Stackelberg game for heterogeneous traffics management in next-generation cellular network

Muhammad Asif1 | Ghani-ur-Rehman2,3 | Muhammad Zubair2 | Muhammad Abid1 | Afzal Badshah3

1 Institute of Information Technology, Kohat University of Science and Technology, Kohat, Khyber Pakhtunkhwa, Pakistan
2 Department of Computer Science & Bioinformatics, Khushal Khan Khattak University, Karak, Pakistan
3 Department of Computer Science & Software Engineering, International Islamic University, Islamabad, Pakistan

Correspondence
Afzal Badshah, Department of Computer Science, and Software Engineering, International Islamic University, Islamabad, Pakistan.
Email: afzal.phdcs120@iiu.edu.pk

Abstract
The innovations in the internet of things and the advent of media-intensive applications have massively increased the data burden on third- and fourth-generation (wireless cellular technology) mobile networks. The existing cellular networks face an overloading issue due to the growing rate of data traffics resultantly reducing the quality of service (QoS) in terms of delay and throughput. To overcome this issue, mobile network operators are searching for well-organized ways to support such a massive data flow. Mobile data offloading schemes through small cells such as WiFi can be implemented to provide a lucrative and effective solution. A game-based quality of service model for heterogeneous traffic to achieve the quality of service parameters is proposed. This model deals with a trade-off between mobile network operators and access points, allocating economic incentives by mobile network operators to access points for saving the spectrum. The model is simulated in MATLAB and the preliminary analyses proved the intense impact of the model on the offloading ratio and energy consumption by achieving superior results in the aforementioned parameters.

1 | INTRODUCTION

In the past two decades, communication technologies have widened rapidly. The major developments are the rapid evolution of cellular communication technologies from the second-generation (2G) to third-generation (3G) and 3G to 4G-long term evaluation (4G-LTE). Such developments are mainly focusing on the need for higher bandwidth, low network latency, better energy efficiency, and reliable network connectivity for media hungry applications such as watching TV live, voice over IP (VOIP), social media, and downloading music [1].

The wireless data traffic ratio is increasing because of many factors like the introduction of smart devices and internet of things (IoT). Such communication devices generate more traffic than basic featured phones. The second factor contributing to this increasing load is the growth in mobile network connection speed. For instance, 4G-LTE-A produces 15 times more traffic than a 3G network. The common generated traffics in this regard are social sharing, video, audio, and cloud-based services. All these traffic types are the starving media. According to the Cisco Visual Networking Index (CVNI) at the end of 2014, the mobile-generated traffic ratio was increased from 2.2 Exabyte to 3.8 Exabyte. By the end of 2016, the traffic grew by 75% and the growth rate is expected to be 55% by the end of 2020. The ratio of global mobile traffic increased to eightfold between 2018 and 2021. In this huge traffic ratio, the 66.6% traffics deals will be video associated [2, 3].

The increasing ratio of traffic gave rise to the overload issue in the existing cellular networks due to which, most of the mobile users experience long latency, low throughput, and network outage, especially during the peak usage time [4, 5].

Mobile users experienced low quality of service (QoS) due to increasing mobile users traffic and it creates a big issue for the cellular network operator. To handle this overload issue, the mobile network operators (MNOs) must employ diverse techniques to fill the gap between the fast budding demand of various traffics and the shortage of the bandwidth of the existing deployed networks. To control the congestion in the spectrum,
many solutions such as optimizing, scaling, and offloading are used. Mobile data offloading (MDO) is one of the feasible solutions to reduce the burden on cellular networks because of some valuable features. These features are higher bandwidth available to mobile users, reduced services cost, higher data rates, high revenues, and reduced congestion of cellular networks, and save energy efficiently.

To control congestion, data offloading is one of the best choices that deliver data for cellular users. The mobile offloading can be categorized into two main approaches such as user-initiated approach and operator-initiated number approach. Based on the technical and economical issues, we consider the operator-initiated approach for the arising issue. Many advanced technologies like WiFi, WiMAX, Femtocell, IP flow mobility, and opportunistic communication are used for the offloading [6].

WiFi is considered a worthwhile solution for offloading due to the built-in capabilities of smartphones which provide easy availability, low cost, deployment, and free spectrum for mobile users. The operators that benefit from WiFi offloading are increased network coverage and capacity, new revenue sources, and improved customer satisfaction. Statistics show that 60% of traffic was offloaded to the WiFi network from cellular network by the end of 2016 and this may be increased up to 63% by 2021. The industry and market consider WiFi is the best innovation for offloading. It has some characteristics such as vast unlicensed bandwidth, high throughput, and client experience, total ownership cost, advanced security, and QoS, expanding of WiFi hot spot and WiFi complement to 4G LTE-A easily. The WiFi architecture provides faster connections, low battery drain, is easier to use, and has reduced handshake.

Many techniques are being employed to model offloading issues such as fuzzy logic (FL), game theory (GT), and reinforcement learning (RL) [7].

One famous model of applied mathematics is called GT and it is used in the decision-making scenario. Game theory has many applications in various fields such as political science, statistics, biology, mathematics, and computer science.

To manage the fair cooperation between mobile base station (MBS) and access points (APs) and to obtain QoS performance, we use GT. The main motivation of MBS and APs is the need for enhanced QoS for mobile users. QoS is the ability of a network to provide quality service, that is, by acquiring maximum bandwidth, reducing error rates, and improving overall network performance to the users [8]. In the case of cellular networks, QoS must ensure the service provided by the provider in terms of what the user pays for it. There must be an improvement in overall network elements like latency, error rate, and up-time.

In NGN (next generation networks) [9], the QoS provision is a challenge for mobile network providers [10]. The addition of more bandwidth is not a feasible solution due to high cost, deployment, and legal requirements. The use of WiFi for offloading as a supplementary technology in the existing network is a growing need of the day. For its implementation, an appropriate technique of offloading will be required to provide quality services. Figure 1 shows the NGN QoS requirements. The users has many applications and each application has different QoS requirements. The NGN has the responsibility to provide QoS-based services to the end users. To enhance the different QoS parameters such as offloading ratio, response delay, energy consumption, in low cost, is the theme of this work which is achieved by bringing together the relevant material to get a crystal clear idea of the situation and then derive a mathematical model to analyse it for practical observation [11].

Different techniques, for example, barging-based solution [12] and Rubinstein bargaining and Vickrey-Clarke-Groves (VCG) [13], have been proposed to alleviate the congestion issue of the NGN. However, these two techniques have some of the drawbacks such as (i) no QoS performance parameters are considered in the model calculation. It only considers the MNO and access point owner (APO) revenue metric. All bids sent to APO have equal priority. There is no differentiation scheme applied to it which may cause congestion. (ii) The barging model considered the distribution of generated benefits among MNO and APO and it does not consider the user satisfaction level.

The proposed scheme is different from these techniques in different ways such as it considered the optimization of offloading by categorizing traffic types based on the incentive scheme. Detailed numerical simulations have been performed to find the optimal ratio of the traffic types which can maximize the offloading. QoS parameters are considered in our model based on the incentive approach where the dependency of optimization on several QoS parameters is checked. They show some non-trivial results. This study also provides a way to optimize the number of APs for offloading which could be of practical importance.

The followings are the key contributions of the proposed work.

- We address the service quality issue for various data types for many applications between the carrier and provider of the NGNs. We designed the incentive model based on the traffics types using the Stackelberg approach. To facilitate the analysis, the proposed model devises the interaction between the public WiFi and MBS. In offloading the mobile users submit a request to the public WiFi, then WiFi sends requests in the form of bids to a base station and the base station offers incentives based on the traffic types in a fair way to assure optimal offloading, QoS service level, and a maximum net profit.
- The proposed model finds the optimal number of the WiFi for offloading based on the user’s density in the location that will diminish the normal network operating cost per Mbps.

![FIGURE 1 QoS requirements for NGN](image-url)
The proposed model also checks the congestion ratio with and without offloading.

- Besides, the Nash equilibrium is proven to be existing by theoretical analysis. Simulation results show that the proposed approach achieves a near-optimal solution. In the proposed model theoretical analysis shows that the Nash equilibrium exists in the game that shows the win-win position. We used MATLAB for experimental analysis and compare performance with another opposite algorithm that shows better performance in the tenure of reducing power by 40% in downloading and 70% in offloading, reduce delay 50% in downloading, and 90% in offloading.

- Such a study will be useful for providing initiatives towards linking optimal control theory and GT for the congestion problem.

The rest of the paper is organized as follows. Section 2 reviews the related studies, Section 3 proposes the game-based model, Section 4 discuss the results and discussion, and finally, Section 5 concludes the study.

2 | RELATED WORK

Due to the demand for a faster network for smartphone applications, the interest in mobile communications is emerging rapidly. User satisfaction such as QoS achievements is the key issue for MNOs. In the articles [14, 15], the authors considered the mobility parameter in communications among mobile hosts and base stations. The authors studied the existing approach with advantages and disadvantages and also highlighted the future research direction. In [16], the authors discussed the issue of QoS requirements for traffic offloading capabilities of HetNets. To solve this problem, the author designed a QoS-aware user association algorithm. The work claimed to have better simulation results than comparative techniques.

Due to the huge traffic and media-hungry application, the NGNs have the problem of unfair channel allocation under various QoS requirements [17, 18].

To solve this problem, the researcher planned QoS-based power adjustment algorithm. The analytical and numerical evolution’s show better QoS achievements. In [19], the author discussed the issue of LTE downlink scheduling and needed the QoS scheme for resource allocation that achieves high throughput. The authors designed a time-domain Knapsack algorithm. The performance is evaluated with the respective two parameters, that is, fairness index and system throughput. Due to high-speed network requirements, security is the basic issue for NGNs and different applications have various QoS requirements, for example, military has security basic requirements.

In paper [20], the author studied the verification and privacy-preserving QoS-based schemes for NGNs and also discussed the future directions at the end. Video conference traffic requires high QoS. Therefore, to achieve the maximum QoS, the author designed Call Admission Control (CAC) Protocol [21] based on priority. The video data is considered to have high priority. The authors claimed to have the maximum QoS, reduced delays, and maximum use of bandwidth in their simulation results.

As discussed in [23], call blocking in cellular networks degrades the QoS of the users which indirectly causes economic loss and low customer satisfaction. The author proposed a scheme for channel allocation that will consider user behaviour and real-time traffic information. The simulation results showed the low call blocking ratio and achieved the maximum QoS. To improve cellular spectral efficiency, some authors proposed a radio resource management (RRM) technique. The scheme is said to put a very small impact on communication during implementation. This work also ensured various QoS needs of intelligent transportation systems (ITS) applications [24].

Due to this huge traffic and a fast internet connection, the existing cellular networks face congestion issues that will require the urgent need for offloading traffics through other best possible balancing networks. The basic of offloading and various technologies for offloading are the main issues in offloading discussed in [25]. In a paper [26], the authors presented the cellular networks offloading methods. They considered the basic types of offloading such as delayed and none delayed in detail and also discussed the various offloading technologies.

In [27], the author studied the performance of offloading by using WiFi as the third party for offloading. Most users are considered to use smartphones for downloading and uploading various applications. The experiment outcomes show the superior offloading ratio. In [28], the authors considered the overload issues in 4G-LTE networks. They considered third-party WiFi as an excellent option to diminish the traffic load on the 4G-LTE network.

In [29], the authors considered the same offloading technology for offloading and discussed the architectural details of WiFi technology for offloading. In [30], the charging issue of WiFi technology for offloading is discussed. The designed algorithm shows the small load on the MBS.

In [31], spectrum utilization is considered as the key issue in WiFi technology for offloading. The authors designed the Nash Bargaining (NB)-based algorithm for channel allocation. MDO through third-party WiFi requires the intelligence-based incentive scheme that provides the trade-off between MBS and APs such as good net profit and satisfactory traffic offloading for the mobile customer. To achieve these two objectives between macro-cells and small cells requires collaboration and compromise proposal. We revisited a lot of previous algorithms based on the incentives issue between micro-cells (MBS) and small cells (APs). In [32], the authors studied the two-stage sequential offloading through WiFi. The simulation results showed that it is advantageous for both the supplier and users. The two phases, multi-leader and follower game using a Stackelberg model for WiFi offloading, are discussed.

In [33], the results showed that the proposed model sets the finest charge scheme for users. In [34], the multi-leader (ML), multi-follower (MF) Stackelberg game for offloading is discussed. The simulation outcome showed equilibrium achievement. In [35], the researcher judged the metrics of delays tolerance incentive cost and designed algorithm that...
investigates the trade-off among offloaded traffic and QoS levels during the offloading process.

Mansouri et al. [36] set an offloading market by taking two types of APOs. The first one is price-taking APOs and the second one is price setting. The work studied the problem of profit maximization of MNOs by introducing a Stackelberg game that has three stages. The coordination among the MNOs and the APOs is formulated. To obtain the equilibrium, the authors designed an interactive algorithm for the MNO and APOs. H. Zhang et al. [37] studied the difficulty of resource allocation in cognitive small cell networks based on efficient and fairway. To obtain a fair distribution of resources, the authors designed a scheme by using the NB GT. The NB GT proved the effectiveness of the game.

In [38], the authors presented the challenges and necessities of the front haul technology in ultra-intense cloud small cell network (5G Long-Term Evaluation-Ultra UDSCNets) for both the licensed and unlicensed spectrum. The work studied the ability concert of such networks when mm-wave was used for both front haul links and access links (between UEs and RRHs). The paper [39] discussed the channel allocation problem. They designed a multi-channel algorithm for channel allocation for the communication of users. The experimental results showed a higher throughput performance.

In [40], the author takes the issue of load imbalance and traffic congestion issues for mobile users which degrade the service-level quality of the users. The arising issue is solved through the cooperative game NB solution and the experimental results show the optimal offloading ratio as compared to the existing solution.

In [41], the author takes the issue of QoS requirements and transmission reliability. The author designed a framework based on the multiple-input multiple-output (MIMO) technology that considers the space-frequency block coding method. The simulation results can achieve better performance.

In [42], the author takes the issue of delay requirements of the users and addressed the arise issue through a backbone-based on-demand data forwarding strategy that assigns the resource on demand base. The outcome shows the improved performance in data forwarding. This paper [42] discusses the computation offloading issue of how to increase the computing capacity of mobile devices. Lagrange multiplier–based scheme is developed for an optimal solution. The simulation result shows that optimal computation offloading performance.

Due to the huge traffic and high demand for QoS 5G faces the bottleneck problem of spectrum [43]. To improve the spectrum, the author developed an algorithm based on a dispersed power control game with a pricing system with various modulation schemes which improve the performance. In [44], the author discussed the QoS aware scheme for improving the capacity of LTE and developed priority-based scheduling queues which improve the performance as compared to existing techniques.

In [45], the author discusses the spectrum efficiency issue which usually degrades due to the high growth ratio of mobile user traffics. To manage the spectrum efficiently the author designed an algorithm based on a scheme called TVWS TV White Space. The detailed review of TV white spaces is discussed in [46].

In [47], the author considers the cellular traffic overload issue. The author proposed an incentive-based scheme using the Stackelberg three-stage model that improves the user satisfaction level without affecting the MNO revenue. The proposed algorithm is compared with the existing algorithm, but the simulation result proves that the proposed algorithm achieves better performance in terms of MNO revenue and user certification level. The rapid increase in the number of mobile devices and the mobile application that creates the issue of QoS level for mobile users are discussed in [48]. To address this issue the author proposed an algorithm based on a game-theoretic approach called directed acyclic graph-enabled mobile offloading (DAGMO). The numerical analysis proved that the proposed framework achieves high performance in terms of time and computation cost as compared to existing techniques.

In [49], the author discusses the issue of high offloading latency during the offloading data between multiple networks. The author proposed a framework called block chain-based Wi-Fi offloading. The proposed scheme is based on operator-assisted offloading which ensures a high level of trust and reliability. The simulation result shows that the proposed scheme achieves high performance as compared to other techniques. The user-centric offloading scheme in 5G wireless networks does not consider the network context issue for mobile users. In [50], the author proposed an incentive-based framework that used the basic theory of the Markov decision process and stochastic geometry. The experimental result shows that the proposed framework outperforms QoS requirements and network conditions.

In [51], the author considers the delay-constrained issue for different application in the WiFi offloading that will degrade the QoS for mobile users and revenue of the MNO. To address the subject issue, the author proposed an incentive-based scheme based on novel delay constraint and reverse auction (DRAIM). To achieve the optimization, the proposed framework will use the concept of Dynamic Programming Winner Selection Method (DPWSM) and Greedy Winner Selection Method (GWSM). The simulation result shows that the proposed framework is superior in terms of traffic load and MNO payoff. In [52], the author discusses the mobility and congestion issue in next-generation vehicular networks, which badly affect the QoS level for the data-hungry mobile application. The author proposed an algorithm based on Q-learning, an RL algorithm that selects intelligent roadside units (RSUs) for optimized data offloading. The proposed scheme is also called an intelligent reward-based data offloading. The guaranteed QoS is the achievement of the proposed algorithm.

In [53], the author takes the network efficiency degradation issue due to the huge traffic and media-hungry mobile applications. To address this issue, the author proposed an intelligent scheme called a satisfaction-based dynamic bandwidth reallocation (SDBR). The experimental result shows that the proposed scheme maximizes overall revenue and fulfilling the QoS necessities of the users. In [54], an ITS of the mobile user’s mobility is the key issue for the mobile network operator (MNO). To
address this, the author proposed a novel mobility model that works based on trip timetables and train timetables. The result obtained from the experiment shows the 98% accuracy of the proposed scheme.

MDO through device-to-device (D2D) communication technology is an efficient way to reduce the traffic rate on cellular infrastructure, but energy efficiency is the main issue in such an MDO and is discussed in [55]. To address this issue, the author designed an algorithm called narrative energy competence optimization scheme that has been planned through a joint optimization transmit power and cache policy that will use the theory of stochastic geometry. The experimental result shows the best performance in terms of energy efficiency as compared to the existing techniques. In [56], the author discusses the frequency issue in 5G networks. The author considers that now the light-fidelity (Li-Fi)-based technologies play a vital role in bandwidth management and designed a scheme based on swarm intelligence algorithm. The resulting evaluation shows the effectiveness in terms of system throughput and spectral efficiency. Table 1 provides the assessment of the proposed game with some presented schemes.

| Paper and authors | Contributions | Limitations | Comparison with proposed game |
|-------------------|---------------|-------------|-------------------------------|
| Geo et al. [12]   | The Nash bargaining solution is designed for the offloading that analyses the interaction among one MNO and Multiple APs. | It will consider the multiple APs scenario for offloading. The maximum or minimum APs consideration will affect the offloading process such as more cost and congestion offloading. So detrimental to the optimal number of APs is the weakness of this technique. | The proposed model considers the factor of APs for offloading. It will find the optimal number of APs based on the users’ density according to the area of communication. |
| Park et al. [13]  | The congestion issue in the offloading is solved through a game model called Vickery Clark and Rubinstein bargaining technique. The proposed model enhances QoS in communication networks. | This model considers all requests from users on an equal priority basis, which creates the starvation problem. This model only considers the cooperating game concept. | Our proposed model offers incentives based on the traffic categories based on the non-cooperative game. |
| Thien et al. [22] | Energy and throughput are the key factor in the offloading process. To control these parameters the author designed an algorithm based on the NBS theory. | This model considers specific parameters of QoS, it will consider the offloading situation in the Testing phase, but non-offloading testing is the lack of this technique. | The proposed model is based on a non-cooperative game. It will consider various QoS parameters for evaluation. The performance is also tested in the non-offloading situation. |

3 | GAME-BASED MODEL FOR QoS MANAGEMENT IN NGN

To provide the QoS-based services to the users, the model uses the non-operative GT approach. This model used the Stackelberg approach which is a two-stage game-based approach based on incentives. The overall structure of the proposed model is shown in Figure 2. There are two phases of the proposed scheme. The first phase may represent the player 1 of the game and second phase player 2 of the game.

In the first phase, the MBS offers incentives based on traffic types. The traffics types taken are video, audio, and text data to set the optimal incentives to earn maximum profit from mobile users.

In the next phase, APs will compete with each other to maximize their profit by offloading more traffic and type of traffic which has the maximum rate of incentives. So the AP found optimal packages for uploading and downloading data with maximum speed. The MBS will offer incentives in a predetermined range and the proposed model will find out optimal incentive rates on the basis of traffic types.

To manage the proper trade-off between leader and followers, the MNO uses the non-cooperative game base model to achieve maximum profit and maximum offloading ratio. The model uses the operator-initiated–based offloading in which the operator has the control over subscribers. The model uses special and commercial WiFi which is called carrier WiFi which has some special characteristics such as high range and high capacity for the offloading. The model will work in the troupe and each type of traffic will be considered a member. Some propositions are also utilized to prove the state of Nash Equilibrium and Unique Equilibrium between the MBS and APs in terms of their profit and load management. The proposed model considers the QoS requirements of each application based on the incentive.

**First phase:** Mathematically this game is represented as a troupe:

\[
U(l_v) = \beta_v \frac{h_v - \rho V h_v}{\sum_{m \in M} I_m}.
\]

The utility for video-type traffic will be calculated using the above function in the single tier as given in Equation (1), where \( U \) is a utility function for input type \( l_v \), \( \beta_v \) represents incentive rate for video type, \( h_v \) is the offloaded video traffic, \( \rho V \) is the per-unit cost, and \( I_m \) is the unit data offloaded for the \( m \)-th instance of time belongs to ‘Time’ \( t \). The function is developed to estimate utility gained from video-type traffic. The cost
multiplied by offloaded traffic is the total cost to be subtracted from the profit gained.

\[ U(l_A) = \beta_A \frac{l_A}{\sum_{i \in I} l_A} - \rho_A l_A. \]  

(2)

Similarly, the utility for audio type in a separate tier can be determined by using the given function and is given in Equation (2), where \( U \) is a utility function for input type \( l_A \), \( \beta_A \) represents incentive rate for audio type, \( l_A \) is the offloaded audio traffic, \( \rho_A \) is the per-unit cost, and \( l_A \) is the unit data offloaded for the \( m \)th instance of time belongs to ‘Time’ \( t \). The function estimates utility gained from audio type traffic. The net profit is gained by subtracting the product of per-unit cost and offloaded audio traffic.

\[ U(l_T) = \beta_T \frac{l_T}{\sum_{i \in I} l_T} - \rho_T l_T. \]  

(3)

The utility gained by textual data will be estimated using the above function in the same manner and is given in Equation (3), where \( U \) is the utility function for input type \( l_T \), \( \beta_T \) represents incentive rate for text type, \( l_T \) is the offloaded text traffic, \( \rho_T \) is the per-unit cost, and \( l_T \) is the unit data offloaded for the \( m \)th instance of time belongs to ‘Time’ \( t \). The function estimates utility gained from text type traffic. The total payoff is calculated in Equation (4):

\[ U(l_m) = \beta_V \frac{l_V}{\sum_{i \in I} l_V} - \rho_V l_V + \beta_A \frac{l_A}{\sum_{i \in I} l_A} - \rho_A l_A + \beta_T \frac{l_T}{\sum_{i \in I} l_T} - \rho_T l_T, \]  

(4)

where \( \beta_V \neq \beta_A \neq \beta_T \). In the above game, \( U \) represents the utility function for input type \( l_m \), the offered incentive is represented by \( \beta \) in the first stage that will be utilized in the second stage for offloading by APs, \( \rho \) represents paid cost, and \( m \) represents the troupe of the three types of traffics of \( m \)th AP, and \( l_m \) represents the total data offloaded by \( m \)th AP. The general form of the game is given in Equation (5):

\[ G = ((P_i, (S_x)_i \in t), (U_x)_i \in t)). \]  

(5)

In this game, \( P \) represents players, \( S \) represents strategies, and \( U \) represents payoff earned.

\[ D = D(l_V) + D(l_A) + D(l_T) \] is the derivative of the payoff function, where \( D \) is applied to the utility functions defined earlier with respect to offloaded video, audio, and text types traffic as given in Equation (6).

\[ D_{V,A,T} = \beta_V \frac{\sum_{i \in I} n \neq s_i l_V}{\sum_{i \in I} l_V^2} + \beta_A \frac{\sum_{i \in I} n \neq s_i l_A}{\sum_{i \in I} l_A^2} + \beta_T \frac{\sum_{i \in I} n \neq s_i l_T}{\sum_{i \in I} l_T^2} - (\rho_V + \rho_A + \rho_T). \]  

(6)

The derivative function collectively represents the first step rate of change in the utility function. The offloaded traffic multiplied to cost factor is eliminated while the profit factor is downgraded with respect to offload traffic \( l_m \).
The second-order derivative of the above function is given in Equation (7):

\[
D_{U_{\text{BR}}(l_{\text{hm}})} = -2 \left[ \sum_{n \neq s} \frac{n l_{n}}{l_{s}^{2}} + \frac{1}{3} \beta_{l} \sum_{n \neq s} l_{n}^{2} \right] + \frac{4 \lambda}{\omega} \beta_{l},
\]

The negative factor of the \(D^2\) which is \(-2\) shows that the result will be negative or less than zero which shows its concavity on the part of a utility function.

The strategy represents strategies, and is convex while \(P\) is flat, therefore, the game mentioned earlier achieved Nash Equilibrium.

The achievement of the best response for the optimization problem is the exceptional best possible result for the non-cooperative offloading game.

\[
\text{maximize} \quad U_{\text{hm}}(l_{\text{hm}}) \\
\text{subject to} \quad l_{\text{hm}} \leq c_{\text{hm}},
\]

where \(U_{\text{hm}}\) means the payoff of the heterogeneous traffics and \(l_{\text{hm}}\) means heterogeneous traffic offloaded based on the offered incentives by MBS which cannot exceed the instantaneous rate.

The \(N\) APs are rivaling each other to augment their income in terms of offloading so the values of the best response given in Equation (8) followed by the condition given above achieve unique equilibrium among the APs.

\[
l_{\text{hm}}^{*} = \left[ \frac{\beta_{l} (K - 1)}{\sum_{n \neq s} \rho_{\text{hm}}} - 1 \right] \left( 1 - \frac{(K - 1) \rho_{\text{hm}}}{\sum_{n \neq s} \rho_{\text{hm}}} \right),
\]

where \(l_{\text{hm}}^{*}\) is the maximum heterogeneous traffic that can be offloaded for the \(m\) AP which is computed through this equation. \(\beta_{l}\) represents incentive offered for heterogeneous traffic, \(K\) is constant to limit the offered incentives below the MBS profit, and \(\sigma_{l}\) is the accumulated power cost for particular AP.

**Second phase process:** In the second stage, base station overall net profit can be calculated as:

\[
U_{\text{MBS}}(\beta_{m}) = \delta \sum_{n \in P} l_{\text{hm}} - \delta \sum_{n \in P} l_{\text{hm}}.
\]

Here \(\delta\) is spectrum utilized per unit. Since \(\beta\) is profit on the part of AP and should be subtracted from MBS profit because it is a shared part of the profit, the MBS aims to get the most out of its net profit by solving the following optimization.

\[
\text{maximize} \quad U_{\text{MBS}}(\beta_{m}) \\
\text{subject to} \quad (\beta_{m}),
\]

where \(\beta_{m}\) is required to approach its maximum value while \(U_{\text{MBS}}(\beta_{m})\) shows the total payoff of the MBS for heterogeneous traffics with offered incentives \(\beta\) to APs by MBS.

\[
\text{Max} = \left[ \frac{\delta_{\text{hm}} - \beta_{m}}{\sum_{n \neq s} \rho_{\text{hm}}} \right] \left[ 1 - \frac{(K - 1) \rho_{\text{hm}}}{\sum_{n \neq s} \rho_{\text{hm}}} \right].
\]

Maximum MBS profit can be calculated in the same way as defined for AP as given in Equation (10). The maximum offloaded traffic function from Equation (8) has been substituted in Equation (9).

Optimal economic incentives can be defined by using step-up Lagrangian of the logarithmic evaluation for the value of \(U_{\text{MBS}}(\beta_{m})\). It can be calculated in Equation (11) as follows:

\[
\beta_{m} = \frac{\lambda \sqrt{\lambda^{2} + 8 \delta_{\text{hm}} \omega}}{4 \omega},
\]

where \(\lambda\) is Lagrange multiplier, \(\delta\) is spectrum and \(\omega = l_{\text{hm}} / \beta_{m}\), and \(K\) is constant defined above. The notations and symbols that are used in the proposed scheme are presented in Table 2. In this article, we have used many words or phrases in a shortened form. It may be used to utilized space, time, and pass up duplication of long words. We represent the full form of the abbreviations used in Table 3.

### 3.1 Diagrammatic illustration of game

Figure 3 represents the different elements of the game. The game consists of five basic elements such as players, information, actions, strategies, and payoff function of the game. Each box of the figure represents related information of the proposed game. Players mean that how many entities are involved in the game. Action means possible choice selection made by the player to obtain NE, and strategies represent a plan of the
action. The payoff represents the outcome of the game which depends on the action of all players.

Phases of game and explanation

1. **MDO game** $G = \{P, S, X, U\}$:
   GT is a method of mathematics explaining the phenomenon of conflict and partnership between informed decision makers who are intelligent. The equation shows the MDO game. $G$ is the name of the game, $P$ represents players that are involved in the game, $S$ represents the possible action of the players, $U$ represents the utility function that may be called payoff function that players achieve after the required actions such as maximum offloading and maximum revenue.

2. **Players of the game** $G = \{P\}$:
   In a game, a player is an agent who makes sensible decisions when the game is performed. In our proposed game the players involved are MBS, AP, and mobile users. The $P$ represents the finite set of players that are involved in the game.

3. **The strategy of the game** $G = \{S\}$:
   One of the possible actions among the behaviour given is a strategy of the game. This phase represents the complete plan in the offloading game. In our proposed game we have to use the non-cooperative game model called the two-stage Stackelberg model for the decision regarding certain actions of the players. The $S$ represents the strategy space of the proposed offloading game.

4. **Utility function also called pay off function of the game** $G = \{X\}$:
   A pay-off is an amount that is also related to a utility. For a player/game, it poses the desirability of a result of the decision. At the end of the game, the payoff is a sort of reward a particular player gets. The actions of other players limit this incentive. The proposed game payoff function is QoS that is achieved by the mobile users from the networks and the maximum net profit that MNO is achieved.

### 3.2 Algorithm for proposed model

This algorithm is developed on the basis of formulae derived previously which take MBS, some APs, and defined incentive rates as input. The total cost is calculated on the basis of the cost paid for offloading traffic. Offloaded traffic is calculated in normal and best response cases. MBS net profit is calculated to obtain a state of equilibrium. The optimal incentive is calculated to get the maximized profit by MBS. The main steps in the proposed game-based algorithm are given below.

1. Each mobile user estimates the initial time through computing the volume of traffic transporting data and the signal-to-noise-plus-interference ratio (SINR). In the exhibition, each public WiFi monitors its channel position at the same time.
2. All the mobile users send a request based on their requirements to the nearest public WiFi.
3. Each public WiFi decides optimal offloading for mobile users with a discount rate.
4. The public WiFi sends the request of mobile users to the mobile network operator for optimal incentive based on the traffic types for fair scheduling.
5. After the traffic-based bids to MNO, MNO should determine the optimal incentives, rates for various data types through a proposed model.
6. The public WiFi and MNO calculate the patience variables of their own.
7. Finally, the equals-based benefit is distributed between the MNO and APOs in terms of QoS service level offloading and maximum income from offloading.
ALGORITHM 1 Algorithm for traffic-based incentive schema for QoS applications

INPUT: MBS, APs, \( \beta_{ht} \)

Initialize: \( \text{Cost, } \lambda \)

1: Calculate Cost
2: for \( I = 1 : X \) do
3: Cost = Cost + \( \alpha(I) \)
4: End For
5: Calculate Normal Offload volume
6: for \( I = 1 : X \) do
7: \( l_{hm} = l_{hm} + \left[ 1 - \left( K - 1 \right) \alpha \right] \frac{\text{Cost}}{\text{Cost}} \)
8: End For
9: Calculate Best Offload Volume
10: \( l^*_{hm} = \left[ \beta_{ht} \left( K - 1 \right) \alpha \right] \frac{\text{Cost}}{\text{Cost}} \left( 1 - \left( K - 1 \right) \alpha \right) \frac{\text{Cost}}{\text{Cost}} \)
11: Calculate MBS Net Profit
12: for \( I = 1 : P \) do
13: \( U_{\text{MBS}}(\beta_{ht}) = \delta \sum_{d \in P} l_{hm} - \delta \sum_{d \in P} l_{hm} \)
14: \( \lambda(K + 1) = \lambda(k) + \alpha(k) \beta(k) - \beta^N \)
15: Calculate Optimal Incentive Value
16: \( \beta(k + 1) = \frac{\lambda(k) + \sqrt{\lambda(k)^2 + 4 \delta M}}{2 \delta} \)
17: End

Five basic modules are included in this algorithm. MBS is responsible to calculate the total cost per AP by accumulating cost per unit data. The cost is calculated through a loop in line numbers 2 to 4. The cost will be used in subsequent modules iteratively to calculate normal offload volume and best offload volume using the equation formulated and simplified in this work.

Normal offload volume is estimated in lines 7 and 8 while best offload volume is computed on line 13 using the average and best cases formulated in the proposed model.

Net profit and optimal incentive are the main outputs of the model which are calculated in modules 4 and 5 in lines 16 to 20 and 21 to 23. Different variables are declared on a need basis. The formulae used were derived in the proposed model.

Simulations are tested under the various conditions and some diagrams are formulated using third-party tools to exhibit entire tables of data in a meaningful way. MATLAB was used as the main tool for simulation. Algorithm 1 presents the traffic-based incentive schema for QoS applications.

### TABLE 4 Parameters for experimental simulation

| Parameter                                      | Values          |
|------------------------------------------------|-----------------|
| Simulation area                                 | 2500 \times 2500 m |
| Number of base station                         | 1               |
| Transmission range                             | 2500 m²         |
| Bandwidth of MBS                               | 20 MHZ          |
| Battery transmission power of MBS              | 46 dbm          |
| Range of transmission                          | 400             |
| Number of the APs                              | 20              |
| AP type is                                     | Carrier WiFi    |
| Range of AP transmission                       | 500 m           |
| Battery transmission power of MBS              | 20 dbm          |
| Bandwidth of WiFi                              | 2.4 GHz         |
| UEs data transmission duration                 | 90, 120, 32, 70 |
| Number of UEs                                  | 10              |
| Battery capacity                               | 100 packets     |
| Mobility model                                 | Random view model |
| Simulation time                                 | 24 h            |

4 | PERFORMANCE EVALUATION

In this section, an experimental tool MATLAB [57] was used to conduct the performance experiments of the game-based model for offloading. MATLAB is the extended version of the 2019 MATLAB. This makes it possible to simulate the quality of service model (QOSM) numerical solution. The experimental setup, QoS performance metrics, and outcomes are shown in the next subsections.

4.1 | Simulation setup

After the analytical study, we conduct some of the experiments in MATLAB to analyse the manifestation of the planned QoS-based game model for offloading. We compared the performance of the proposed game-based offloading scheme with other existing schemes in order to see the domination. In the performance evaluation, we consider various QoS offloading parameters and other various network conditions. The experiments were taken in the dense area where a typical 3G/4G-LTE is deployed and most of the mobile users are using the internet in peak time and off-peak time and download and upload media hungry mobile applications such as audio, video, and social media. The parameters which are used during experiments are given below. Table 4 indicates the simulation parameters.

The experimental area is denoted by a 2500 \times 2500 m rectangular network which is fixed. The number of nodes that are mobile users is limited to 200 represented by UE, having a random wave model. The area is divided by the number of UE we get an area per UE is obtained. In the estimated area, we consider one MBS that is located at the centre of the area with high mobile user bulk, and hence the high traffic order.
Moreover, our model has per MBS implementation structure therefore, only one MBS will be tested at a time. The public WiFi is arbitrarily distributed in the high-density area that is typically 20 in the number which is calculated. Divided area by several AP. We will get area per AP. The deployed base station and public WiFi bandwidth and frequency (resource) are 20 MHz and 2.4 GHz. The handoff is executed when the mobile users across the estimated range of BS such as 2500 m². The APS and mobile users in the range [0, 500]. The traffic volumes follow the specified power levels of a base station and WiFi such as 46 dBm and 20 dBm.

### 4.2 Metrics

The simulation uses QoS metrics for offloading such as offloaded traffic ratio, latency, energy efficiency, and optimal numbers of the APs as parameters of performance within a network. The probability of offloading ratio was computed as the percentage between the number of the data uploaded and downloaded to the target mobile users using APs. The latency is calculated as the complete time taken by a packet for reaching from source to target is known is latency. Energy efficiency represents the power consumption level of the base station, AP, and the smartphone. The optimal number of APs depends on the area users-level ratio.

### 4.3 Results and discussion

In this section, the results of the proposed scheme are discussed and compared with other techniques.

#### 4.3.1 Offloading effect on traffic types based on offered incentives

In the first experiments, the MBS offers the incentive for various data types based on the proposed game-based model for heterogeneous traffic types. In this experiment, the minimum and maximum value of incentives $\beta$ is tested for different types of traffic separately through MATLAB simulation and their numeric values are put to a bar graph to make their comparison in order to get their brief manifestation. In the graph, we see that text data got more offloading as compare to other data types but that purely depends on the mechanism through which the incentives are offered. Because text data is of low priority while live video streaming has a high priority to stream without any interruption, therefore, offloading of such traffic would be required in an intelligent manner. To obtain the optimal net profit for MNO the base station sets the right ratio for various applications type and on the other side, AP takes incentive from MBS based on the users demands applications. The performance result can also be seen in Figure 4. The graph shows the offloading ratio effect based on the offer rate. The model set the right incentive rate for each type of data then AP use these rate and get an optimal offloading ratio.

#### 4.3.2 Optimal number of APs for offloading

In this experiment, the proposed model calculates the optimal number of APs for the offloading because our model uses AP as the third party for offloading. The more deployment of APs cause the more cost for MNO and less deployment of the APs may cause the congestion for mobile users so set to optimal number of APs for offloading because of the trade-off between the number of APs utilized and the offloading ratio of the traffic as such more APs will cost more. In the simulation scenario as mentioned earlier and the optimal number of APs is determined to be 8 for the given problem. The constant rate of incentive-based on four types of traffics, that is, real, video, audio, and text were offered. Different types of traffic reached their peak points on the introduction of eight APs while a minor change in offloading for the aforementioned problem was observed after eight APs. The proposed model has been observed significant offloading and reduced the congestion for various traffics on the introduction of eight APs and after eight the mobile users found gradually traffic increase in offloading ratio. The performance result can also be seen in Figure 6. The figure shows that

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**FIGURE 4** Offloading effect on traffic types based on offered incentives
the offloading effect starts from 1 because when AP is less then 1 no offloading occurs. On the introduction of the AP1 offloading effect of each traffic is different such as real type offloading ratio is below 1 video type reach to 1 audio 2 and text reach to 4. The experiment result shows the effect on various APs but on 8 we found the optimal point for selection. After 8 APs the offloading ratio result is decreased and more AP causes a more cost for MNO because the MNO hires the commercial carrier WiFi for offloading.

4.3.3 Comparative analysis w.r.t offloaded traffic ratio picocells-wise

Models for the comparative analysis in forthcoming simulations are as under:

QOSM: QoS aware based model for offloading in the NGN using game-based approach.

CBIM: contract-based incentive mechanism for delayed traffic offloading in cellular networks.

This experiment shows the performance of offloading ratio of the proposed technique. The result shows that the proposed model uses the incentive base approach and scored 4.5 in comparison to 3.9 of the CBIM model which shows its effectiveness. The QOSM offloading traffics ratio is increased due to the selection of most select digit of APs for offloading which grows the capacity. The APs non-cooperative selection as in the Nash Equilibrium (NE) will lead to an optimal offloading ratio. The performance result can also be seen in Figure 7. The figure shows the QOSM model achieves the offloading ratio up to 4 on 8 APs while the CBIM offloading ratio is 3 because the QOSM uses a traffic-based incentive mechanism.

4.3.4 Comparison of energy efficiency assessment

The forthcoming graph shows the energy efficiency of the proposed QOSM in contrast with the existing CBIM. The performance of the proposed algorithm is proved better measured the efficiency in terms kbps/w and scored up to 12.8 kbps/w while the CBIM is recorded up to 11.8 kbps/w. The overall energy efficiency of CBIM ranges from 6 to 11.8 while the proposed rendered efficiency from 6.4 to 12.8 which shows its overall lead over the previous model. We observed in the experiment results that QOSM energy efficiency is improved due to the selection of optimal number of APs. The optimal number of APs and also a small cell can provide better energy efficiency than a large base station due to lower transmission power. The QOSM effectively offloads more traffic from the primary channel to a secondary channel in an intelligent manner due to which it achieves higher system energy efficiency. The performance result can also be seen in Figure 9. The QOSM energy efficiency is good because it alleviates the congestion and overhead problem of the communication.
4.3.5 Comparison of latency assessment

In the next simulation, latency is shown on the vertical axis while data is taken on the horizontal axis. The total time taken by a packet for reaching from source to target is known as latency. Standard 4G channels with 60 ms of latency is taken with the congestion in the network due to which, observable latency is 85 to 90 ms. The proposed model picked 90 ms of transfer rate and dropped it up to 60 ms on the eighth packet. It performed well as compared to the previous model on both ends. The results performance also shows that the proposed scheme produces a good performance in terms of latency when compared to a scheme in which there is no strategy traffic-based consideration in the offloading model. The proposed model reduced the congestion on the main base station due to the offloading scheme which diverts the traffic from the primary channel to secondary channel due to which the proposed scheme reduced the latency ratio of the traffic. The performance result can also be seen in Figure 10. The QOSM manage the proper cooperation and agreement between both players which led to reduced latency in the communication.

4.3.6 Comparison of QoS achievement assessment

The next graph estimates the QoS achievement with different techniques using the same suggested algorithm in terms of different QoS parameters such as offloading ratio, response delay, and energy efficiency. We tested GT, FL, Neural Network Algorithm (NNA), and RL but the GT is proved to be best among them. GT scored up to 27 points while FL up to 26. The economy matter is one of those reasons due to which the use of GT may be more affordable and suitable in many situations rather than considering the tough QoS management. In our proposed game economy matter is involved such as the leader try to maximize his net profit from the followers and the followers try that offload traffic with less price rate so we the results performance that GT achieves the supreme performance. The performance result can also be seen in Figure 5.

4.3.7 Comparison of WiFi offloading impact on heterogeneous network

The last experiment we made to show the effect of WiFi offloading on the heterogeneous network and its contribution
TABLE 5 QoS performance results of proposed algorithm and existing algorithms

| Parameters                  | Proposed algorithm | Existing algorithm |
|-----------------------------|--------------------|--------------------|
| Offloading ratio (%)        | 85                 | 60                 |
| Energy or power level (J)   | 210.33             | 178.5              |
| Latency (s)                 | 102.3              | 45.6               |
| Incentive affect the data type (%) | 90               | 52                 |
| Optimal number of APs       | Low cost           | High cost          |
| Network disbursement ($)    | 300                | 600                |

as a third-party tool in the network traffic flow in contrast with the cellular network only. We first tested only the cellular network for the mentioned parameters. Then with WiFi network inclusion and record data of both the settings which are put to graph given below. We noticed the profound impact of the WiFi network on traffic flow in a heterogeneous network.

In QoS achievement, the WiFi network marked 80% and in load management, it split more than 75% on getting a share of only 40% in profit and 30% in network worth. The throughput of WiFi offloading increases linearly with respect to the users number. The offloading through WiFi has supreme performance because it provides fast data rates with high service quality, low power transmission, and easy handshaking. Experiment results also show that in congested area WiFi offloading increased network capacity, new revenue sources for MNO. The performance result can also be seen in Figure 8. This result shows that WiFi offloading is one of the good solutions to reduced the traffic burden on the cellular network with low cost and easy technical management.

QoS performance comparison with other techniques are summarized in the Table 5. The conclude summary show that proposed method achieve better performance as compare to existing method.

5 CONCLUSION AND FUTURE WORK

We designed a mechanism to overcome the overload issue in existing cellular networks. To reduce the burden on existing cellular networks, offloading through WiFi is a low cost and an efficient solution. By considering the QoS requirements of diverse applications we put forward a novel ‘QoS based model for heterogeneous traffics using game-based approach’. The proposed model finds a trade-off between MBS and APs. According to the proposed model, the reimbursement to AP comes from the offered economic incentives and the reimbursement to MBS is achieved by the reducing load and economy spectrum. We have done the analytical modelling and proved that the proposed game achieves a unique Nash equilibrium (NE). After establishing a mathematical model, we implement it in MATLAB and different simulations were made to test the QoS-based achievement of the proposed model. Some simulations are simplified for presentation and the result is presented in a precise manner. From the experiments and simulations, the following conclusions were acquired: maximum and minimum incentive values have a significant impression on offloading in heterogeneous network hence it is a matter of extreme importance to share the offered incentives fairly between MBS and APs. During analysis, the proposed model is compared with the prevailing model in terms of offloading ratio and energy efficiency, the proposed model has surpassed the existing model in performance of both the parameters.

The proposed model is well suited with GT due to the real-world financial implication, therefore, the author has got a natural tendency to GT which is proved through simulations experimentally. The addition of WiFi as a third-party instrument to eradicate the burden on the cellular network has a profound impact on data management in low cost which is established as such that it grubs 80% QoS and near to 80% traffic in just 40% profit and getting worth of about 40% only which show that addition of WiFi to congested networks is a viable solution to eliminate this congestion.

The proposed game solution using other supplementary technology to offload traffic is also an issue to be resolved through future work. Security and privacy of end-users in a heterogeneous network are open to being researched in the future. Fair load balancing in an NGN is an open issue for future research.

ORCID
Afzal Badshah https://orcid.org/0000-0002-3444-4609

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