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Neural Network and Genetic Algorithm Approach to Optimal Channel Allocation and Adaptive Handoff Prioritization for Congestion Control in Mobile Networks

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Abstract

This study developed an Optimal Channel Assignment and Adaptive Handoff Prioritization Scheme (OCAHPS) for controlling congestion in mobile networks. The OCAHPS consist of a Neural Network and Genetic Algorithm (Neuro-Genetic, NG) scheme designed to solve the channel assignment problem formulated as a combinatorial optimization problem, and an adaptive handoff prioritization algorithm that uses the NG algorithm as a decisive component of its channel assignment process. The scheme was implemented and tested on two different simulation environments developed in MATLAB based on demand instances of the Philadelphia standard benchmark problem of channel assignment and peak hour demand instances of a Nigerian mobile network service provider (NIGMobile) with high traffic. The performance evaluation parameters used were Call Block Probability, Call Drop Probability and Percentage Technical Congestion. The study shows that OCAPHS was more efficient and provides better network performance when compared with existing schemes.

Keywords: *Channel assignment, Handoff prioritization, Congestion control, Neural network, Genetic Algorithm*

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1. Introduction

Channel assignment is viewed as a large-scale dynamic optimization problem with multiple goals and constraints in a stochastic environment. Intelligent based approach (Swati and Sedamkar, 2012; Sonavane and Sedamkar, 2012), evolutionary algorithms (Chia et al., 2012), Neural Network (Salau et al., 2013; Moradi, 2011), Fuzzy logic (Ansari et al., 2012) and other computational intelligence approaches (Deepak et al., 2012; Atayero and Luka, 2012; Deepak et al., 2012; Aizaz and Ravishankar, 2012) have been employed alone or in combination with others (Aizaz et al., 2012) to solve the Channel Assignment Problem (CAP). Among the evolutionary algorithms, genetic algorithm (GA) plays important role with the exhibition of implicit parallelism associated with the ability to effectively explore information over large search spaces. In this work, Genetic Algorithm was combined with Neural network (NN) to address the CAP. The advantage of these approaches being that they consider environmental dynamics and the intelligence strategies can be adapted in accordance with information obtained in the behaviour of the environment. GA and NN have been successfully combined to solve similar optimization problems (Reshamwala et al., 2014).

Handoff is the procedure of passing an on-going call from one cell to another within a mobile network as a user moves through the network. To improve the cellular network performance, an efficient handoff prioritization procedure is required when a user is switching between the cells (Kaur and Kaur, 2014; Goswani and Patel, 2014; Solanki and Rafiq, 2014). Every handoff needs network resources to pass the call to the next base station and failure for handoff to occur promptly would lead to a reduction in the Quality of Service (QoS) below an adequate level and connection will be dropped. The purpose of the handoff procedure is to preserve on-going calls when the mobile station is moving from one cell to another (Nayak et al., 2015; Goswani and Patel, 2014; Kar and Nayak, 2014). Having an on-going call dropped is more frustrating to a customer than blocking a new call. Hence, most existing handoff schemes give primacy to handoff calls at the expense of good quality of service for new calls. Unfortunately, this sometimes leads to channels being kept idle for used by handoff calls while new calls are being blocked because channels are not available to assign (Solanki and Rafiq, 2014; Asuquo et al., 2014; Kaur and Kaur, 2014). This justifies the need for more efficient schemes that provides acceptable QoS for handoff calls and new calls. Such schemes will also reduce congestions in mobile networks.

Different methods have been offered to reduce handoff dropping probability. One approach is to prioritize handoff call over new calls (Khan, 2010). Basic methods in handoff prioritization schemes are guard channels (GC), call admission control (CAC) and handoff queuing schemes. Sometimes these schemes are combined to obtain better results (Goswani and Patel, 2014). The most common approaches for prioritizing handoff calls are the guard channel approach and the handoff queuing approach (Bilal et al, 2016). In guard channel approach, the probability of successful handoff is improved by simply reserving a number of channels exclusively for handoff calls. The remaining channels are equally accessed by handoff and new calls. However, this led to a poor utilization of the scarce channel resources since guard channels are sometimes left unused at no-peak hours and yet inaccessible by new calls which are sometimes blocked due to non-availability of channels to service them. Another issue with guard channels is the choice of the number of guard channels to reserve. According to Bilal et al. (2016), a large number of guarded channels leads to a very small call drop probability, but it will also lead to a very high call block probability (CBP) because more channels are reserved for handoffs calls which could lead to starvation of channels for new calls.

In the call admission control scheme (Khan, 2010) a choice is made to admit new call requests into the network or not. The arrival of new calls continuously estimated. If found to be higher than a predefined threshold, some calls are blocked regardless of whether channels are available or not, this is to ensure a decrease in handoff call drop probability. In Queuing handoff call prioritization scheme (Khan, 2010), the handoff calls are placed on queue when all the channels are occupied. When a channel is available, it is assigned to one of the handoff calls in the queue. A thing common to these schemes is that they decrease call dropping probabilities and increase call blocking probabilities. We proposed an algorithm that provides an acceptable QoS for new calls while prioritizing channel allocation to handoff calls. The decision to grant access to new calls is determined by the threshold values set for the call drop probability and traffic intensity in the network. The neural network and genetic algorithm (neuro-genetic) CAP solution was integrated into the algorithm to decide the best channel to select from the central pool for assignment when no guard channel is available.

One major effect of congestion in a mobile network is that it brings about poor quality of service for both new and handoff calls. Congestion Control can either be reactive or proactive (Jose et al., 2015). A reactive Congestion Control has a feedback on the channel state and reacts based on that value compared to a threshold. The major drawback is that it reacts after congestion is detected; that is, it only tries to manage the congestion. A proactive Congestion Control on the other hand has a built-in model about the network environment and factors that triggers congestion in the network. Hence for each channel allocation, the effect of that allocation is considered for both the immediate and future state of the network in the channel selection process. Such congestion control techniques are focused on avoiding congestion rather than managing it. There are various techniques for congestion control in mobile networks among which are the Automatic Call Gapping (ACG), the Token Bank (TB) and the Call Admission Control (CAC). The idea in ACG is to decrease call attempt rate by permitting just one call attempt per stated gap interval. Input regulation is used in TB to protect an entity from being overloaded. CAC is a common approach to controlling congestion in GSM network. It is used to control the number of calls allowed into the networks and ensure the network is not congested.

2. Materials and methods

2.1 Optimal channel assignment and adaptive handoff prioritization scheme

The proposed optimal channel assignment and adaptive handoff prioritization scheme (OCAHPS) is a dynamic channel allocation and handoff prioritization algorithm with guard channels and call admission control. The scheme combines genetic algorithm and neural network methodologies to decide the best channel to select from a central pool for assignment to a cell when all guard channels in the cell are engaged. The work was implemented in two parts:

Firstly, a Neuro-genetic (NG) algorithm for dynamic channel allocation that jointly considered CCC, CSC and ACC as an integral part of the channel allocation process rather than selecting a channel before checking if the constraints are satisfied is proposed (Ugege and Ojesanmi, 2017). The solution also considered the need to optimize frequency (channel) reuse and reservation across the network and hence included all three soft conditions in the function that was formulated and optimized. The results were compared with works by Jyorthi *et al. (*2015), Hong and Lin (2015), and Tirmizi *et al.* (2015). Secondly, an adaptive handoff prioritization algorithm (AHPA) that uses the NG algorithm as a decisive component of its channel assignment process and compared with works by Kar and Nayak (2014), Ali (2016), Chavan and Sarasu (2014) and performance evaluation parameters obtained from a leading mobile network service provider in Nigeria (NIGMobile) was also proposed. The improvement on existing works is centred on:

i. The proposed algorithm used multiple parameters including call drop probability and traffic intensity to decide the accessibility to the fixed nominal channels by new calls and admittance of the new call.
ii. The proposed algorithm gave special consideration to the handoff calls but ensured an acceptable QoS for new calls by not reserving guard channels solely for handoff calls at the expense of new calls.
iii. The number of guard channels is kept constant while access to the channels by new calls is dynamically controlled rather than having to calculate the number to reserve per time.
iv. The neuro-genetic algorithm is employed in the handoff prioritization algorithm to select the best channel from the central pool when there is no guard channel to assign.

2.2 Proposed neuro-genetic algorithm for the CAP

All three hard constraints are represented with a compatibility matrix *C* which is an (*N* x *N*) symmetric matrix as shown in Equation (1), where *N* is the number of cells in the network. The following can be deduced from the matrix:

i. The diagonal elements C_{ii} represents the CSC, which is the minimum frequency separation distance between any two channels used in cell i.
ii. If $C_{ij} = 0$; there is no constraint in channel reuse in between cell i and j.
iii. If $C_{ij} = 1$; there is a CCC, If $C_{ij} = 2$; there is a ACC and If $C_{ii} >= 1$; there is a CSC

$$C = \begin{pmatrix} \mathbf{C_{11}} & \mathbf{C_{12}} & \cdot & \cdot & \cdot & \mathbf{C_{1N}} \\ \mathbf{C_{12}} & \mathbf{C_{22}} & \cdot & \cdot & \cdot & \mathbf{C_{2N}} \\ \cdot & \cdot & \cdot & & & \cdot \\ \cdot & \cdot & & \cdot & & \cdot \\ \cdot & \cdot & & & \cdot & \cdot \\ \mathbf{C_{N1}} & \mathbf{C_{N2}} & \cdot & \cdot & \cdot & \mathbf{C_{NN}} \end{pmatrix} \quad (1)$$

An assignment/allocation channel by cell matrix A represented with Equation (2) reflects which channel has been allocated to which cell. $A_{i,j}$ is 1 if channel j is assigned to cell I, and 0 otherwise. Also a demand vector D of dimension $\{d_1 \ldots d_N\}$ where d_i is the number of channels required in cell i in order to satisfy channel demand.

$$A = \begin{pmatrix} \mathbf{A_{1,1}} & \mathbf{A_{1,2}} & \cdot & \cdot & \cdot & \mathbf{A_{1,cel}} \\ \cdot & & & & & , \\ \cdot & & & & & \cdot \\ \cdot & & & & & \cdot \\ \cdot & & & & & \cdot \\ \mathbf{A_{cha,1}} & \mathbf{A_{cha.2}} & \cdot & \cdot & \cdot & \mathbf{A_{cha,ce}} \end{pmatrix} \quad (2)$$

In addition to the hard constraints, the proposed solution also considered the soft constraints to address the need to optimize channel reuse and reservation across the network. The set of Equations (3) to (8) define the approach to the formulation and representation of the CAP as an optimization problem incorporating all three hard constraints (CCC, CSC and ACC) and soft conditions (PC, RC and LR). Equations (3) and (4) are related to the functions used in Moradi (2011) for the CCC, ACC and CSC hard constraints. Equations (5), (6) and (7) are similar to functions used by Deepak *et al.* (2012) to represent the soft conditions. Equation (8) is introduced to the combined functions used separately by Moradi (2011) and Deepak et al. (2012) to arrive at Equation (9) which is now the new optimization function for the CAP problem in this work. Parameters used in the equations:

cel = Number of cells in the network
cha = Number of dynamic channels in the central pool
k = cell in which a call arrived ($1 \le k \le cel$)
$E_{ACC,CCC}$ = Energy function for adjacent channel and co-channel constraints
$ACCC_{kjip}$ =Adjacent channel and co-channel constraint between channel j selected by cell k and channel p used by cell i
CSC_{jp} = Co-site constraint between channel j and channel p selected for use in the same cell
E_{PC} = Energy function for packing condition
E_{RC} = Energy function for resonance condition
RC_{ik} = function determining whether cell I and k belong to same reuse scheme
E_{LR} = Energy function for limiting rearrangement
Mcha = Maximum number of dynamic channels allowed for use in a cell
E_{Mcha} = Energy function for Mcha
CCC_{ik} = co- channel constraint between cell i and k for using same channel
$dist_{ik}$ = distance between cell i and k in the network

$$E_{ACC,CCC_k} = \sum_{j=1}^{cha}\sum_{i=1}^{cel}\sum_{p=1}^{cha} V_{k,j} * A_{i,j} * ACCC_{kjip} \tag{3}$$

k = 1, 2, …, cel
where

$$ACCC_{kjip} = \begin{cases} 1 \ if \ i \neq k \ and \ C_{ki} > 0 \ and \ j - (C_{ki} - 1) \le p \le j + (C_{ki} - 1) \\ 0 \ otherwise \end{cases}$$

Equation (3) states the adjacent channel constraint and co-channel constraint. Both constraints are considered together because they can be represented by the value of $C_{i,j}$ when $i \neq j$. Here $V_{k,j}=1$ if channel j is assigned to cell k, otherwise $V_{k,j}=0$. k is the cell in which a call arrives. The energy function ($E_{ACC,CCC}$) rises when a channel j which is assigned to a cell i is considered for assignment to cell k and such choice will lead to interference. It thus guarantees that solutions that will not lead to interference gives superior fitness values. $A_{i,j}$ is the ijth element in the assignment Matrix A (Equation 2), the value is 1 if channel j is allocated to cell i, and 0 if not allocated. Equation (4) states the *Co-site* constraints. This is considered based on the value of C_{jp} in the compatibility matrix C.

Equation (5) states the packing condition.

$$E_{CSC_k} = \sum_{j=1}^{cha}\sum_{p=1}^{cha} V_{k,j} * A_{k,p} * CSC_{jp} \tag{4}$$

k = 1, 2, …, cel
where

$$CSC_{jp} = \begin{cases} 1 & if \ j \neq p \ and \ p - (C_{kk} - 1) \le j \le p + (C_{kk} - 1) \\ 0 & otherwise \end{cases}$$

$$E_{PC_k} = \sum_{j=1}^{cha}\sum_{i=1}^{cel} V_{k,j} * A_{i,j} * \frac{(1 - CCC_{ik})}{dist_{ik}} \tag{5}$$

k = 1, 2, …, cel
$i \neq k$

The energy decreases if channel j assigned to cell k is also selected by cell i and $CCC_{ik} = 0$. Energy reduction depends on the distance between i and k. The PC recommends that channels already being used in some cells be considered for reuse in other cells as close as possible without interference so as to maintain a minimal number of channel usage by the network thereby reducing the likelihood of future call blocking in other cells. Satisfaction of this condition further reduces the energy function. Equation (6) states the resonance condition.

$$E_{RC_k} = \sum_{j=1}^{cha}\sum_{i=1}^{cel} V_{k,j} * A_{i,j} * (1 - RC_{ik}) \tag{6}$$

k = 1, 2, …, cel
$i \neq k$

The value of RC_{ik} is 1 when cells i and k are in the same reuse scheme and 0 if not. The RC as far as possible ensures the assignment of same channels to cells belonging to same reuse scheme. Equation (7) states the limiting rearrangement condition.

$$E_{LR_k} = \sum_{j=1}^{cha} V_{k,j} * A_{k,j} \tag{7}$$

k = 1, 2, …, cel

The value of E_{LR_k} decreases by 1 when the assignment of a channel j to an existing call in a cell k is maintained even when a new call arrives and a channel has to be assigned to that call; thereby maintaining the channel assignment to existing calls in the new assignment configuration resulting from the admission of a new call. Hence limiting the reassignment of channels. Reassignment of channels could bring about a reduction in the call blocking probability but the complexity involved but in time and computation is high. Hence the need to limit such rearrangement to a low level. The limiting rearrangement condition is therefore employed to avoid excessive reassignment in a network (Wu et al., 2010).

Equation (8) is to control the allocation of channels to cells already assigned the maximum number of channels (M_{cha}) stated for each cell in the network. When the number of channels already assigned to a particular cell has reached M_{cha}, the value of this function is increased thereby increasing the entire energy function and making such configuration not resulting as the optimal result.

$$E_{Mcha_k} = Mcha - \sum_{j=1}^{cha} V_{k,j} \qquad (8)$$

k = 1, 2, …, cel

From Equations (3) to (8), the energy function E for cell k becomes

$$\sum_{j=1}^{cha}\sum_{i=1}^{cel}\sum_{p=1}^{cha} V_{k,j} * \ A_{i,j} * ACCC_{kjip}$$

$$+ \sum_{j=1}^{cha}\sum_{p=1}^{cha} V_{k,j} * \ A_{k,p} * CSC_{jp} -$$

$$\sum_{j=1}^{cha}\sum_{i=1}^{cel} V_{k,j} * \ A_{i,j} * \frac{(1 - CCC_{ik})}{dist_{ik}} +$$

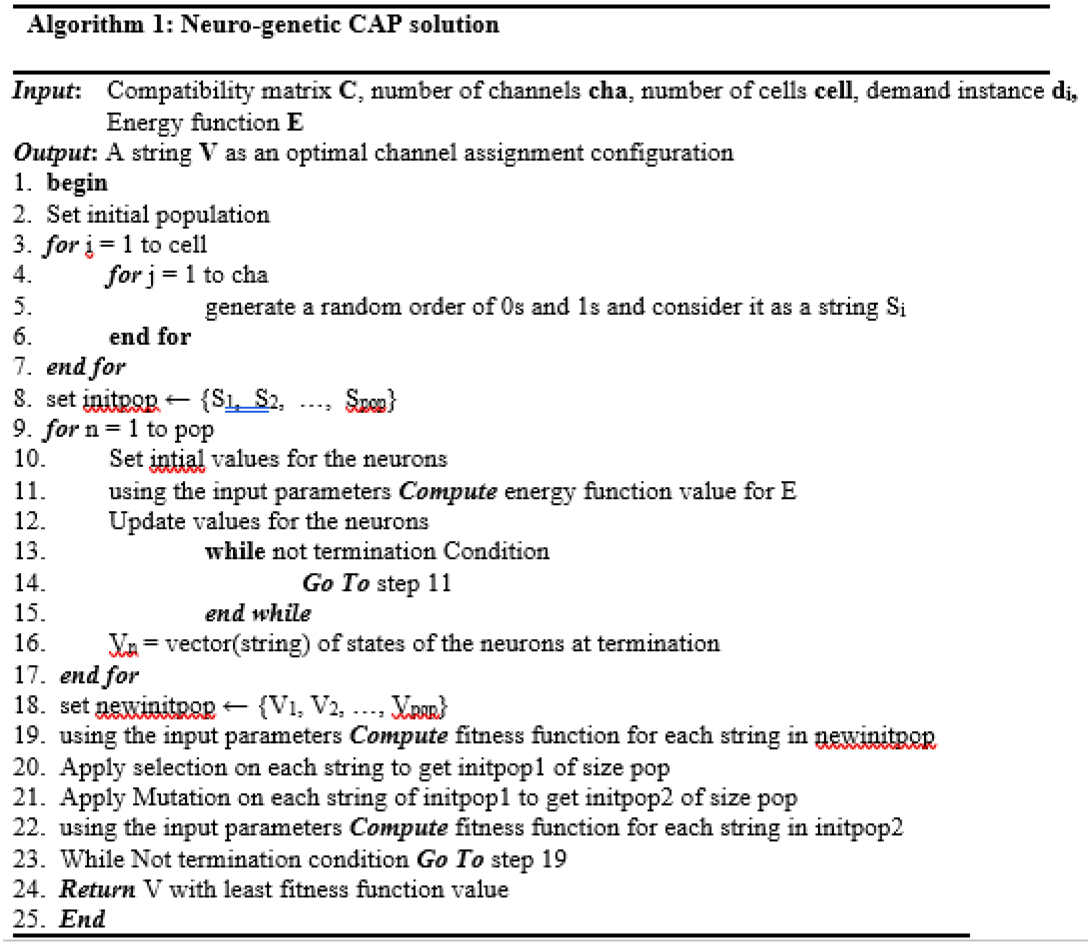
$$\sum_{j=1}^{cha}\sum_{i=1}^{cel} V_{k,j} * \ A_{i,j} * (1 - RC_{ik}) - \sum_{j=1}^{cha} V_{k,j} * \ A_{k,j}$$

$$- \left(Mcha - \sum_{j=1}^{cha} V_{k,j} \right)$$

$$E = E_{ACC,CCC} + E_{CSC} - E_{PC} + E_{RC} - \ E_{LR} - E_{Mcha} \qquad (9)$$

The task becomes to optimize the energy function represented in Equation (9) subject to constraints represented by Equation (3) through (8) which constitute the solution space. Neural network was used to generate an initial population of feasible solutions for the genetic algorithm process. From the solution space, solutions were randomly selected to form the initial population for the genetic algorithm process. To ensure a feasible optimal solution, each of the solutions was used to initialize the neural network and then trained to produce a feasible solution. Each status of the Neural Network (neuron values) is equivalent to the values in each chromosome of the genetic algorithm and is a solution instance for the channel assignment problem. This is a representation of the assignment/distribution of channels across the network at that instance. Eventually the chromosome that emerges as the optimal solution becomes the best channel allocation solution based on the channel demand by cells at that specific time.

Algorithm 1 is the NG Algorithm which was implemented in MATLAB. Though there are several standard network models for benchmarking CAP solutions, the Philadelphia network model with 21 cells network has been the most commonly used (Cheeneebash and Rughooputh, 2014). The Philadelphia Network model was therefore adopted for this work.



Algorithm 1: Neuro-genetic CAP solution

```
Input:  Compatibility matrix C, number of channels cha, number of cells cell, demand instance $d_i$,
        Energy function E
Output: A string V as an optimal channel assignment configuration
1.  begin
2.  Set initial population
3.  for i = 1 to cell
4.          for j = 1 to cha
5.                  generate a random order of 0s and 1s and consider it as a string $S_i$
6.          end for
7.  end for
8.  set initpop ← {$S_1$, $S_2$, …, $S_{pop}$}
9.  for n = 1 to pop
10.         Set intial values for the neurons
11.         using the input parameters Compute energy function value for E
12.         Update values for the neurons
13.                 while not termination Condition
14.                         Go To step 11
15.                 end while
16.         $V_n$ = vector(string) of states of the neurons at termination
17. end for
18. set newinitpop ← {$V_1$, $V_2$, …, $V_{pop}$}
19. using the input parameters Compute fitness function for each string in newinitpop
20. Apply selection on each string to get initpop1 of size pop
21. Apply Mutation on each string of initpop1 to get initpop2 of size pop
22. using the input parameters Compute fitness function for each string in initpop2
23. While Not termination condition Go To step 19
24. Return V with least fitness function value
25. End
```

Fig. 1 shows the Philadelphia network model of 21 cells used in one of the simulation. Apart from this, a different simulation environment was created based on data from a leading mobile network service provider in Nigeria at peak hour data in a densely populated geographical area with high traffic load. This was done to mimic a real life mobile network environment as much as possible.

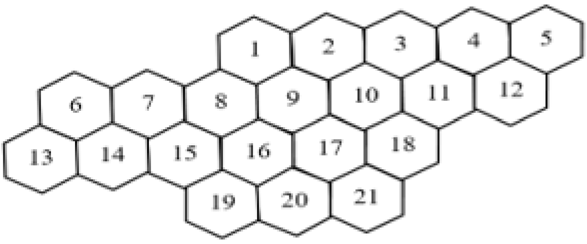


Fig. 1: Cellular geometry of the Philadelphia network model

The first simulation environment was based on D_1 (a demand instance of the Philadelphia network problem (Elhachmi and Guennoun, 2011)), the second was based on data from a leading Nigerian mobile network service provider.

D_1 = [8 25 8 8 8 15 18 52 77 28 13 15 31 15 36 57 28 8 10 13 8]

2.3 Proposed handoff prioritization algorithm

Algorithm 2 is the proposed adaptive handoff prioritization algorithm. The algorithm takes into consideration the traffic intensity and the call dropping probability in the network. Both parameters are used to determine if access to the guard channels should exclusively be for handoff calls or otherwise. The algorithm therefore ensures that guard channels are not kept for handoff calls when it is not necessary to do so. This is intended to achieve more optimal utilization of the channel resources while maintaining a good QoS for both handoff and new calls.

The algorithm grants new calls access to use the guard channels when the Traffic Intensity (TI) and/or the Call Drop Probabilities (CDP) are below the set Thresholds. A handoff call is only dropped under the condition that no guard channel is available and no channel could be assigned from the central pool. The NG algorithm for the CAP was used to select the best channel to allocate from the central pool when no guard channel is available. Parameters used in the algorithm:

TI = traffic intensity = cha_used/tot_cha)
CDP = call dropping probability = HC_rej/ Tot_H_calls
H_calls = handoff calls
N_calls = New calls
TI_threshold = Traffic intensity threshold
CDP_threshold = Call drop probability threshold
HC_rej = Handoff calls rejected
NC_rej = New calls rejected
Tot_H_calls = Total Handoff calls = H_calls + HC_rej
Tot_N_calls = Total New calls = N_calls + NC_rej
Tot_nom_cha = Total nominal channels
cha = Total dynamic Channels
Tot_cha = Tot_num_cha + cha
guard_cha_used = guard channels in use
The Network % Technical Congestion = Total blocked call/ Total call attempt *100

2.4 Proposed system architecture

In the system architecture for the optimal channel assignment and adaptive handoff prioritization scheme (OCAHPS) shown in Fig. 2, the network parameters and the fitness function are available to both the genetic algorithm and neural network modules of the Dynamic channel allocation section of the system. The neural network module of the system is used to make the randomly generated initial solutions (chromosomes) of the GA feasible solutions before applying the genetic operations to generate an optimal solution. The optimally selected channel from the centralized dynamic channels is allocated to serve either a handoff calls or a new call depending on the type of call for which the request is made. The value of the traffic intensity and/or call dropping probability determines whether the fixed guard channels are accessed only by the handoff calls or otherwise. The controller blocks new calls from accessing the fixed guard channels only when the value of the traffic intensity and/or the call dropping probability is above the threshold values. This is to ensure that at high traffic intensity, channels are reserved to take care of handoff call as it becomes necessary to do so at such moment. These channels are released for both new calls and handoff calls when the traffic intensity is low because it is not necessary to make reservation for handoff calls at such time.

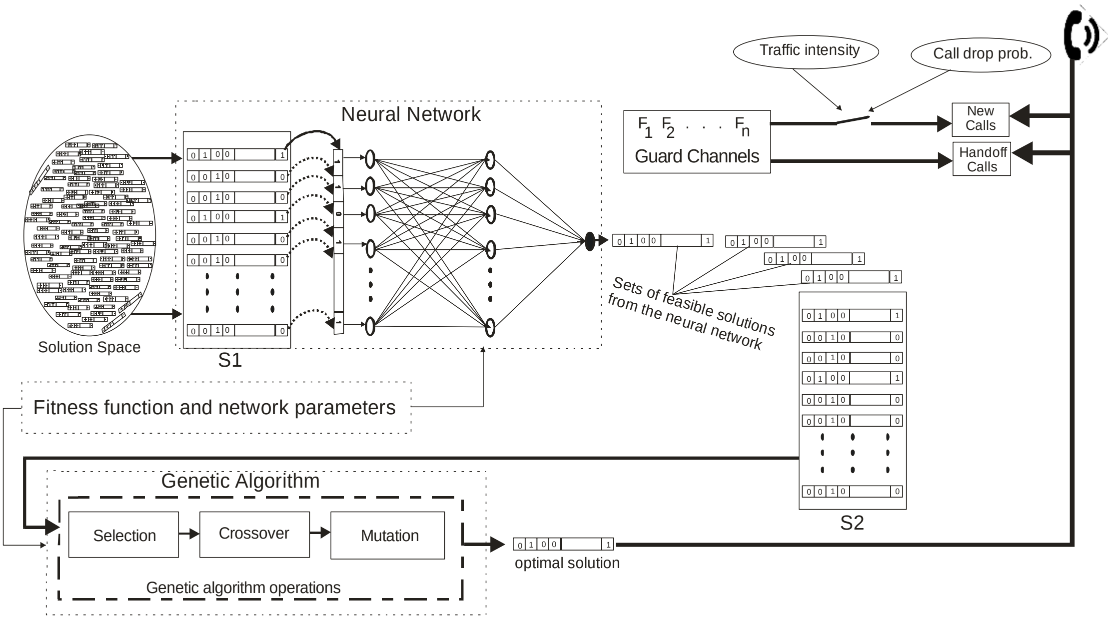
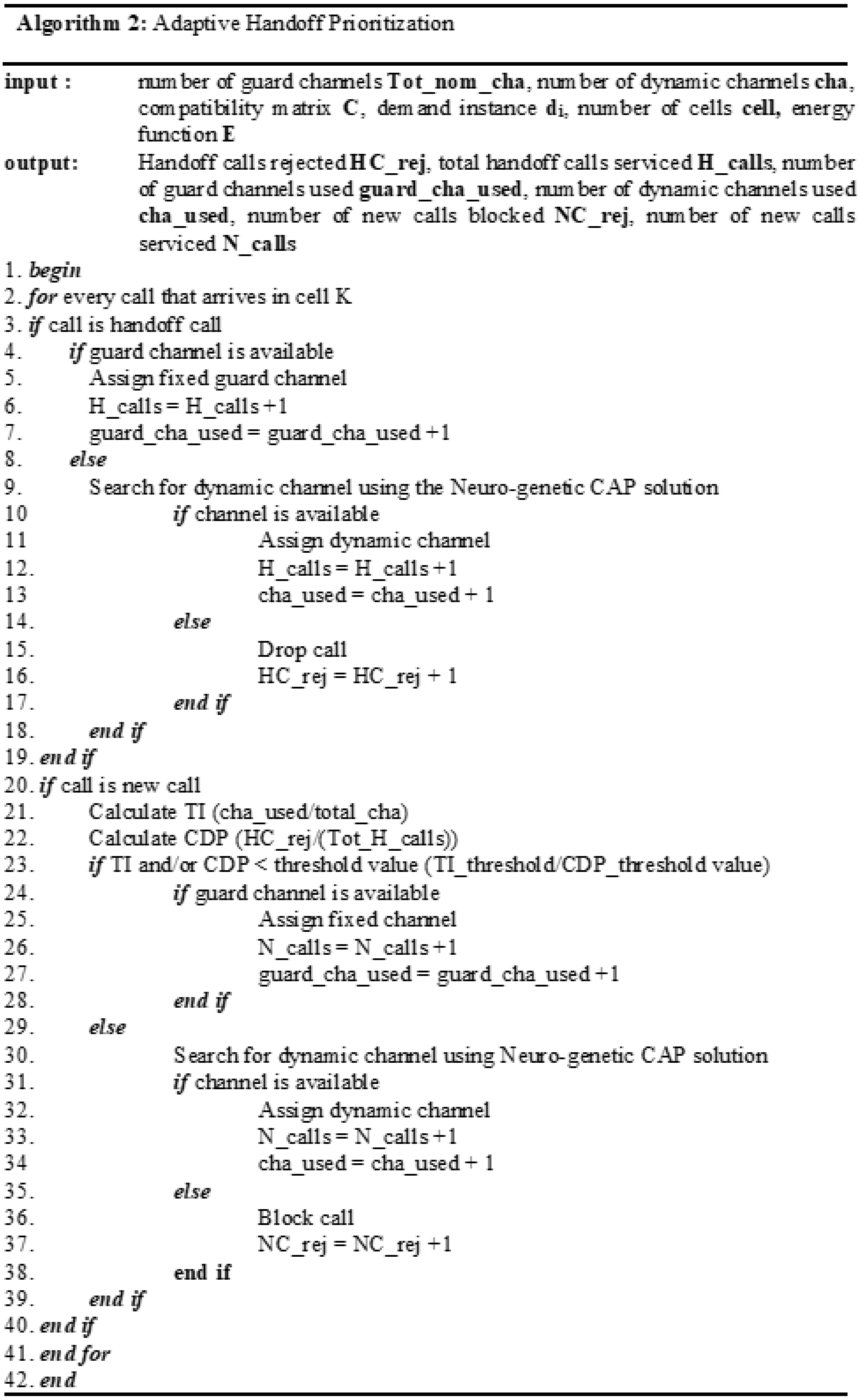


Fig. 2: OCAHPS system architecture



Algorithm 2: Adaptive Handoff Prioritization

input : number of guard channels **Tot_nom_cha**, number of dynamic channels **cha**, compatibility matrix **C**, demand instance d_i, number of cells **cell**, energy function **E**

output: Handoff calls rejected **HC_rej**, total handoff calls serviced **H_calls**, number of guard channels used **guard_cha_used**, number of dynamic channels used **cha_used**, number of new calls blocked **NC_rej**, number of new calls serviced **N_calls**

```
begin
for every call that arrives in cell K
if call is handoff call
    if guard channel is available
        Assign fixed guard channel
        H_calls = H_calls +1
        guard_cha_used = guard_cha_used +1
    else
        Search for dynamic channel using the Neuro-genetic CAP solution
            if channel is available
                Assign dynamic channel
                H_calls = H_calls +1
                cha_used = cha_used + 1
            else
                Drop call
                HC_rej = HC_rej + 1
            end if
        end if
end if
if call is new call
        Calculate TI (cha_used/total_cha)
        Calculate CDP (HC_rej/(Tot_H_calls))
        if TI and/or CDP < threshold value (TI_threshold/CDP_threshold value)
            if guard channel is available
                Assign fixed channel
                N_calls = N_calls +1
                guard_cha_used = guard_cha_used +1
            end if
        else
            Search for dynamic channel using Neuro-genetic CAP solution
            if channel is available
                Assign dynamic channel
                N_calls = N_calls +1
                cha_used = cha_used + 1
            else
                Block call
                NC_rej = NC_rej +1
            end if
        end if
end if
end for
end
```

3. Results and discussion

3.1 Neuro-Genetic algorithm results from simulations based on D_1

Fig. 3 compares the call blocking probabilities of the neuro-genetic algorithm with other approaches in solving the CAP using the demand instance (D_1)

of the Philadelphia network model. The result shows a lower call blocking probability in comparison with other approaches. From the result, the proposed NG algorithm (GANN) with a CBP of 0.021 shows that it is more efficient than other approaches: Genetic algorithm alone (GA) by Jyorthi et al. (2015), Genetic algorithm and Simulated annealing (GASA) by Tirmizi et al. (2015), Genetic algorithm and Fuzzy Logic (GAFL) by Hong and Lin (2015) with CBPs 0.072, 0.024 and 0.058 respectively as the traffic load increases. Although at a traffic load of less than 130, the combination of Genetic algorithm and Simulated annealing (GASA) had shown more effectiveness than the proposed, congestion becomes an issue when the traffic load is high and at such time efficient schemes are required to proactively control it. The proposed scheme has proved to be more efficient at such high traffic load in a network. At the highest traffic load of 481, the proposed is able to service 97.9% of the calls, GASA, 97.6%, GAFL 94.2% and GA 92.8%.

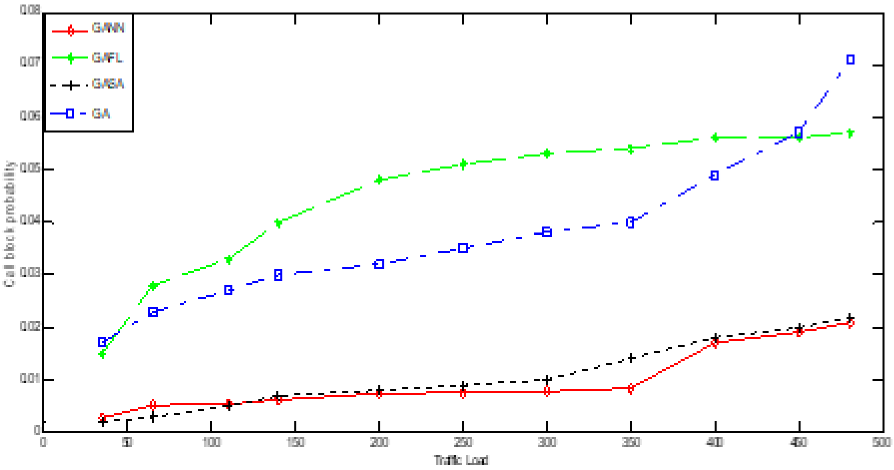


Fig. 3: Call Block Probabilities of the various schemes.

3.2 Channel assignment results

Fig. 4 shows the call block probability of the proposed scheme and that of NIGMobile at peak hour; D_2 was from NIGMobile. From the figure, the proposed scheme showed better performance with a lower call block probability both at low traffic load and high traffic load. The highest call block probability of the proposed was 0.039 at a traffic load of 2886 as against that of NIGMobile (NIGCBP) which went as high as 0.058 at the same traffic load. Meaning that the proposed scheme is able to service 96.1% of the calls as against 94.2% of the network service provider.

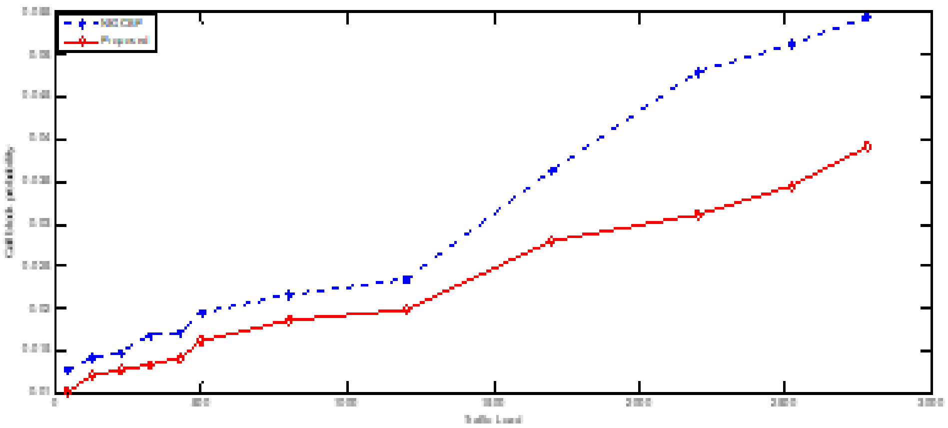


Fig. 4: CBP of the proposed and that of NIGMobile

3.3 Handoff prioritization

Fig. 5 shows the CDP of the proposed scheme to be lower than that of other schemes: Call admission control with fuzzy logic (CACFL) and Adaptive channel allocation with guard channel sharing (ACAGCS) at high traffic load with the exception of optimal bandwidth allocation with call drop prohibition (OBACP) by Ali (2016) that had adopted an unrealistic zero CDP. The CDP of the proposed scheme did not exceed 0.017 even at high traffic load. The CDP of CACFL by Kar and Nayak (2014) and ACAGCS by Chavan and Sarasu (2016) went as high as 0.04 and 0.05 respectively at high traffic load. It is unrealistic for a mobile network to have a zero CDP as in OBACP. The proposed scheme has therefore proved to be more efficient with a far lower CDP than the existing schemes. The proposed scheme was able to service 98.3% of the handoff calls even at the highest traffic load of 481 as against 96% and 95% of KN2014 (CACFL) and CS2016 (ACAGCS) respectively.

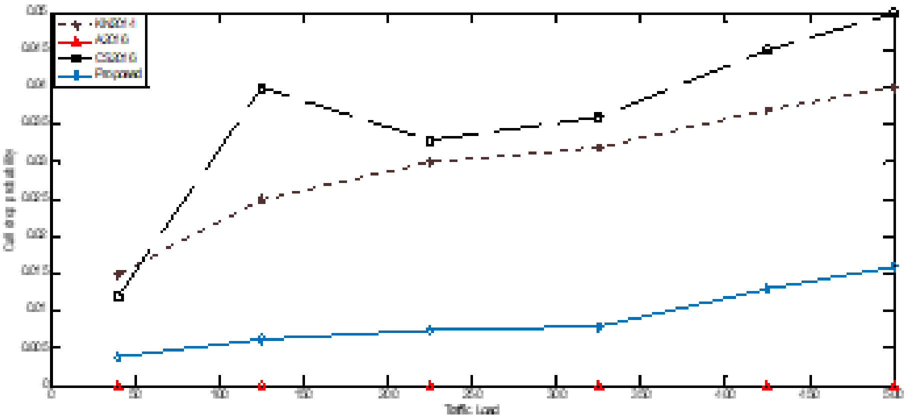


Fig 5: CDP of existing schemes and proposed scheme

Fig. 6, compares the CBP of the proposed scheme with existing schemes. The CBP of CS2016 was slightly lower than that of the proposed scheme at a traffic load of between 40 and 340 but beyond that, the proposed scheme outperforms all other schemes and even at low traffic loads. CS2016 at low traffic load allows new calls to use any available guard channel but these channels become unavailable as the traffic builds up and handoff and other priority calls increases. From the results, the proposed scheme clearly outperforms other schemes at peak hours when the traffic load is high. The proposed scheme had produced lower CBP of at most 0.022 at high traffic load when efficient handoff prioritization is required to avoid congestion and ensure adequate QoS for all calls. CBP of CS2016, KN2014 and A2016 went as high as 0.045, 0.071 and 0.090 respectively at high traffic load. The proposed scheme was therefore still able to service 95.8% of the new calls even at high traffic load when handoff prioritization is fully effected with channels reserved to service the handoff calls. CS2016, KN2014 and A2016 serviced 94.5%, 92.9% and 91% of the new calls respectively. The very high CBP of A2016 is obviously due to the non-realistic zero CDP adopted by it.

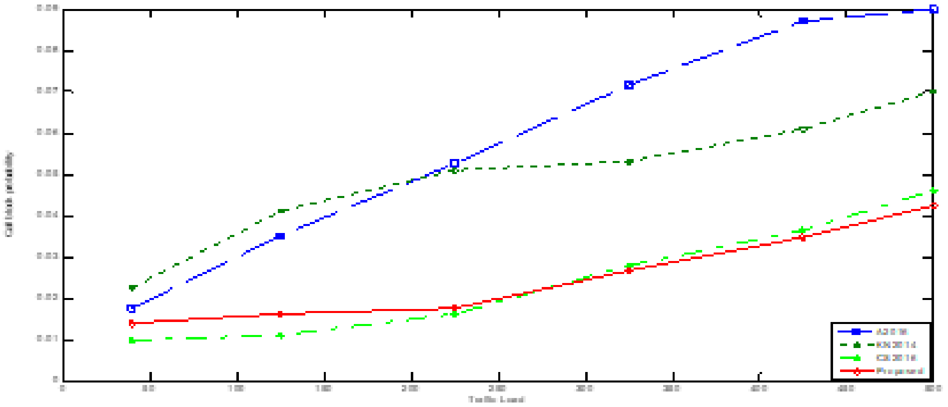


Fig 6: CBP of existing schemes and proposed scheme

Fig. 7 compared the CDP of the proposed scheme with that of NIGMobile (NIGCDP). The scheme produced a lower CDP at the highest traffic load. While the highest value of the proposed CDP was 0.033 at highest traffic load of 2886, that of NIGCDP was as high as 0.046 at high traffic load. Obviously in this network the traffic is dense and mobile station's mobility is high (of the 2886 calls, 799 are handoff calls). With the proposed scheme, 96.7% of the handoff calls were serviced successfully while 95.4% of the handoff calls were successfully serviced in NIGCDP.

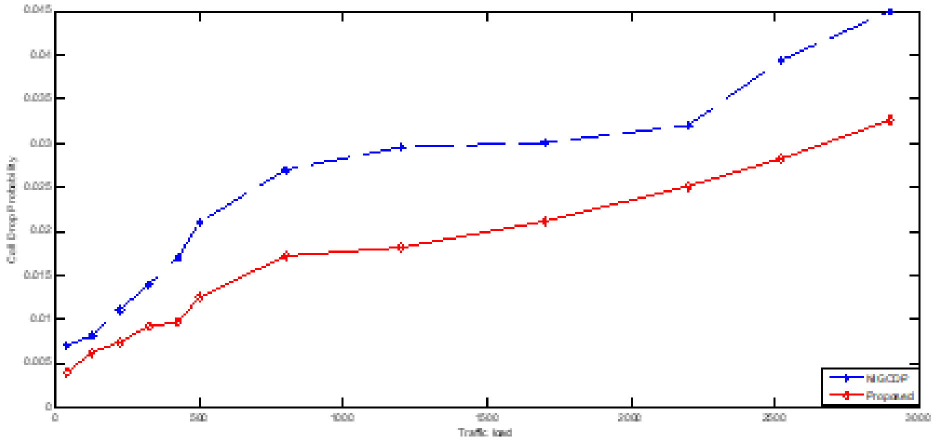


Fig. 7: Call drop probability of the proposed and that NIGMobile at peak hour demand instance D_2

Fig. 8 compares the CBP of the proposed scheme with that of NIGMobile (NIGCBP) at peak hours in a high traffic load network. 799 of the total 2886 calls were handoff calls. The proposed scheme had produced lower CBP of at most 0.039 at highest traffic load of 2886 compared to that of NIGCBP which was as high as 0.059 at the same traffic load. Meaning with the proposed scheme, 96.1% of the new calls are serviced while 94.1% new calls were serviced in NIGCBP

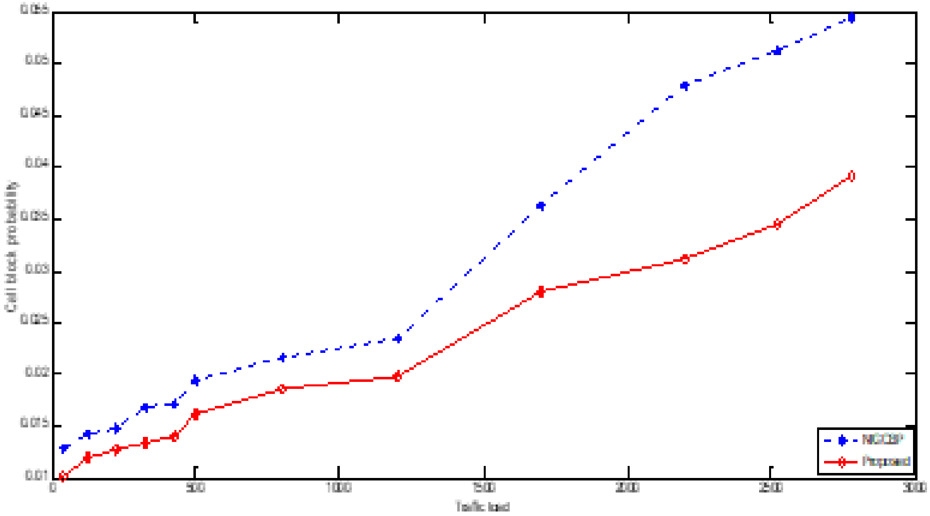


Fig. 8: Call block probability of the proposed and NIGMobile at peak hour demand instance D_2 with 799 handoff calls

Fig. 9, compares the % technical congestion of the proposed scheme with that NIGMobile at varying traffic loads in the high traffic load network. The proposed scheme performed better than NIGMobile. The % technical congestion of the proposed scheme at peak hour and highest traffic load of 2886 was 0.43% while that of NIGMobile was 0.56%. The proposed scheme has therefore demonstrated to be more efficient in congestion control than NIGMobile based on the peak hour demand instance D_2.

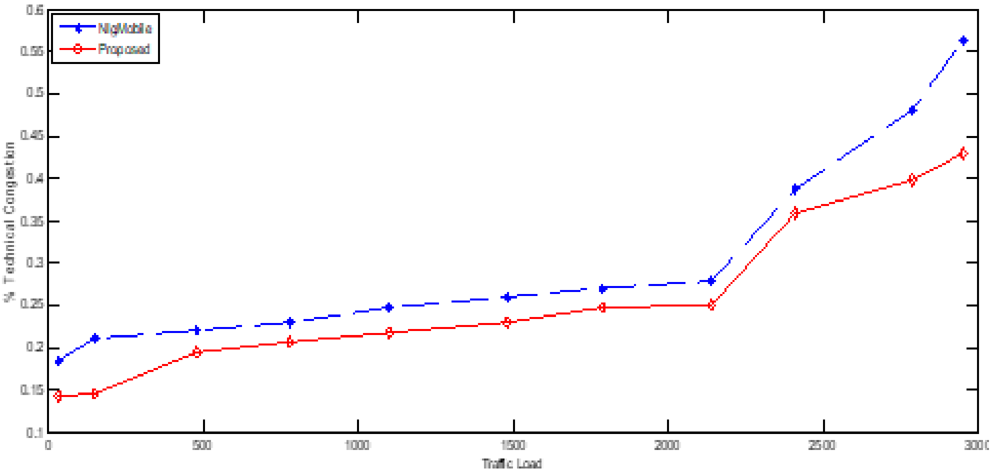


Fig. 9: Technical Congestion of the proposed and that of NIGMobile at peak hour demand instance D_2

4. Conclusion

This work has proposed a neuro-genetic DCA solution to the CAP that combined neural network and genetic algorithm to select the best optimal solution with full consideration for all hard constraints and soft conditions built into the channel selection process. Simulation results showed that the neuro-genetic (DCA) solution provided a significantly lower call blocking probability than other approaches compared with it as the traffic load increases. The priority often given to handoff calls has brought about a drop in the QoS for new calls as handoff prioritization often leads to an increased call blocking probability. One of the primary aims of this work was to remove idleness of channels reserved for handoff calls while new calls are being blocked for lack of channels to service them. Reserved guard channels were kept solely for the use of handoff calls only when the call drop probability or/and the traffic intensity of the network exceeds the set threshold value. The simulation results showed a better performance by the scheme at highest traffic demands with lower call drop probability and call block probability in all the simulation environments. The scheme also kept the number of guard channels fixed and rather dynamically controlled access to the guard channels by new calls. The lower call drop and call block probabilities from the simulation results is a clear prove of a better optimal channel utilization by the scheme and improved QoS for both new and handoff calls. The scheme also proved to be more efficient in congestion control compared to that of a leading mobile network service provider in Nigeria. It showed a lower percentage (%) technical congestion at both low and high traffic loads.

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