of multiple technologies enhances speed, reliability, and coverage, especially in hardened environments. The hybrid method combines mobile networks such as 4G and Wi-Fi to improve connection performance, reduce latency, and increase data transfer speeds. Hence, the device (e.g., smartphone) can use cellular and Wi-Fi networks simultaneously in the hybrid mode technology, either by aggregating to increase the overall speed or by smart switching to improve stability and connection quality [36]. Hence, data traffic is automatically transferred between Wi-Fi and mobile devices, as shown in Figure 1. Table 2 illustrates the features of the hybrid offloading technique compared to a one-directional method.

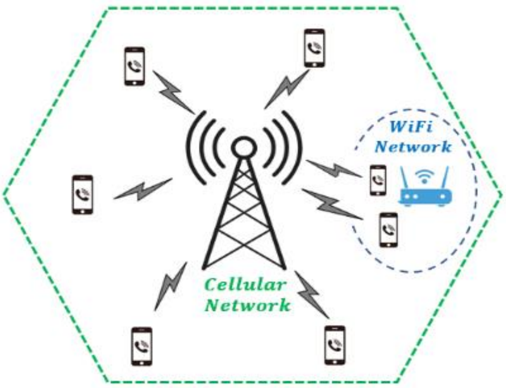

Figure 1. Main cellular (3GPP) network co-located with the alternative Wi-Fi (non-3GPP) network

Table 2. Comparison between the hybrid and one-direction offloading algorithms

Property	Cellular to Wi-Fi	Hybrid Cellular/Wi-Fi
Offloading direction	One-way	Bi-directional
Adaptive to network conditions	No	Yes
Handling the Wi-Fi bottleneck	No	Yes
Power-aware	Sometimes	Often integrated
Suited for a dense network	Less	More

3.2 Traditional ANDSF, cellular/Wi-Fi offloading algorithm

Offloading between the cellular and Wi-Fi networks can be achieved using network access control mechanisms, namely ANDSF [37], that allow users to connect to a reliable Wi-Fi network when available, rather than staying on the cellular network. Some advantages of Hybrid Wi-Fi/Cellular Offloading are shown in Table 3. The ANDSF is designed to help User Equipment (UE) find non-3GPP access networks, such as Wi-Fi, that can be used for data communications aside from 3GPP access networks, like LTE, and to give the UE rules governing the connection to these networks. There are many challenges [23, 33, 38] faced by ANDSF in achieving this; some challenges may be presented in connecting networks as follows:

1) Switching networks and connecting loss: Whenever users are switching between networks, there is generally a delay or momentary disconnect. Hence, in rapidly changing environments (such as inter-cell mobility), policies may become outdated.

2) Wi-Fi security and cellular networks: Cellular networks are considered more secure compared with public Wi-Fi, which has a higher chance of hacking.

3) Power efficiency: Frequent searching for Wi-Fi networks consumes more than average power within a short time.

4) Static policies are non-dynamic (less adaptive to real-time changes): They rely on pre-configured policies (static policies) by the operator and do not adapt to immediate network changes. For example, if a Wi-Fi network suddenly becomes congested, the UE will not detect this until it is too late.

5) Lack of support for individual applications: ANDSF cannot direct traffic from a specific application (such as YouTube) to a specific network. All decisions are based on general criteria (such as signal strength).

Table 3. Benefits of hybrid cellular/Wi-Fi offloading

Benefit	Impact
Reduced cellular overload	Offloads up to 60–70% of mobile traffic to Wi-Fi [39].
Improved user experience	Seamless streaming, faster downloads.
Cost savings	Users save on cellular data; operators reduce infrastructure costs.
Energy efficiency	Wi-Fi consumes less power than LTE/5G for large data transfers.

3.3 General functions of a CLB

The general key operation functions of the CLB in a real cloud computing context are described as follows [40, 41]:

- Distribution of traffic among several servers: It allows for the distribution of incoming network traffic across a pool of backend servers so that the load is kept off individual servers. This results in more responsive and available applications.
- Autonomous failover and health monitoring: The distributed load balancers or CLBs manage incoming requests and distribute them to a pool of backend servers so that no one server remains overloaded by controlling the workload around servers hitting trouble or experiencing downtime. Therefore, it increases the application's responsiveness and availability.
- Elasticity and scalability: Control lists, being dynamically scalable, cause traffic loads to vary. Thus, control lists can efficiently deal with traffic even while experiencing a high outburst of traffic or with a load increase.

4. THE PROPOSED MODIFIED ANDSF BASED ON CLB

The traditional ANDSF relies on static policies to route traffic between cellular 3GPP and Wi-Fi non-3GPP without considering real-time network overcrowding and connectivity speed fluctuations. Hence, to improve an ANDSF offloading algorithm, the concept of the CLB mechanism is adopted to ensure dynamic adaptation to network conditions. To the best of the authors' knowledge, no prior research study has employed the concept of the CLB mechanism in the operation of the ANDSF algorithm.

4.1 Modifying the network selection mechanism in ANDSF

Instead of relying solely on the priority of pre-stored networks (such as automatically switching to Wi-Fi when available). However, one may wonder what the consequences are when the Wi-Fi becomes congested. Hence, it is required to continuously monitor the status of both cellular and Wi-Fi networks using metrics such as RTT, which indicates the network response time; the packet loss to measure the packet loss rate; and data throughput to estimate the actual data speed of each network. Here, it is required to balance the load between the Wi-Fi and the cellular network instead of unexpected switching. The mathematical formulations for each of the parameters in the given sequence are as follows:

a). Calculating RTT, which is the time it takes for a data packet to get from a device to a destination and back again. It is measured as in Eq. (1).

$$rtt = t_{response} - t_{sent} \quad (1)$$

where, $t_{response}$ denotes the time when the response is received; t_{sent} represents the time when the packet is sent.

Hence, Eq. (1) will be rewritten for each type of network (cellular and Wi-Fi), where the subscripts "cellular" and "Wi-Fi" specifically indicate that the average metric values, such as RTT, packet loss, and throughput, will be determined for each active user connected to the cellular and Wi-Fi networks, respectively.

$$rtt_{cellular} = t_{response_{cellular}} - t_{sent_{cellular}} \quad (2)$$

$$rtt_{wifi} = t_{response_{wifi}} - t_{sent_{wifi}} \quad (3)$$

b). Calculation of Packet Loss (PL): The portion of packets sent that are unsuccessfully received is known as packet loss. It is computed as follows:

$$PL(\%) = \frac{P_{TX} - P_{RX}}{P_{TX}} \quad (4)$$

where, P_{TX} is the number of sending packets; P_{RX} is the number of packets that are successfully received.

Hence, the packet loss in a cellular network can be expressed as follows:

$$PL_{cellular(\%)} = \frac{P_{TX_{cellular}} - P_{RX_{cellular}}}{P_{TX_{cellular}}} \quad (5)$$

Likewise, for the Wi-Fi network, the packet loss is:

$$PL_{wifi(\%)} = \frac{P_{TX_{wifi}} - P_{RX_{wifi}}}{P_{TX_{wifi}}} \quad (6)$$

c). Calculating Throughput (TP) (Download and Upload Speed): The data transfer rate, expressed in megabits per second (Mbps), is known as throughput, as expressed in the following equation:

$$TP = \frac{total\ amount\ of\ data\ transfered}{T_{seconds}} \quad (7)$$

Now, the rate of downlink and uplink for both cellular and Wi-Fi networks can be calculated as follows:

$$TP_{cellular_{DL}} = \frac{DL_{cellular}}{T_{seconds}} \quad (8)$$

$$TP_{cellular_{UL}} = \frac{UL_{cellular}}{T_{seconds}} \quad (9)$$

where, *DL* and *UL* represent the amount of data transferred in download and upload, respectively; $T_{seconds}$ is the time in seconds.

Likewise, for the Wi-Fi network, the data throughput can be calculated as follows:

$$TP_{wifi_{DL}} = \frac{DL_{wifi}}{T_{seconds}} \quad (10)$$

$$TP_{wifi_{UL}} = \frac{UL_{wifi}}{T_{seconds}} \quad (11)$$

d). To determine the power consumption per user when it connects to the cellular network or the Wi-Fi network, the model expressed in Eq. (12) is used. The user device's (UE) overall power consumption is mainly made up of three components: transmission power P_{Tx}, reception power $P_{Rx(i)}$, and idle power P_{Idle}, as follows:

$$P_{UE(i)} = P_{Tx(i)} + P_{Rx(i)} + P_{Idle} \quad (12)$$

where, $P_{Tx(i)}$ is used for sending data, and it relies on path loss and RSS, $P_{Rx(i)}$ is frequently a low value for receiving data, P_{Idle}: used when the UE is connected but not transmitting.

e). Total number of Wi-Fi users connected: The sum of all active devices linked to the Wi-Fi network is the total number of Wi-Fi users, as illustrated in Eq. (13).

$$current_{wifi_{UEs}} = \sum_{i=1}^{N} U_i \quad (13)$$

where, *N* is the total number of devices that the Wi-Fi access point has identified; If a device *i* is connected, the value is 1, else it is 0.

4.2 Procedure for integrating a load balancer in ANDSF offloading

The overall process of the load balancer with the ANDSF offloading algorithm is generally illustrated in Figure 2 and can be summarized in the following seven steps:

Step 1: Using a decision engine in place of static rules

- The traditional ANDSF expects a set of operator policies such as "Prefer Wi-Fi, if available".

- The modified ANDSF delegates offloading actions to a load-balancer decision engine, which considers the real-time performance of the networks.

Step 2: Real-time metrics-gathering

- Continuous extension of ANDSF for collecting defined QoS metrics, namely:
  - RTT, packet loss, signal strength, throughput, and energy consumption
  - Wi-Fi user load and capacity

The above-mentioned are health checks of the load balancer.

Step 3: Assessment of network health

- The load balancer assigns scores to the health of the Wi-Fi and Cellular networks according to the following metrics:

Response time, crowding level, number of users, and power usage. These scores are the basis for offload decisions.

Step 4: Slow start logic implementation

- Begin with minimum users offloaded to Wi-Fi (small "weight");
- If Wi-Fi continues to do well, an incremental increase in offloaded users is allowed.
- The threshold LB_THRESHOLD is set to apply the linear increase after the exponential phase, similar to the slow start threshold (ssthresh).

Step 5: Dynamic user rebalancing

- In the case of Wi-Fi overcrowding, reduce the number of users offloading and bring them back to the cellular network.
- Simulates adaptive scaling of a load balancer, thus protecting performance.

Step 6: Updating and delivery of the ANDSF policy

The specification for ANDSF permits the dynamic allocation of weight parameters for offloading instructions periodically delivered by the load balancer module instead of delivering static rules.

Step 7: Implementing the feedback loop

Having the system react in real-time is maintained by keeping updated with users and the radio network controllers' ongoing feedback.

Hence, the main improvements added to ANDSF are as follows: dynamic policy engine, real-time offloading decisions, load balancing techniques, and, to the fullest extent possible, maximizing user experience and network efficiency. Table 4 shows the equivalent concepts that have been adopted and applied from the load-balancer mechanism.

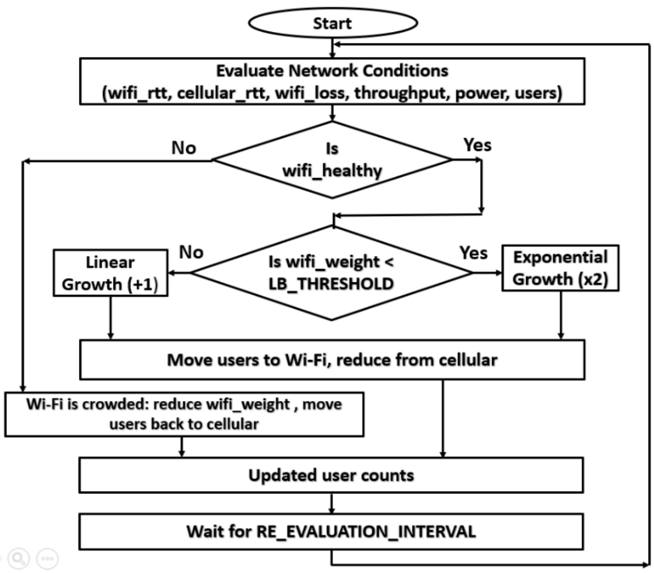

Figure 2. General flowchart of the proposed dynamic offloading process

Table 4. The correlation of the proposed offloading system to the CLB concept

Load Balancer Meaning	Offloading System Mapping
Weight of traffic	Total number of users on the network
Slow start	User offloading gradually
Weight adjustment	Distribution of loads in balance
Failure of the health check	Return users to a healthier network.
Errors and latency in the backend	Indicators of network performance

The modified ANDSF offloading algorithm has superior features, as shown in Table 5. It can be split into 2 cooperating algorithms: In Algorithm 1, the network conditions are taken into account and sensed at all times. In Algorithm 2, the real-time input serves as the basis for dynamic offloading decisions.

Algorithm 1: Network_Monitoring()

Input = None (uses real-time sensors/APIs)

Output = Wi-Fi_status: A dictionary comprising the Wi-Fi user count, power, throughput, loss, and current RTT. cellular_status: Cellular is the same.

```
Function Network_Monitoring():
Wi-Fi_status = {
"rtt": measure_Wi-Fi_rtt(),
"loss": measure_Wi-Fi_loss(),
"throughput": measure_Wi-Fi_throughput(),
 "power": measure_Wi-Fi_power()
"users": count_Wi-Fi_users()
  }
cellular_status = {
"rtt": measure_cellular_rtt(),
"loss": measure_cellular_loss(),
"throughput": measure_cellular_throughput(),
 "power": measure_cellular_power()
 }
 return Wi-Fi_status, cellular_status
End
```

The proposed adaptive offloading control algorithm is described in Algorithm 2.

Algorithm 2: CLB_ANDSF_Offloading()

Input = Wi-Fi_status, cellular_status from **Algorithm 1**; System constants: RTT_THRESHOLD, LOSS_THRESHOLD, MAX_WI-FI_USERS, INITIAL_WI-FI_WEIGHT, INITIAL_CELLULAR_WEIGHT, LB_THRESHOLD RE_EVALUATION_INTERVAL.

Output = Updates the number of users on Wi-Fi or Cellular, and maintains adaptive load balancing.

```
// Initialize values
 Wi-Fi_weight = INITIAL_WI-FI_WEIGHT
cellular_weight =
INITIAL_CELLULAR_WEIGHT
 LB_THRESHOLD = Overcrowding_Threshold
Loop Forever:
Wi-Fi_status, cellular_status = Network_Monitor()
Wi-Fi_healthy = (
Wi-Fi_status["rtt"] < RTT_THRESHOLD AND
Wi-Fi_status["loss"] < LOSS_THRESHOLD AND
Wi-Fi_status["users"] < MAX_WI-FI_USERS
AND
```

```
Wi-Fi_status["throughput"] > cellular_status["throughput"]
 Wi-Fi_status["power"] < cellular_status["power"]
  )
IF Wi-Fi_healthy THEN
IF Wi-Fi_weight < LB_THRESHOLD THEN
Wi-Fi_weight = Wi-Fi_weight × 2
ELSE
Wi-Fi_weight = Wi-Fi_weight + 1
ENDIF
cellular_weight = cellular_weight - Wi-Fi_weight
move_users_to_Wi-Fi(Wi-Fi_weight)
ELSE
Wi-Fi_weight = max(Wi-Fi_weight - 1, MIN_WI-FI_WEIGHT)
cellular_weight = cellular_weight + 1
move_users_to_cellular(cellular_weight)
ENDIF
PRINT "Wi-Fi Users:", Wi-Fi_weight, "Cellular Users:", cellular_weight
SLEEP(RE_EVALUATION_INTERVAL)
End
```

Table 5. The acquired features for the modified ANDSF

Feature	Traditional ANDSF (Static)	Modified ANDSF (Adaptive) Based CLB)
How it works	Static - Depends on pre-defined policies.	Dynamic - Operating with the real-time feedback from a CLB, it adaptively transfers users across networks.
Decision-making mechanism	-If Wi-Fi is available, it will switch directly to it. -If not available, the device remains on 4G/5G.	- The evaluation of Wi-Fi and cellular performance is conducted periodically. - The decision of offloading is dependent on the current RTT and user needs.
Measure network quality before switching	No RTT, packet loss, or bandwidth before switching.	Before each decision cycle, real-time load balancing measurements are used to track RTT, packet loss, throughput, and user count.
Conversion method	Switching is sudden when Wi-Fi is available, which may result in data loss or delay.	Gradual switching via Sliding Window, which maintains connection stability.
Transmission rate control	There is no control over the transmission rate between networks.	The load balancer's key job responsibilities are adjusting the number of users offloaded depending on thresholds and network performance.
Ability to return to cellular service when needed	No smart fallback to the cellular network when Wi-Fi degrades.	If the Wi-Fi becomes overloaded, some users are gradually switched back to the cellular network.
Impact of switching on user experience	May cause sudden disconnection or data loss when switching from cellular to Wi-Fi.	The elastic, gradual reassignment of user control is intended to achieve offloading with less contention, delay, and data loss.

5. SIMULATION RESULTS AND DISCUSSIONS

To assess the differences between modified dynamic ANDSF offloading and classical ANDSF, a network simulation that quantifies data throughput, latency, energy consumption, and the percentage of packet loss rate is conducted using Python-based models with custom logic. With one base station and overlapping Wi-Fi coverage, a single-cell network topology with variable numbers of mobile users (UEs) was assumed. Individual RTT, packet loss, and traffic profiles for each user are modeled, enabling dynamic assessment of offloading performance under increasing load. The parameter settings are illustrated in Table 6.

Table 6. Simulation parameter settings

Parameter	Value/Description
No. of UEs	800
Bandwidth (Cellular, Wi-Fi)	20 MHz
UE mobility speed	0.5–1.5 m/s (pedestrian mobility)
Wi-Fi type	Wi-Fi 6 (802.11ax)
Cellular tower type	Macro cell
Simulation area	500 m × 500 m
Antenna system	(2 × 2) Multiple Input Multiple Output (MIMO)
Multiplexing	Orthogonal Frequency Division Multiplexing (OFDM) systems
Re-evaluation interval	5 seconds

Figure 3 shows the performance of the modified ANDSF in terms of data throughput. The average throughput of the modified ANDSF algorithm was noticeably higher than that of the original method. While the original algorithm stays between 4 and 4.5 Mbps, the updated algorithm starts at about 10 Mbps and goes up to more than 12 Mbps. Cloud balancing enables the system to dynamically adjust to overcrowding, as demonstrated by the updated algorithm's stable performance. The traditional ANDSF approach has low throughput, which shows that it is not very adaptable to growing user numbers. It can be noticed that the CLB uses real-time network load and capacity to intelligently divide user traffic between cellular and Wi-Fi networks. The system guarantees optimal resource utilization by rerouting users to the most capable and least congested network, which significantly boosts overall data throughput.

The impact of the proposed algorithm on the latency. Theoretically, as illustrated in Figure 4, the dynamic ANDSF-based offloading lowers latency against its static counterpart, which never monitors network conditions such as RTT, packet loss, or overload. In the conventional approach, users are switched from one network to the other whenever one of the points looks available for the users in an unmanaged way, while in the dynamic environment, it should utilize a type of load-balancing approach that offloads users in a controlled fashion to avoid losing Wi-Fi to overload. Further, when performance deteriorates, it allows a fallback to the cellular network so that the users can still have a consistent, low-latency service. Sudden surge traffic and queue buildup can be avoided through the real-time adjustment offered by the newly employed approach, hence ensuring a smoother and faster data streaming scenario. In other words, by sending users to networks with lower current RTT and less queuing, the load balancer reduces latency. Data travels through quicker and less crowded routes because overloaded paths are avoided in real time, lowering end-to-end latency.

Regarding the consumed energy, due to the smart dynamic ANDSF offloading, energy consumption is kept low as demonstrated in Figure 5, whereas the static method wastes energy. This is because the dynamic version performs load balancing on users according to the actual network quality, thus preventing the Wi-Fi or cellular network from being overloaded. Keeping the balance prevents overload and retransmissions caused by them, which consume too much power. Moreover, users are offloaded only if Wi-Fi offers good conditions so that devices do not spend much time searching for a network, switching, which is an energy-wasting process. Such energy-focused, efficient, and adaptive behavior has much less consumption of power as compared to the static method, whereby users are offloaded regardless of the network performance. Hence, the proposed method selects reliable and effective network paths to prevent pointless retries and lengthy idle waits. The load balancer lowers the energy consumption of radio interfaces on user devices by preserving optimal link quality and cutting down on active transmission time. Lower power consumption results from less time spent on crowded or unreliable links.

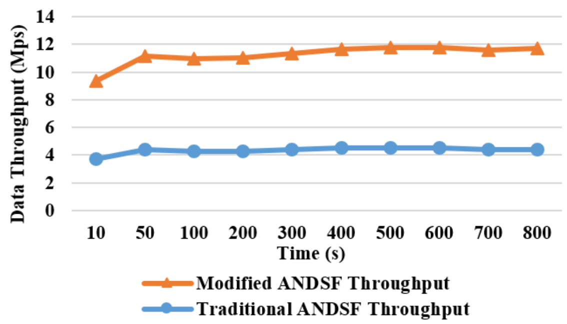

Figure 3. The system performance in terms of data throughput

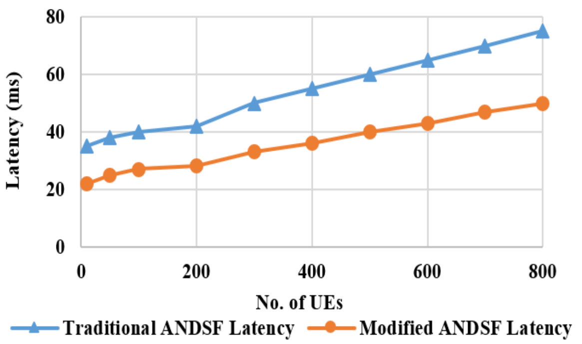

Figure 4. The system performance in terms of latency

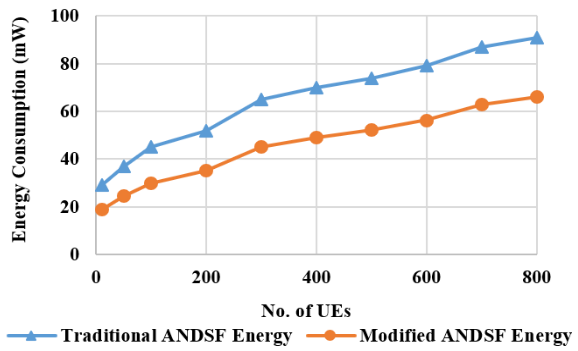

Figure 5. The system performance in terms of energy consumption

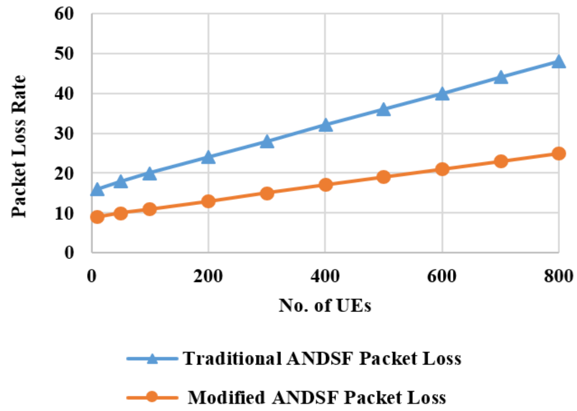

Figure 6. The system performance in terms of packet loss rate

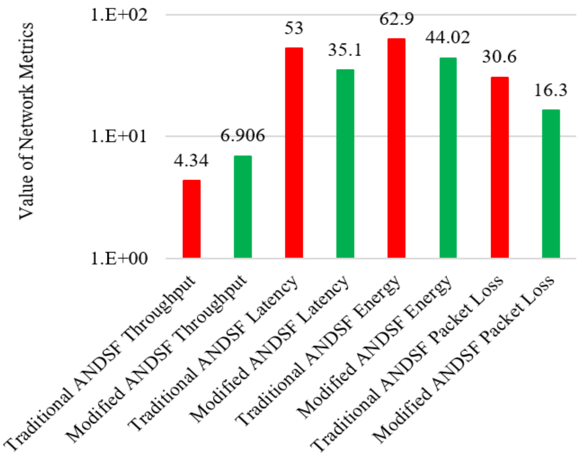

Figure 7. The overall comparison of system performance between the traditional and the modified ANDSF

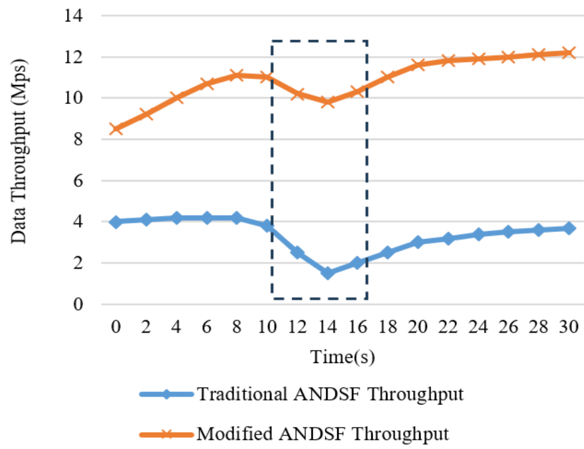

Figure 8. Performance evaluation of the proposed algorithm under a sudden increase in the number of UEs

Likewise, using a dynamic ANDSF offloading method that can be monitored before offloading users and based on current network conditions (RTT, packet loss, and overload) results in a much lower packet loss rate than the static method, as shown in Figure 6. Users are thus moved to Wi-Fi only when having a high level of capacity and quality, hence minimizing packet collision and drop. The static method, more or less offloading users when it sees fit, may overload the Wi-Fi network. On the other hand, the dynamic method compositely prevents overloading with load-balancing logic gradually to aid the network's stability and, ultimately, bring down packet loss. By offloading traffic from erratic links and actively monitoring network dependability, the CLB lowers packet loss. In order to maintain high-quality transmission and significantly reduce packet loss during mobility or congestion, users are dynamically routed to the network with superior performance. Figure 7 shows a comparison of the performance of the point of interest network parameters. By calculating the percentage of increase for the data throughput, and the percentage of decrease for the latency, energy, and packet loss. The following results are obtained: the throughput is enhanced by 59%, while latency, energy, and packet loss are minimized by 33%, 42%, and 46%, respectively.

The last simulation scenario is represented by duplicating the number of UEs manyfold in a certain simulation time to testify to the performance of the modified dynamic ANDSF compared to the traditional static ANDSF offloading algorithm. In Figure 8, the number of UEs is duplicated three times between 10 s to 16 s. The results unequivocally show that, especially in situations of unexpected overload, the modified dynamic ANDSF offloading approach, which incorporates a load balancer mechanism, performs noticeably better than the Traditional Static method. Because of its strict, policy-based switching, the conventional approach experiences a sudden and protracted decrease in throughput when the number of Wi-Fi users spikes. The modified approach, on the other hand, maintains higher throughput with faster recovery, adaptively modifies user distribution, and rapidly detects congestion. This demonstrates its resilience, responsiveness to changes in the network in real time, and capacity to maintain stability and performance under conditions of dynamic load.

6. CONCLUSIONS

Nowadays and soon, the situation is worsening for licensed cellular networks, particularly in high-traffic regions where smart devices and vehicle applications with heavy data usage are drastically increasing. Hence, a significant rise in data-intensive apps necessitates addressing the problem of data overload on mobile networks. To improve the effectiveness of mobile data offloading between cellular and Wi-Fi networks, this research suggested a dynamic offloading strategy based on a CLB mechanism. The results of thorough simulation experiments showed that, particularly as the number of users rises, the suggested algorithm performs noticeably better than the conventional ANDSF method in terms of data throughput, latency, energy consumption, and packet loss rate. In the traditional static ANDSF, decisions on offloading are made by the established, predetermined rules and policies. As a result, performance or fairness may suffer from Wi-Fi overloading or underutilization of cellular. Hence, integrating the CLB mechanism into the ANDSF mechanism significantly improves. This modification makes the offloading system smarter and more adaptive to actual network conditions, rather than relying on fixed decisions. As a suggestion for further research to expand the suggested modified dynamic ANDSF offloading methodology. Instead of depending only on real-time measurements, employ machine learning to forecast user mobility patterns or overload to proactively manage offloading decisions. Additionally, expand the simulation to incorporate dynamic bandwidth conditions and realistic user mobility.

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