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Non-prioritized channel assignment improvement based on call traffic intensity and artificial neural network

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ABSTRACT

The non-prioritized (NP) channel assignment model is characterized by a high call dropping probability (CDP) of handover calls and an increasing mobile call traffic volume due to the proliferation of mobile devices. In this study, the one-dimensional Markovian NP model has been improved upon using an artificial neural network (ANN) as a prediction mechanism of CDP using predicted traffic intensity and channel parameters to assign calls of different types to channels. A simulation comparison of the CDP of existing NP channel assignment with the NP with traffic intensity (CDPT) and with the ANN traffic intensity prediction model (CDPANN) was carried out and the study shows that the CDP was reduced drastically when the NP channel assignment with ANN assisted trained model was used putting signal quality into consideration. The CDPT has reduced CDP by 3%, 15%, and 40%, while the CDPANN has reduced CDP by 6%, 20%, and 50% for signal quality factors of 0.2 (poor), 0.5 (good), and 0.8 (very good) respectively. This study has shown that under varying radio frequency signal quality conditions, the ANN assisted channel assignment approach will help minimise the problem of high CDP associated with NP channel assignment and thereby improve ubiquitous mobile communication.

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1. INTRODUCTION

The fast advancement of wireless communication networks has led to an increase in demand for mobile communication devices in recent years, with exponential growth in mobile communication call traffic, which is dictating an obvious need for more communication channels [1], [2]. Moreover, this constant advancement of wireless communication has increased the quality demand of various cellular networks [3], because the spectrum accessible to cellular systems is limited, a channel assignment method that is consistent with the aims of increasing channel capacity and reducing the expected high call dropping rate due to increased user traffic is required [4], [5]. A mobile station (MS), a base station (BS), and a mobile switching center (MSC) make up a fundamental cellular system [6]. The MSC is a network switching subsystem component that uses a channel assignment scheme to assign a voice channel to the MS [7], [8]. Channel assignment is assigning separate orthogonal or partially overlapped orthogonal channels to all the nodes in the communication range. The channel assignment method selected has an influence on system performance, particularly in terms of how calls are handled when a mobile user is moved from one cell to another [9]-[14]. Through analysis and simulation study, it was shown in [15]-[17] that dynamic guard channel (DGC) assignment scheme based on channel utilization reduces the call blocking probability in comparison to non-prioritized (NP), prioritized guard channel (PGC), and prioritized guard channel with queue (PGCQ)/buffer but has the obvious disadvantage of tradeoff of quality of service (QoS) between originating new calls and handover calls. On the other hand, the guard channels' reservation and prioritized queuing assignment schemes give undue advantages to handover calls at the expense of originating new calls. Hence, the worst case is the NP channel assignment method, which prioritizes handover calls contrary to the mobile communication principle and with a very high call dropping probability (CDP) [16]-[18].

Omitola and Srivastava [18] considered the channel borrowing admission control scheme in LTE/LTE-A femtocell-macrocell networks and some system bandwidth were reserved for handover calls which can be borrowed by non real-time (NRT) new calls when handover calls are not available to reduce call blocking probability and it was discovered that the integration of channel borrowing with admission control was advantageous in terms of resource utilization, and reduction in call blocked and call dropped. The researchers [19], prioritized and NP schemes were considered. It was discovered that new calls have a higher call blocking probability in the NP scheme, which gives more consideration to handoff requests. The experience of high call blocking probability of new calls is due to the prioritization used. The researchers [20] looked into an optimal channel reservation (OCR) policy, which was designed for users that move from one cell to another, either from a 5G cell to a 4G cell, and so on. The policy reserves channels in relation to the target handoff CDP. The policy was applied to the global system for mobile communication (GSM) 900, and it was found that the CDP was below the target while the call blocking probability was minimized.

To reduce the likelihood of traffic and provide higher-quality services in heavily congested cellular communication systems, a NP channel assignment scheme that reuses a voice channel was implemented to reduce the likelihood of blocked calls and increase the traffic carrying capacity of cellular systems. The significance of this research work is to create a better communication system for the public by enhancing service quality and avoiding communication system interruptions. It is to provide equal merit to new, and handover calls in a system [15]. The conceptual representation of a NP channel assignment scheme for a cellular communication system with channel capacity C being the total number of assignable channels is presented in [21]-[23] and the state transition diagram is depicted in Figure 1. Two types of traffic are arriving at the BS switch that is originating new calls traffic λ_n and ongoing handover calls traffic λ_h, transiting one BS to another. The admitted calls are serviced at the rate μ on a first-come, first-served (FCFS) basis, and the traffics have equal contention for channel allocations.

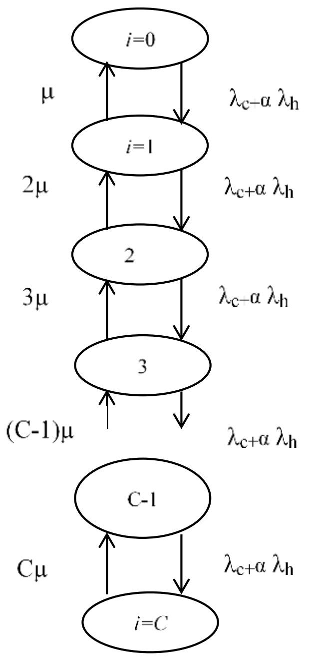

Figure 1. Markov chain states transition diagram of NP channel assignment [21]-[24]

From the state transition diagram of Figure 1 [21]-[24] presented the state probability of NP channel assignment as (1) where P(i) is the probability of the system occupying any state in the interval $0 \leq i \leq C$ and the state is number of calls assigned to channels applying superposition theory or number of busy channels. The normalization constant $P(0)$ is obtained by summing all the state probabilities and is given as (2):

$$P(i) = \frac{(\lambda_n + \alpha\lambda_h)^i}{i!\mu^i} . P(0), 0 \leq i \leq C \tag{1}$$

$$P(0) = \left[1 + \sum_{i=1}^{C} \left(\frac{\lambda_n + \lambda_h}{\mu}\right)^i . \frac{1}{i!}\right]^{-1} \tag{2}$$

It has been said in [21]-[24] that when all the channels are busy or assigned that is the system is in the state C with state probability $P(C)$, then the new call (originating from the BS) blocking probability $P_C(B)$ and the handover CDP $P_H(D)$ for handover traffic are equal. Hence, $P_C(B) = P_H(D) = P(C)$ when $i = C$.

It has been said in [25]-[27] that channel estimation models and invariably channel assignment models are designed with mathematical models, but complex environmental factors like multipath fading, distortions, and channel noise, to mention a few, affect the performance of these models [19]-[24], [28]. These impairments decrease the system's performance. Recently, artificial intelligence (AI) has been explored for the area of wireless communication, such as machine learning based-wireless receivers. A survey of the different machine learning algorithms utilized for the network and communication aspects of vehicular movement was carried out [29]. The authors compared the machine learning based-solution to the conventional approach. Various machine learning algorithms such as support vector machine (SVM), artificial neural networks (ANNs), deep neural networks (DNNs), and their applications to communication, such as mobility prediction, dynamic routing, and congestion control, were highlighted. While [30] surveyed the exploration of machine learning for 5G wireless networks integration into the smart devices and how to efficiently analyze the stored data in them, make intelligence decisions, and observe the environments using various machine learning based solutions, [31] looked into the deep learning techniques for 6G wireless communication in the physical layer. These include feed-forward neural networks (FNN), DNNs, and autoencoder for channel modeling, source coding/decoding, and end-to-end communication, respectively. This shows the importance of AI algorithms in wireless communication even in the case of channel assignment as the algorithms can learn the relationship among different variables in the models and help resolve complexities in unrealistic assumptions and improve performance of channel estimation models [25], [32], [33] utilizing the simulation data obtained. This forms the basis of this study, which is channel assignment improvement in cellular communication using an ANN approach, and it is expected that high CDP will be reduced, and call quality will be improved.

2. METHOD

The design of NP channel assignment scheme based on traffic intensity presented in this article is such that the call traffics are assigned channels based on the traffic intensity to ensure conservation of scarce radio resources so that the total number of channels for originating new calls is K. It is variable and determined by the intensity of both traffic types. Hence, the assignable number of channels for handover calls becomes $C - K$, which is also variable because C, the channel capacity is constant and K is variable. The Markovian state diagram of the NP channel assignment presented in Figure 1 is applicable to the proposed NP channel assignment method based on traffic intensity. This is because it is based on FCFS, and the superposition theorem is equally applicable. The conceptual diagram with the ANN traffic comparator is shown in Figure 2, which combines the traffic using arrival rates based on the superposition theorem.

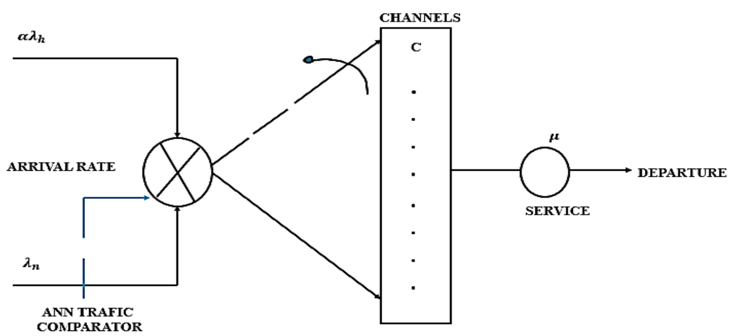

Figure 2. Conceptual view of ANN traffic predictor

It considers the signal quality α at a specific distance, and instant where ρ_n and ρ_h are the traffic intensity of originating new calls and of handover calls, respectively, as given in (3) and (4). In (5) defines the channel capacity for the originating new calls based on traffic intensity [17]. The state model equations were derived from the state diagram.

$$\rho_n = \frac{\lambda_n}{\mu} \tag{3}$$

$$\rho_h = \frac{\alpha\lambda_h}{\mu} \tag{4}$$

$$K = \frac{\rho_n}{\rho_n+\rho_h}.C \tag{5}$$

The normalization constant $P_{NP}(0)$ for the NP channel assignment based on traffic intensity using the Markov chain is given as (6) while state probability $P_{NP}(i)$ of the model for new calls arrival is given as (7) and the blocking probability of the originating new calls at the BS is $P_C(B)$ given as (8).

$$P_{NP}(0) = \left[1 + \sum_{i=1}^{K} \frac{{\rho_n}^i}{i!}\right]^{-1} \tag{6}$$

$$P_{NP}(i)=\sum_{i=1}^{K} \frac{{\rho_n}^i}{i!}.P_{NP}(0) = \sum_{i=1}^{K} \frac{{\rho_n}^i}{i!}.\left[1 + \sum_{i=1}^{K} \frac{{\rho_n}^i}{i!}\right]^{-1}, 0 \leq i \leq K \tag{7}$$

$$P_C(B) = \frac{{\rho_n}^K}{K!}.\frac{1}{1+\sum_{i=1}^{K}\frac{{\rho_n}^i}{i!}} \tag{8}$$

The blocking probability of new (originating) call $P_C(B)$ and CDP $P_H(D)$ for handover call traffic are equal in the conventional NP scheme but are not equal for this modified model because channel allocation is traffic intensity determined though the same Markov chain transition diagram is applicable because allocation is based on FCFS. Hence, the normalization condition for the handover traffic is as given in (9), and the state probability for channel assignment to the handover calls is given in (10). The handover calls can only be dropped when all the channels assignable based on traffic intensity have been fully allocated; therefore, the handover CDP $P_h(D)$ for the NP channel assignment scheme based on traffic intensity is given by (11). Call traffic arrival rate was modelled using a Poisson distribution.

$$P_{NP}(0) = \left[1 + \sum_{i=1}^{C-K} \frac{{\rho_h}^i}{i!}\right]^{-1} \tag{9}$$

$$P_{NP}(i)=\sum_{i=1}^{C-K} \frac{{\rho_h}^i}{i!}.P_{NP}(0) = \sum_{i=1}^{K} \frac{{\rho_h}^i}{i!}.\left[1 + \sum_{i=1}^{C-K} \frac{{\rho_h}^i}{i!}\right]^{-1}, 0 \leq i \leq C-K \tag{10}$$

$$P_h(D) = \frac{{\rho_h}^{C-K}}{(C-K)!}.\frac{1}{1+\sum_{i=1}^{C-K}\frac{{\rho_h}^i}{i!}} \tag{11}$$

The experimental setup for the ANN model has an input layer of four input neurons that characterize the data set's four properties. When I=1:20, the for loop was used to optimize the number of neurons in the hidden layer (where I signifies the hidden layer size) as shown in Figure 3. The inputs were alpha, arrival rate of new calls, arrival rate of handover calls, and CDP. CDP based on traffic intensity (CDP_TI) in (11) was used as the output. The data was fed to the neural network model after it had been cleaned, pre-processed, and encoded. The design of the ANN model was done in such a way that 70% of the data was used for training and 30% was used for testing. This procedure used supervised learning, in which the network was given an input vector during training and generated an output vector. This output vector was contrasted with the desired or goal output vector. An error signal was produced if the actual output vector varied from the target output vector. This is a Feed-forward ANN where data travels in one direction between the input and output nodes. The same tiers of nodes used to transmit data forward were not used to transmit information backwards. A sigmoid function was employed as an activation function, although a rectified linear activation unit (RELU) function could be a preferable alternative. The dataset was trained using the Levenberg-Marquardt algorithm, and MATLAB R2020a was used to run the simulation.

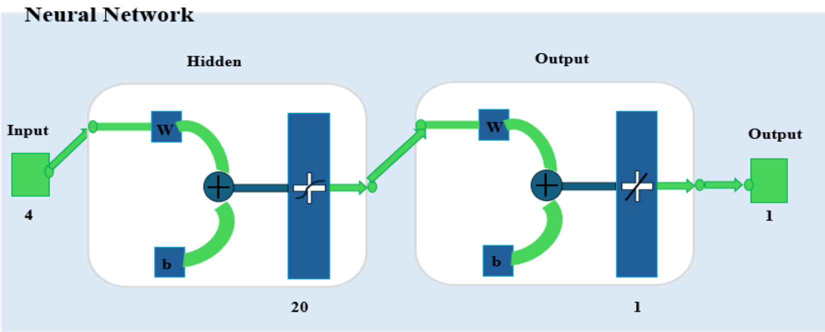

Figure 3. Experimental neural network setup

3. RESULTS AND DISCUSSION

The results of simulation experiments carried out in this study are presented and discussed in this section. Comparative simulation studies of the three models were carried out to determine their performance with respect to handover CDP. Simulation parameters and assumed values are presented in Table 1 and are the same for the three handover scenarios experimented based on the signal quality, which is dependent on the distance of the MS from the BS that is degrading from high (0.8) to low (0.2) and also serves as a mobility factor. Consideration was given to congestion through high traffic arrival rate and other system parameters, including service rate being held constant. The simulation was repeated for varied signal quality factors, and the results are presented graphically in Figures 4 to 6, respectively, and discussed.

Table 1. Simulation parameters and assumed values

S/N	Parameter assignment/assumption table	
1.	BS transmitter power	23 dBm
2.	BS antenna gain	18 dB
3.	MS antenna gain	0 dB
4.	Propagation model	Free space model
5.	BS antenna height	+30 m above ground
6.	MS antenna height	+2 m above ground
7.	RSS quality factor	MS distance from BS based, 0.8 (high), 0.5 (good), 0.2 (low)
8.	Signal fading	12 dB
9.	System service rate	1.0
10.	RSS threshold	4 dB
11.	Number of channels	12
12.	Type of handover	MAHO

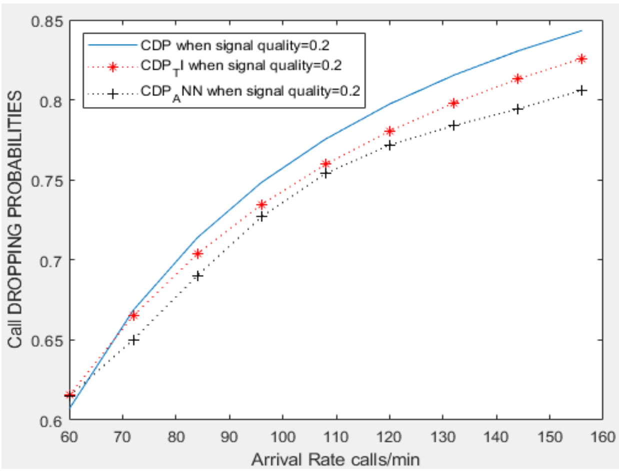

Figure 4. CDP with traffic intensity and CDP with ANN against call arrival rate for the signal quality α=0.2

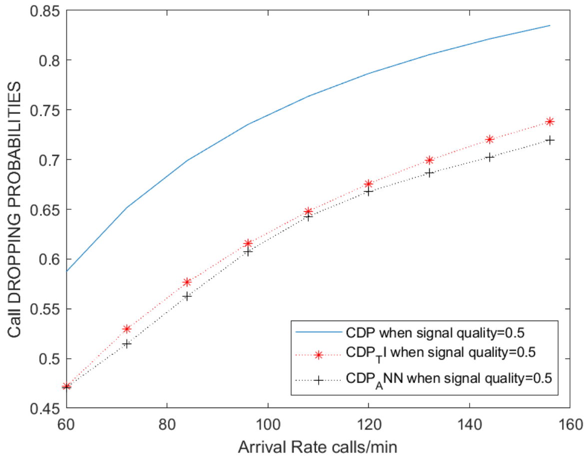

Figure 5. CDP with traffic intensity and CDP with ANN against call arrival rate for the signal quality α=0.5

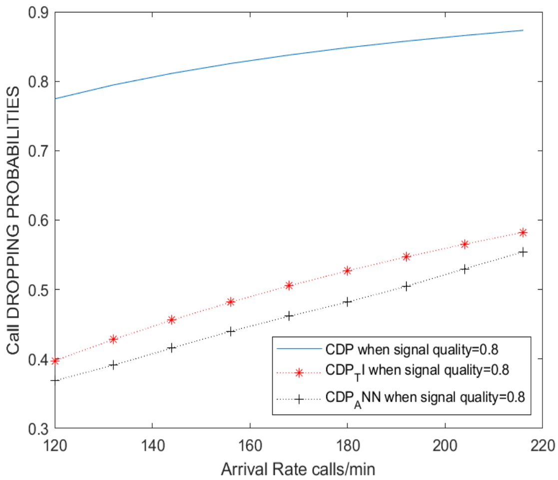

Figure 6. CDP with traffic intensity and CDP with ANN against call arrival rate for the signal quality α=0.8

The graph in Figure 4 shows that even with a signal quality of 0.2, there was still a difference in the CDP values of the conventional model when compared to call dropping probabilities with traffic intensity (modified model) and the ANN-trained model. However, compared to the rest, the CDP with ANN was lower. Figure 5 shows that there was a significant difference in the CDP values without traffic intensity and ANN at a good signal quality of 0.5. Both the CDP with ANN and the CDP with traffic intensity were reduced. However, compared to the rest, the CDP with ANN was lower and better.

The graph in Figure 6 shows a further decline in the values of the CDP for both the modified and ANN models, showing the effect of good signal quality on handover, as it is common knowledge that signal strength is an important factor for a successful handover in mobile communication. Hence, the modified model and the ANN trained model both showed improved performance for much better signal quality, with reduced CDP, with the ANN trained model being the least. Both the CDP with ANN and the CDP with traffic intensity were reduced. However, the CDP with the ANN was significantly better and had less probability of call drops than the others. Additionally, it was shown that using ANN reduces call drops better, even at high call arrival rates, which also depicts a state of system congestion.

4. CONCLUSION

This research work has been able to solve the problem of high CDP of NP channel assignment in mobile communication handover by using the one-dimensional Markov chain analysis to model the states and to derive the CDP of NP channel assignment scheme based on traffic intensity which is a modified NP channel assignment method to reduce the high CDP. The data from the simulation experiment was used to train an ANN-based version of the modified NP channel assignment model developed in this study to investigate the effect of trained ANN on the model. This brought about further enhancement of the model to predict traffic intensity and the corresponding CDP as a mechanism of assigning handover calls to a channel. The simulation study carried out showed that when the signal quality is over 80%, the high CDP of the conventional NP channel assignment was drastically reduced by 40% by the NP channel assignment based on traffic intensity only and a 50% reduction in call drops using ANN assisted model for NP channel assignment in MAHO. With this finding, it has been established that a significant reduction in high CDP of NP channel assignment is achievable using the ANN-assisted model, which obviously has dual adverse effects of improved call quality and reduced call drop rate in cellular networks with the signal quality measurement. Moreover, future works can be towards the deployment of this model in real-world network environments of different architectures and enhancing channel assignment schemes and queueing models of cellular network handover with deep learning models.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Oritsematosan Laura Whyte	✓	✓	✓	✓	✓	✓	✓		✓		✓			
Omolola Faith Ademola						✓				✓	✓			
Gabriel Oluwatobi Sobola						✓				✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors hereby declare that there is no known conflict of interest concerning this article.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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