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REDUCTION AND CONTROL CONGESTION IN MULTI-TIER 4G-LTE-A NETWORK USING HYBRID ARTIFICIAL INTELLIGENCE TECHNIQUE

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Abstract

This paper presents the reduction and control of congestion in multi-tier 4G-LTE-A network using hybrid artificial intelligence technique. The study addressed the crucial requirement of maintaining Quality of Service (QoS) in 4G networks to support real-time multimedia applications and seamless packet streaming in wireless networks.The paper identified the need to address congestion, considering multiple congestion constraints, including throughput, loss, and load factor. To overcome this challenge, a Genetic Algorithm (GA) was integrated with the Datagram Congestion Control Protocol (DCCP) for congestion detection and control. The GA-DCCP approach effectively detected congestion and dynamically adjusted the data reception rate to prevent overload, thus mitigating congestion-related issues. The result of simulation and evaluation of the model presented that the effectiveness of the proposed GA-DCCP approach, and achieved average throughput of 89.03% during testing which showcased improved data transfer efficiency. Furthermore, the validation results indicated a significant 26.06% improvement compared to the network without GA-DCCP, confirming the efficacy of the proposed solution.

Keywords: Congestion; Artificial Intelligence; Genetic Algorithm; Multi-Tier Network

1. INTRODUCTION

Recently, in many developing and undeveloped countries have been faced with huge deficiency of cash. Nigeria's case is particular to the monetary policy introduced by the Central Bank of Nigeria (CBN)which is engineered to address a more complex problem of corruption and at the same time stabilize the economy. To this end, the policy is channelled towards more of cashless policies which has triggered high rate of online transaction in the country and since the inception on the 10th February, 2023; many Nigerians have turned to the internet for financial transactions (Inwalomhe, 2023). Today the network infrastructures all over the country has witnesses high rate of traffic 24/7 never envisaged prior to the network design, and as a result users have witnessed series of technical problems such as latency, interference, poor throughput, losses, etc, which has affected quality of user experience. In addition, the conventional multi-tier network which are in place to manage this problem via congestion control mechanisms lack the cognitive intelligence to detect the problem formulation and also the adaptive load balancing scheme to ease the congestion problem strategically (Shami*et al.*, 2018). Over the years, many literatures have furnished congestion management schemes in multi-tier network, utilizing techniques such as Random Early Detection (RED) algorithm as revealed in Al-Allaf and Jabbar, (2020);however, Abdel-Jaber and Nardone (2020)argued that RED requires parameters tuning to be more effective and proposed automatic tuning of network parameters via the computations of drop tail probabilities to improve RED; but despite the success, Mahawish and Hassan (2022) revealed the complexity during the auto-tuning process. Gently RED and nonlinear RED were respectively proposed in (Floyd, 2000) and (Al-Allaf and Jabbar, 2020), but despite their success, the need for a congestion control solution with cognitive intelligence which can provide optimal decision making in critical times remains vital for quality-of-service sustainability (Sulaiman*et al.*, 2022).

Over the years,Artificial Intelligence (A.I) has been applied to solve complex problem in wireless network like congestion control. In Saif*et al*. (2022) hybrid deep learning was applied for congestion control using Naïve Bayes and Support vector machine. Similarly,hybrid deep learning approach was applied in Sulaiman*et al*. (2022) using Long Short-Term Memory (LSTM) and Support Vector Machine (SVM) for end-to-end congestion control in advance wireless network. In addition, a RED based Markov decision algorithm was also applied in Mahawish and Hassan, (2022) for congestion management and achieved low drop packet which is good; nevertheless, these studies gave little attention to the problem identification and focused only on the control aspect.

According to Maab and Omar(2022) congestion problem can be classified into Identification, control and avoidance, in other words, detecting the problem is vital to guarantee optimal control success. Based on this evidence, the studied literatures have not been able to address this congestion problem holistically. Secondly, congestion according to (Richard and Elias, 2000; Remigius*et al.*, 2019; Christopher*et al.*, 2022) is an optimization problem and hence not perfect for machine and deep learning algorithms as observed in the stated literatures. Based on these findings, optimization algorithm for congestion control was reviewed as in Shami*et al*. (2018) which used Particle Swarm Optimization (PSO) technique to solve the problem of congestion via the finding the optimal bias values of user association, with emphases on the optimization of the network spectral efficiency. Amen *et al*. (2019) improved the PSO load balancing in LTE-A network, conducting a dynamic user association to finding the user optimal bias values. These studies were able to control congestion, but gave room for improvement in the detection aspect.

In Majeed*et al*. (2022) a solution for congestion detection and control was presented using Distributed Congestion Control Protocol (DC-CP). The approach considers buffer information of the radio network controller to detection congestion and then performs buffer occupancy analysis to control the overload. In Iyengar*et al*. (2021) and Bishop *et al*, 2021, transport layer protocols such as the User Datagram Protocol (QUDP) has been applied in the transport layer for congestion control, however Adel and Waleed (2018), argued that they are not reliable and proposed a light weight Datagram Congestion Control protocol (DCCP) using retransmission and catching algorithm. This was validated through comparative analysis with the existing DCCP protocol and was able to achieve better congestion performance.The result achieved overall showed good quality of service to some extend users can manage and attracted the interest of this study as foundation for improvement, especially during congestion detection. To this end, this research proposes the application of an artificial intelligence which used genetic algorithm to detect the congestion problem on the multi-tier network and improve the DCCP, for optimal congestion management performance in multi-tier radio access network.

2. METHODOLOGY

The research methodology used in the study involves a combination of experimental and simulation approaches. Initially, the experimental approach was employed to characterize a 4G multi-tier network. This involved collecting real-world data from the network to understand its performance and behaviour. Once the characterization of the network was completed, the research identified the problem of congestion based on the analysis of the collected data. To address the problem, the research developed an algorithm for monitoring and localizing congestion. This algorithm aimed to detect and identify cell where congestion was occurring within the network. The algorithm was designed to analyze network parameters such as throughput, latency, packet loss, or other relevant metrics to determine the presence of congestion. Furthermore, the algorithm was integrated into a DCCP. DCCP is a protocol that manages congestion in a network by regulating the traffic flow and resource allocation. By integrating the developed algorithm into DCCP, the research aimed to enhance the monitoring, detection, and control of congestion within the network. The implemented algorithm and the integrated DCCP with congestion control capabilities were then tested through simulation considering varying levels of congestion load factor to assess the algorithm's performance in detecting and mitigating congestion. The case study methodology focuses on an Airtel heterogeneous network, consisting of macro, micro, femto, and pico-cells. The selected case study cell is the macro cell with cell ID AK0367, located at No. 14 Gibbs Street, Uyo, Akwa Ibom, Nigeria, in the heart of the city hub. The geographical coordinates are latitude 5.0334267°, longitude 7.93334°, maximum call capacity per seconds is 1Gbps, and height 90.4 meters. This cell was chosen due to its high population density and significant daily influx of people in and out of the city. The conventional congestion detection mechanism in this cell faces technical challenges, resulting in inefficient load balancing and poor quality of service for users.

3. THE DCCP CONGESTION CONTROL MECHANISM

According to Bruno and Marilia (2013), DCCP is a transport layer-based protocol designed to control congestion among multimedia application in real time. The approach begins with the management of unacknowledged packets sent at a particular time using the congestion window size, to dynamically adjust using the Transmission Control Friendly Rate Controls (TCFR) approach to prevent excess loss and fairness in the system. To detect the congestion problem, the Explicit Congestion (ECN) notification was used to provide early detection of congestion though the size of the packet uploaded, and then the rate-based flow control approach was applied to allow the receiver control the rate at which packet is accepted, so as to prevent congestion.

Overall, DCCP provides congestion control mechanisms suitable for delay-sensitive applications while maintaining network efficiency. It combines adaptive congestion control algorithms, feedback mechanisms, and ECN support to mitigate congestion and ensure reliable data transmission. However, (Josip*et al*., 2021; Adel and Waleed, 2018), DCCP is not reliable for effective control of congestion. Some of the reasons for its unreliability includes lack of real time congestion detection capacity, inability to capture enough parameters which indicates congestion, etc. to address this problem, this research presents an artificial intelligence approach which was used to optimize the DCCP performance and develop an improved DCCP mechanism for congestion detection and control. The DCCP algorithm is presented as;

3.1 The algorithm of the traditional DCCP; (Algorithm1)

1. Start
2. Initialization of congestion window size
3. Set congestion window (CWND)
4. Increase the CWND exponentially for every acknowledged packet
   %Congestion Avoidance:
5. Set CWND threshold
6. For (CWND > threshold); enter the congestion avoidance phase.
7. Increase Round Trip Time (RTT).
   %Apply Congestion Detection:
8. Monitor for signs of congestion, with equation 3.1
9. Rate Control (RC) to reduce CWND
   %Fast Retransmit and Recovery:
10. When packet loss is detected through duplicate acknowledgments, trigger fast retransmit.
11. Repeatedly retransmit the lost packet(s) without waiting for a timeout.
    % ECN Support:
12. React to explicit congestion notification (ECN) marks by reducing packet sending rate
    %Rate-Based Flow Control:
13. Allow the receiver to control the sending rate by providing feedback.
    %Re-evaluation and Adaptation:
14. Continuously monitor network conditions, adjust congestion control parameters, and update the congestion window (CWND) accordingly.
15. Return
16. End

3.2 Development of the Congestion Detection Mechanism

In the previous section, the DCCP mechanism was presented and the need for its optimization. An artificial intelligence solution is proposed to detect the issues and address the problem. To achieve this, Genetic Algorithm (GA) was proposed due to its ability to solve optimization problem. From the literatures reviewed, many techniques (Kohler *et al*., 2006; Jawad*et al*., 2013; Nicholas *et al*., 2022) were presented for congestion control, with little or no attention to the problem identification before talking control, and as a result has affected the fast response to the problem of congestion.

Furthermore, traditional solution which adopts GA such as (Yosvany*et al*., 2022; Apavatjrut and Kamdee, 2021; Zhu *et al*., 2021) for congestion management never considers multiple congestion parameters such as load factor in Equation 1, throughput in Equation 2, and loss in Equation 3 as the chromosome and hence are not dynamic enough to detect the problem during the fitness and crossover performance. Hence this paper proposes to develop an improved GA which considers these aforementioned congestion parameters and develop solution which detects the congestion problem on time and then control with the DCCP protocol.

3.3 The Improved GA for Congestion Detection

To develop the improved genetic algorithm for the congestion detection, the weights of the pre-defined congestion parameters were considered as chromosomes and used for the fitness test. The benefit of this consideration of multiple parameters is that it ensures that enough chromosomes are available for the fitness test and hence address the problem of pre-mature convergence (Liu *et al*., 2000; Olympia *et al*., 2013; Xiaoqiu*et al*., 2020; Sharma and Chahar, 2022) which occurs when the algorithm was unable to find the optimal solution due to limited chromosomes in the search space. These factors were used to perform a fitness test and identify the problem considering standardized reference point information collected from the domain expert at the Nigerian Communication Commission (NCC) considering the maximum network capacity of the cell as 1Gbps as reported in the Table 1. These values from the table were used to program the reference chromosomes of the congestion detection mechanism. The outcome of the fitness was selected, crossed over and mutated to generate new offspring until the problem of congestion is detected.

TABLE 1: REFERENCE STANDARDS FOR CONGESTION

S/N	Parameters	Reference values
1	Load factor	1.00
2	Throughput	80%
3	Loss	3.5%

The Table 1 presents the reference congestion parameters considered for the fitness test. The Equations used for the evaluation of the objective function were presented in Equations 1 to 3 as;

$$Load\ Factor = \frac{Actual\ Traffic\ Load}{Maximum\ Capacity} \tag{1}$$

$$Throughput = \frac{Data\ Transmitted}{Total\ data\ delivered} \tag{2}$$

$$Losses = \frac{Packet\ Loss}{Total\ Packets\ Sent} \tag{3}$$

The Equation 1, 2 and 3 were used for the determination of the congestion parameters, while the Equation 4 was used for the fitness computation as a weighted sum of these factors:

$$Fitness(C) = w1 * LF1(C) + w2 * LF2(C) + \ldots + wn * LFn(C) \tag{4}$$

Where$LF1(C)$ to $LFn(C)$ present the multi objective functions in Equation 1-3, while $w1$ to $wn$are the weights of the parameters generated from the fitness outcome. The pseudocode of the algorithm is presented algorithm 2, presenting the improved GA which was developed for the detection of congestion in the macro cell considering the multiple aforementioned objective functions for the fitness test and generation of new offspring which eventually reads congestion problem. The Figure 2 presents the flow chart of the algorithm.

The Improved Genetic Algorithm (Algorithm 2)

1. Generate chromosomes population as (P)
2. Evaluate the multi objective function considering Equation (3.2-3.4)
3. Compute the fitness test considering Equation (3.5)
4. Compute fitness score for the chromosomes
5. Select outcomes and of fitness and formulate parent chromosomes
6. Cross over and mutate for offspring randomization
7. Evaluate new offspring
8. Replace old chromosome population
9. Do until congestion condition is achieved
10. Return

3.4 The GA Based DCCP (GA-DCCP)

The GA-DCCP is the new congestion detection and control mechanism developed for the optimization of quality of service in the transport layer. This is developed using the improved genetic algorithm to optimize the traditional DCCP adopted for the study. The algorithm 3 presented the improved congestion detection and control mechanism.

3.8.1 The GA Based DCCP (Algorithm 3)

1. Start
2. Initialization of congestion window as the number of chromosomes
3. Evaluate the congestion window size multi objective function
4. Compute the fitness test considering to determine the congestion window
5. Select outcomes and of fitness and formulate parent chromosomes
6. Cross over and mutate for new congestion window
7. For congestion window threshold
8. Activate Congestion Control Actions:
    a. Reduce the congestion window size (CWND) using TCP-Friendly Rate Control (TFRC)
9. Fast Retransmit and Recovery:
    a. When packet loss is detected through duplicate acknowledgments, trigger fast retransmit.
    b. Repeatedly retransmit the lost packet(s) without waiting for a timeout.
10. ECN Support:
    a. React to explicit congestion notification (ECN) marks by reducing packet sending rate
11. Rate-Based Flow Control:
    a. Allow the receiver to control the sending rate by providing feedback.
12. Re-evaluation and Adaptation:
    a. Continuously monitor network conditions, adjust congestion control parameters, and update the congestion window (CWND) accordingly.
13. Return
14. End

The GA-based DCCP algorithm begins with the initialization of the congestion window size for each chromosome. The congestion window size is then evaluated using a multi-objective function that considers performance metrics. The fitness of each chromosome is computed to determine their performance. Parent chromosomes are selected based on their fitness, and crossover and mutation operations are performed to generate new offspring with modified congestion window sizes. A congestion window threshold is set, and congestion control actions are activated, such as reducing the congestion window size using TCP-Friendly Rate Control (TFRC). Fast retransmit and recovery mechanisms are triggered when packet loss is detected, and explicit congestion notification (ECN) marks are reacted to by reducing the packet sending rate. Rate-based flow control is implemented to allow the receiver to control the sending rate. Network conditions are continuously monitored, and congestion control parameters are adjusted and the congestion window is updated accordingly. The algorithm concludes with the return of the optimized congestion window size.

4. THE IMPLEMENTATION OF THE GA-DCCP ON THE 4G NETWORK

The implementation of a Genetic Algorithm (GA) based Datagram Congestion Control Protocol (DCCP) on a 4G network was facilitated using several MATLAB toolboxes. The Optimization Toolbox provides functions implementing the genetic algorithms what was utilized for the optimization of the DCCP parameters. The Communications Toolbox enables the simulation of GA-DCCP behaviour on a 4G network and the evaluation of performance metrics such as throughput, load factor, and loss rate. The Statistics and Machine Learning Toolbox aids in analysing and evaluating the obtained simulation results through functions for statistical analysis and data visualization. These toolboxes provide a comprehensive set of functions, algorithms, and resources to simplify the implementation process and enable efficient analysis and optimization of the DCCP protocol in a 4G network environment. The Table 2 presents the parameters for simulating the system.

TABLE 2: SIMULATION PARAMETERS

Parameters	Values
Time of simulation (s)	100
Number of users	80
Data rate	10Mbps
Load factor target	0.8
CWND	10packets
Target throughput	800Mbps
Target loss rate	0.05%
Maximum cell capacity	1000Mbps

5. RESULTS

This section presents the performance of the GA-DCCP on the 4G network. The GA-DCCP sampled the population of chromosomes considering the multiple congestion parameters which are throughput, loss and load factor and then use fitness computation to read and determine the offspring through crossover and mutation to detect the congestion problem. The outcome of the fitness computation for the load factor using equation 4 was presented as Figure 1.

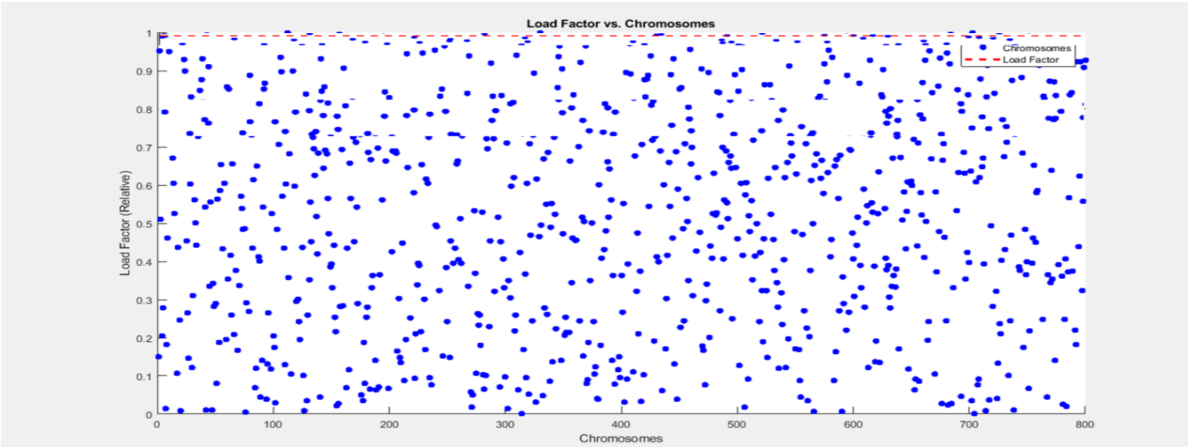

Figure 1: Load factor fitness result.

The Figure 1 presents the performance of the fitness computation for load factor to read congestion. The result used fitness test to determine load factor chromosomes above the factor of one which reads congestion problem. The process according to the GA-DCCP algorithm uses the fitness computation to read the relationship between the actual load and then cell network capacity and then identify all chromosomes of load factor above one which is the peak reference point for determination of congestion. Similarly, the fitness computation for throughput is presented in Figure 2.

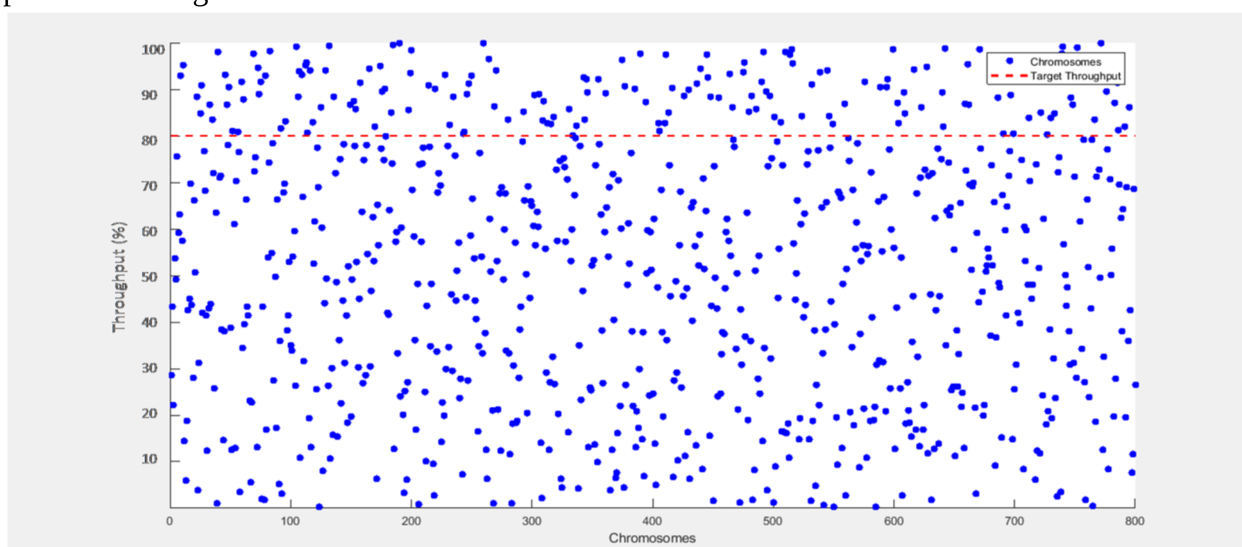

Figure 2: Fitness test for throughput constraints.

The Figure 2 presents the relative throughput of the fitness computation of the chromosomes which represents the congestion problems. The throughput was used to determine when data delivery rate reduced from the specified threshold of 80% which then implied congestion. The objective function of the GA-DCCP was to ensure that the average throughput of the network was maintained above the pre-defined thresholds and ensure quality of service through congestion control. In addition, the fitness result for the packet loss was reported in the Figure 3.

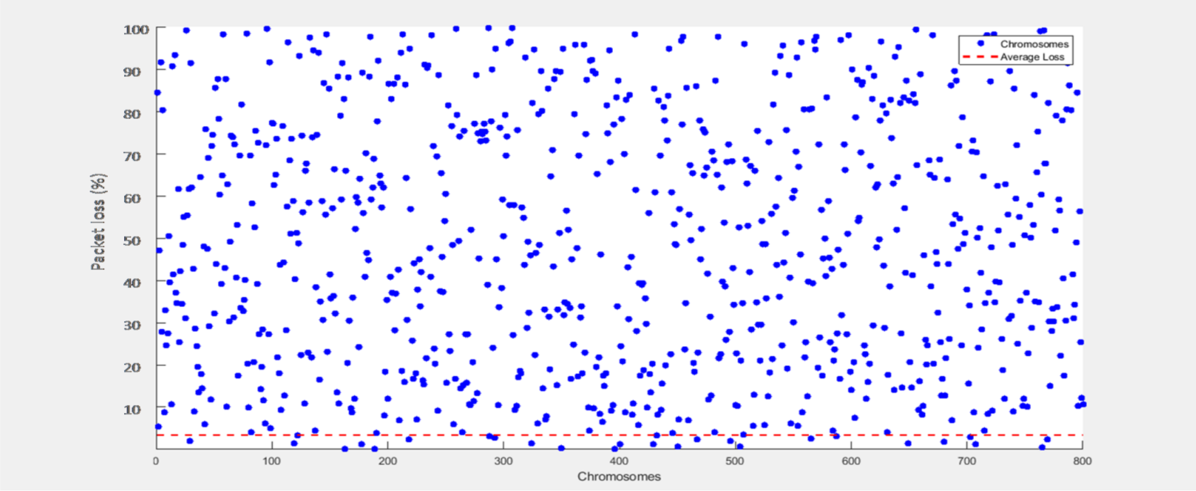

Figure 3: The fitness result for loss determination.

The Figure 3 presents the fitness computation by the GA-DCCP to determine the congestion problem using packet loss. The computation used a packet loss reference of 3.5%to determine chromosome which indicated congestion and then activate the control mechanism.

5.1 Result of GA-DCCP on Congested 4G Network

The previous section presented the performance of the computation process to determine the congestion problem through fitness test, considering the multiple objective functions. To test the effective of the congestion control solution, the GA-DCCP was evaluated on a network with 50 users and each transmitting 10Mbps data, which is an equivalent load of 800Mbps. At this point in the characterization, it was observed that loss has increased to 11.1% which is not acceptable for multimedia application streaming on the network. The packet loss, throughput and load factor performance of the new GA-DCCP was presented in the figure Table 3.

TABLE 3: NETWORK PERFORMANCE WITH GA-DCCP

Time (s)	Packet Loss (%)	Load Factor	Throughput (%)
1	3.32	0.75	88.02
2	3.35	0.76	89.06
3	3.43	0.78	87.03
4	3.35	0.75	89.05
5	3.30	0.76	87.07
6	3.45	0.78	86.03
7	3.34	0.75	85.06
8	3.32	0.74	87.02
9	3.56	0.76	88.07
10	3.34	0.75	89.06
11	3.61	0.77	87.04
12	3.45	0.78	87.07
13	3.46	0.75	88.02
14	3.31	0.77	89.03
15	3.52	0.78	87.06
16	3.64	0.75	87.05
17	3.34	0.75	88.06
18	3.32	0.75	86.07
19	3.54	0.77	87.03

20	3.54	0.76	88.05
Average	3.2345	0.7305	89.4975

The Table 3 presented the result of the packet loss when the GA-DCCP algorithm was tested on a congestion network. The result in table 3 showed that the algorithm immediately identified the problem and then applied the rate-based flow control to offload the traffic by controlling the receiver which adaptive manages rate of data intake. Secondly, the ECN was used to detect the initial loss and then the packet re-transmitted to compensate for loss and ensure quality of service. Overall, the average packet loss rate recorded on the network within 20s is 3.23%. The implication is that the loss rate on the network is within an acceptable tolerance and hence implied good quality of service according to the NCC requirements. The other network indicators of throughput and load factor with the GA-DCCP during congestion congested users were also reported. From the result it was observed that the average throughput on the network is 89% and the average load factor is 0.7. The implication is that the GA was able to detect the congestion problem, and then the DCCP used the rate controller to address the problem and maintain quality of service.

5.2Comparative Analysis

The system validation was achieved through comparative analysis considering the new GA-DCCP and characterized system without GA-DCCP. The comparative table considering throughput was presented in the Table 4.

TABLE 4: COMPARATIVE THROUGHPUT PERFORMANCE

Time Interval (sec)	Data upload (Mbps)	Throughput (%) with GA-DCCP	Throughput (%) without GA-DCCP
7.000-8.000	550	89.4	89.4
8.000-9.000	600	89	87.9
9.000-10.000	650	89	81.4
10.000-11.000	750	89	74.5
11.000-12.000	800	89	60.9
12.000-13.000	850	89	59.4
13.000-14.000	900	89	55.9
14.000-15.000	950	89	51.4
15.000-16.000	850	89	58.6
16.000-17.000	800	89	60.4
17.000-18.000	750	89	74.0
18.000-19.000	700	89	70.9
19.000-20.000	720	89	71.3
20.000-21.000	650	89	81.4
21.000-22.000	600	89	81.9
Average	741.333	89.0267	70.62

The Table 4 presented the comparative analysis of the throughput performance with GA-DCCP and without it. From the table the average throughput recorded for the network with GA-DCCP is 89.03%, while that without GA-DCCP is 70.62%. The implication of the result is that the network with GA-DCCP was able to detect the congestion problem due to increased upload and

then used the rate controller to adjust the receiver, until the load is balanced. The percentage improvement with the GA-DCCP against recorded for throughput is 26.06%, which is good.
From the result it was observed that initially the throughput for both networks were good, until at 2pm when the load keep throughput without GA-DCCP starts to reduce, while that with GA-DCCP remained constant. This implied that at this point, the congestion on the network has resulted to poor quality of service as evident in the throughput result without GA-DCCP as it started to degrade; however, the GA-DCCP based throughput remained constant due to the load control via the adjustment of the rate controller. This process continued until after the peak period of 16:00Hr, when the throughput of the network began to increase. This was due to the reduced load on the network, thus implying that no more congestion. The validation result considering loss rate and load factor was reported in the Table 5.

TABLE 5: COMPARATIVE LOSS AND LOAD FACTOR PERFORMANCE

Time Interval (sec)	Data upload (Mbps)	Loss (%) with GA-DCCP	Loss (%) without GA-DCCP	Load factor without GA-DCCP	Load factor with GA-DCCP
7.000-8.000	550	2.66	2.66	0.55	0.55
8.000-9.000	600	2.81	2.81	0.6	0.6
9.000-10.000	650	2.87	2.87	0.65	0.65
10.000-11.000	750	3.05	3.05	0.75	0.75
11.000-12.000	800	3.23	3.51	0.8	0.8
12.000-13.000	850	3.23	39.6	0.85	0.8
13.000-14.000	900	3.23	4.51	0.9	0.8
14.000-15.000	950	3.23	5.76	0.95	0.8
15.000-16.000	850	3.23	4.24	0.85	0.8
16.000-17.000	800	3.23	3.46	0.8	0.8
17.000-18.000	750	3.08	3.08	0.75	0.75
18.000-19.000	700	2.99	2.99	0.7	0.7
19.000-20.000	720	2.96	2.96	0.72	0.72
20.000-21.000	650	2.87	2.87	0.65	0.65
21.000-22.000	600	2.81	2.81	0.6	0.6
Average	741.333	3.032	5.81	0.7413	0.718

The Table 5 presented the comparative loss rate of the 4G network with GA-DCCP and without it. The result reported an average loss rate of 3.03% as against the network without GA-DCCP with 5.81% loss rate. The implication of the result showed that due to the re-transmission capacity of the DCCP, the loss rate was improved greatly with 47.84% compared with that of the network without GA-DCCP. The comparative load factor in the Table 4.6 presented the network performance with the GA-DCCP and without GA-DCCP. From the result it was observed that with the GA-DCCP, the average load factor is 0.718 as against without the GA-DCCP which reported load factor of 0.7413. The implication is that without the GA-DCCP, the network operated at a close congestion margin which is a problem as this point affects quality of service performance and was the reason behind the poor throughput and high loss rate recorded in the characterized system; however, in the new system developed with GA-DCCP, the congestion problem was detected and then rate controller was used to balance the load, and from the result it was observed that the average load factor was maintained at 0.7.

6. CONCLUSION AND RECOMMENDATIONS

This paper has presented an effective approach for congestion management in multi-tier 4G radio network controllers using artificial intelligence techniques. The study addressed the crucial requirement of maintaining quality of service (QoS) in 4G networks to support real-time multimedia applications and seamless packet streaming in wireless networks.To ensure the sustenance of QoS in 4G networks, a heterogeneous configuration of the network was adopted. This configuration involved deploying smaller cells alongside the main macro cell to facilitate load balancing during congestion scenarios. By utilizing this approach, the network demonstrated improved performance and efficient utilization of resources.The paper identified the need for addressing congestion considering multiple congestion constraints, including throughput, loss, and load factor. To overcome this challenge, a genetic algorithm (GA) was integrated with the Datagram Congestion Control Protocol (DCCP) for congestion detection and control. The GA-DCCP approach effectively detected congestion and dynamically adjusted the data reception rate to prevent overload, thus mitigating congestion-related issues. Through simulation and evaluation, the research demonstrated the effectiveness of the proposed GA-DCCP approach, and achieved average throughput of 89.03% during testing which showcased improved data transfer efficiency. Additionally, the validation results indicated a significant 26.06% improvement compared to the network without GA-DCCP, confirming the efficacy of the proposed solution. Finally, this research has made significant contributions to the field of congestion management in multi-tier 4G radio network controllers. By integrating artificial intelligence techniques, such as the genetic algorithm, with the DCCP, congestion detection and control mechanisms were enhanced, resulting in improved QoS and efficient load balancing.

6.1 Recommendations

These developed techniques should be adopted to improve quality of service in 4G cells located in other part of AkwaIbom state, and Nigeria at large. this will help address congestion problem experienced in the MTN cell during the day across high population density regions.

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