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Performance Analysis Of Neuro-Fuzzy Call Admission Control Scheme For Real And Non Real Time Calls In CDMA Cellular Network

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Abstract

The introduction of Soft handoff increases system capacity in CDMA cellular system. A CDMA cellular system involving real and non-real time calls are considered in this paper. The type of services considered are voice and video which comes in category of real time calls. Data calls are also considered in the category of non-real time calls. The developed model is based on priority reservation for handoff calls along with call queuing. Upper channel restrictions are set for new voice, video and data calls to give priority to handoff calls. Neuro-fuzzy call admission controller is designed for better resource management and efficient call admission to originating and handoff calls. This Neuro-Fuzzy Controller uses the adaptable feature of soft handoff threshold parameters to accomodate important real time and non-real time calls by monitoring current real time call blocking and dropping probabilities. The proposed ASNFC-MC controller is compared with Cut-off priority based call admission control scheme for forced termination probability of call and percentage channel utilization.

1. Introduction

CAC in wireless networks has been receiving a great deal of attention during the last two decades due to the growing popularity of wireless communications and the central role that CAC plays in QoS provisioning in terms of the signal quality, call blocking and dropping probabilities, packet delay and loss rate, and transmission rate. In the first and second generation of wireless systems, CAC has been developed for a single service environment. In third generation (3G) wireless systems, multimedia services such as voice, video, data, and audio are offered with various QoS profiles. Hence, more sophisticated CAC schemes are developed to cope with these changes. The emergences of modern wireless technologies and development in advance mobile communication technologies have enabled the users to use multi-service features on same network. The type of services that can be accessed through these network ranges to primal voice and data service to more advance services like video telephony, browsing, VoD (Video on demand), background media downloading etc. CDMA (Code division multiple access) , which is a multiple access technique has emerged as one of the better techniques in providing these services due to flexibility in transmission rates and better handover features. Macro diversity is provided in CDMA cellular network by this phenomenon of soft handoff [1]. The soft handoff region of the CDMA cellular network is a function of two threshold parameters: T_ADD and T_DROP [2]. The MS during travel through the soft handoff region is connected to more than one BS at same time. The BS involved in soft handoff communication permits handoff delay of no longer than the dwell time in soft handoff region. This dwell period depends on the value of the two threshold parameters. The main aim of this study is to analyze a neuro-fuzzy admission policy for multiclass services sharing the common channels in the network.

Integrated neuro-fuzzy arrangement can combine the parallel computation and learning abilities of neural networks with the human-like information representation and explanation abilities of fuzzy systems. As a result, neural networks become more visible, while fuzzy systems become capable of learning. Due to the advantages of neuro-fuzzy intelligent system like adaptability, learning from experience and human like understand ability, the need of rigorous mathematical modelling can be replaced by simple IF-THEN type of rules.The paper is based on multiclass service in a CDMA cellular network employing soft-handoff. It is based on priority reservation for real time and non-real time handoff calls along with call queuing scheme. Upper channel restrictions are set for new calls to give priority to handoff calls. The handoff queue capacity is considered as function of soft handoff coverage area which depends on the two soft handoff threshold parameters T_ADD and T_DROP. Variation in these threshold parameters is stated in term of variation in handoff call queue capacity. Different value of soft handoff threshold parameters can be set for real and non-real time calls. Neuro-fuzzy call admission controller is considered for resource management of the stated model. The inputs taken for the call admission controller are current real time call blocking probability, handoff data dropping probability and real time handoff call dropping probabilities. Depending on the rule base the value of handoff data call queue capacity, handoff real-time call queue capacity, new voice call threshold and new video call threshold are determined. The neuro-fuzzy call admission controller is tuned for known values of input-output data sets taken from hybrid cutoff priority model [6]. Back propagation method is used for the training of the controller [3] [4].

2. Multi-Class Services

One of the distinctive features of a 3G system is its capability to provide different services such as video conferencing, real-time control and telemetry, streaming audio and video, high-speed data transfers, and so onMulticlass traffic is a combination of both real-time traffic and non-real-time traffic. Real-time traffic includes voice and video while data and graphics comprise non-real-time traffic. Real-time traffic is delay sensitive and non-real-time traffic is error sensitive. It is necessary to characterize the traffic in some meaningful way so that each application can request the desired QoS from the network in a straightforward manner. One way to classify the user traffic is based upon how the network should assign its resources like bandwidth to transport that traffic across the network.The types of traffic can be classified as [3]:

Constant bit rate (CBR) traffic: It is Sensitive to delays. This type of traffic generates fixed-size packets on a periodic basis. Examples are speech, high-quality audio, video telephony, full-motion video, and so on.

Real-time variable bit rate* (VBR) *traffic: This traffic generates variable-size packets on a periodic basis. Examples include variable bit-rate encoded audio, interactive video encoded into an MPEG standard, and so on.

Nonreal-time variable bit rate traffic: This type of traffic can tolerate delays or delay variations. An example is an interactive and large file transfer service [7].

Real-time conversational traffic: This real-time traffic is bidirectional, involving human users at the two ends of a communication link, and is characterized by low end-to-end delays.

Interactive traffic: This class of traffic, which involves man and machine, is based on a request/response from end-points. It is non-real time and may be unidirectional or bidirectional. Examples are web browsing, e-mail etc.

Streaming traffic: This traffic is associated with real-time applications. However, unlike the conversational type, it is unidirectional (between man and machine) and has a somewhat more continuous flow with fewer and shorter inactive/silent periods between information entities. Examples are audio streaming, one-way video, still images etc.

Background traffic: As the name implies, the data transfer for this kind of traffic takes place in the background only when the computer has some real-time left after finishing high-priority tasks. The short messaging service (SMS) in GSM, or the delivery of e-mails from one server to another, falls in this category.

TABLE I. MULTICLASS TRAFFIC

Traffic Class	**Bandwidth Requirement**	**Call Duration (minutes)**	**Required E_b/I_o**	**Examples**
Real Time(RT)	30Kbps	1-10	5-7dB	Voice services
	256Kbps	1-30		Video-phone
	1-6Mbps	5-300		VoD
Non-Real Time (NRT)	32Kbps	0.2-2	1-3.2dB	E-mail, Paging
	64-512Kbps	0.5-600		Web browsing
	1-10Mbps	0.5-20		FTP

3. Adaptive Soft Handoff Based Neuro-Fuzzy Call Admission Controller for Multiclaas calls (ASNFC-MC)

In this section, Neuro-fuzzy CAC model is developed and analyzed for multiclass calls in CDMA cellular network.

The Model:

For the model, let 'M' be the limited amount of code channels available in the channel pool. The types of calls considered in the modeling are real time (voice and video) and non-real time (data) calls. Full channel availability is made for both real time handoff calls and non-real time handoff calls. The number of channels made available for new voice call, new video calls and new data call is limited by upper channel limits for each set of calls. The upper channel limit for new voice call is given by 'U_{nv}', for new video call 'U_{nvi}' and for new data call it is 'U_{nd}'. Whenever a new real time or non-real time call requests for channel and if number of channels in use for these services currently is equal to the upper limit allocated to them, then the requesting new call is blocked. For handling the handoff calls, queuing scheme is used. A handoff request is put in the queue if BS finds that all channels in target cell are occupied. If a channel is released when the queue for handoff requests is not empty, the channel is assigned to request on the top of the queue. The queue for handoff call can be realized due to nature of soft handoff coverage area. Different values of T_ADD and T_DROP can be set for real and non-real time calls. Larger is the difference in these parameters, greater is the queue capacity. A finite queue with capacity 'N' and FIFO (First in First out) characteristic is assumed at the Base Stations for handoff data calls. Similarly finite queue with capacity 'R' and FIFO (First in First out) characteristic is assumed at the Base Stations for handoff real time (voice + video) calls. The System model with limits for new calls and finite queue for handoff call is shown in Fig.2.

For the model, following assumptions are taken into consideration:-

i) The new voice call arriving and handoff voice call generated are considered to be Poisson distributed with arrival rates λ_{vn} and λ_{vh} respectively and are uniformly distributes over the area. The arrival rate of voice traffic is given by $\lambda_v = \lambda_{vn} + \lambda_{vh}$.

ii) The new video call arriving and handoff video call generated are considered to be Poisson distributed with arrival rates λ_{vin} and λ_{vih} respectively and are uniformly distributes over the area. The arrival rate of video traffic is given by $\lambda_{vi} =\lambda_{vin}+ \lambda_{vih}$.

iii) The arrival rate of real time traffic is given as $\lambda_v + \lambda_{vi}$.

iv) The new data call arriving and handoff data call generated are also considered to be Poisson distributed with arrival rates λ_{dn} and λ_{dh} respectively and are uniformly distributed over the area. The total arrival rate of data traffic given by $\lambda_d=\lambda_{dn}+ \lambda_{dh}$.

v) The channel holding time is considered to exponentially distributed with mean rate 'μ'.

iv) For new voice, video and data calls upper limits for channel utilization is set by setting value of U_{nv}, U_{nvi} and U_{dn}.

v) The sum of upper limits for new voice and data call is less than total number of code channels available. ie

$$U_{nv} +U_{nvi}+ U_{nd} < M$$

vi) Finite buffer capacity is assumed for handoff calls and it depends on soft handoff threshold parameters. [2].

vii) Handoff voice call is accepted in system when a free code channel is available out of total 'M' channels.

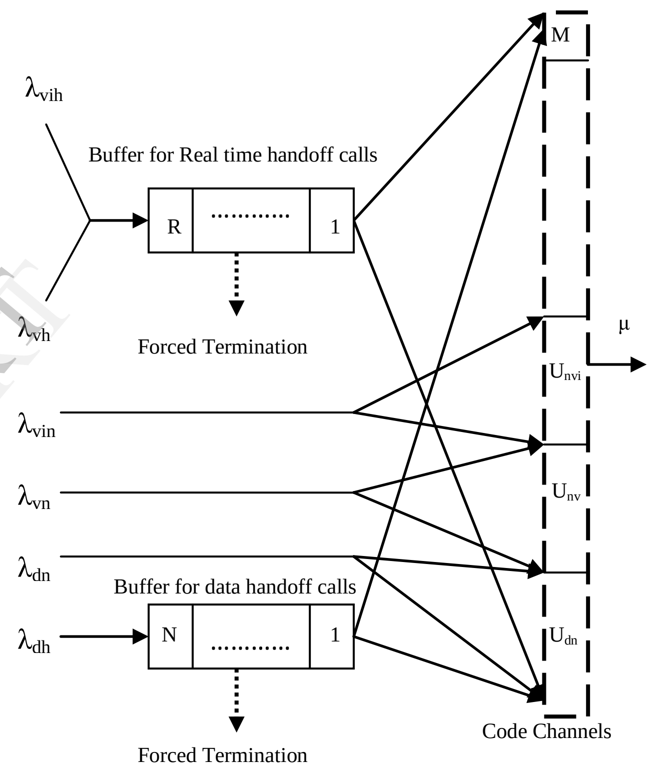

Figure 2. Model of Multiclass CAC using adaptive soft handoff threshold

ASNFC-MC Design:

The Neuro-fuzzy model developed uses the training data from a previously defined analytical model [3]. It is termed as Adaptive Soft handoff based Neuro-Fuzzy Call Admission Controller for Multiclass calls (ASNFC-MC) [5]. ASNFC-MC uses new voice blocking probability (P_{nv}), new video blocking probability (P_{nvi}), handoff data dropping probability (P_{hd}), handoff real time call dropping probability (P_{hr}) as input linguistic variables. The output linguistic variables are handoff data call queue capacity (N), handoff real-time call queue capacity (R), new voice call threshold (U_{nv}) and new video call threshold (U_{nvi}). Five layer neuro-fuzzy controller architecture is used to design the ASNFC [1]. The structure of a neuro-fuzzy system is similar to a multi-layer neural network. In general, a neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules. ASNFC which is generally a multi-layer neural network, so standard training algorithms developed for neural networks, back-propagation algorithm is applied for its learning. During the learning phase, a training input-output dataset is presented to the controller; the back-propagation algorithm computes the system output and compares it with the desired output of the training dataset. The error is transmitted backwards through the network from the output layer to the input layer. The neuron activation functions are modified as the error is propagated. To determine the necessary modifications, the back-propagation algorithm differentiates the activation functions of the neurons [4]. Each layer in the ASNFC system is associated with a particular step in the fuzzy inference process. The details of five layers as shown in Fig.3 are as below.

Layer 1 (input Layer): Each neuron in this layer transmits external crisp signals directly to the next layer. For input variables, P_{nv}, P_{nvi}, P_{hd} and P_{hr} the generalized representation is x_i^n ,where 'i' is the number of linguistic variable and 'n' is the number of current layer. In ASNFC, $1 \le i \le 3$ and $1 \le n \le 5$. If y_i^n is output of layer 1, then $y_i^n = x_i^n$.

2) Layer 2 (Fuzzification Layer): The nodes in this layer are used to fuzzify the received crisp inputs. The terms used to define input linguistic variables are:

P_{nv} (0.0001 to 1.0) = {Low (L), Medium (M), High (H)}, P_{nvi}(0.0001 to 1.0)= {Low (L), Medium (M), High (H)}, and P_{hd} (0.0001 to 1.0) = {Low (L), Medium (M), High (H)} and P_{hr}(0.0001 to 1.0)= {Low (L), Medium (M), High (H)}. The activation function of a membership neuron is set to the function that specifies the neuron's fuzzy set.

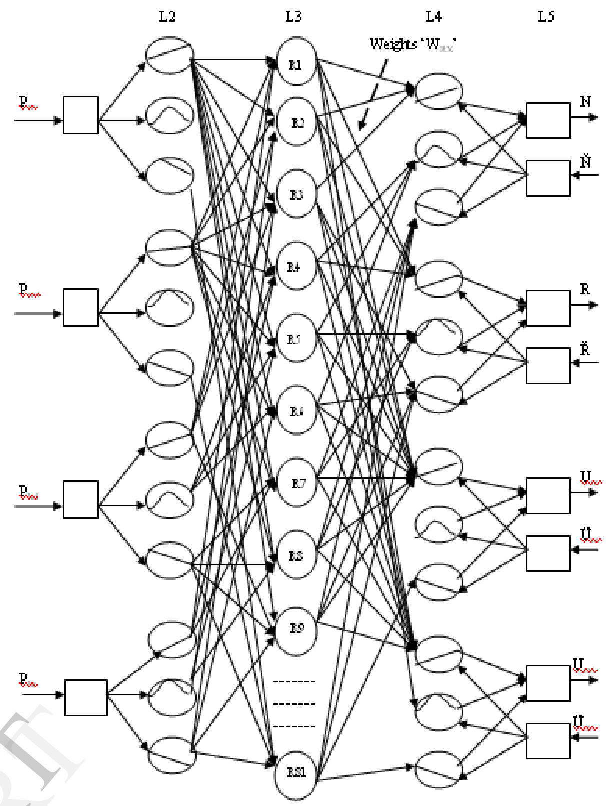

Figure 3. Structure of ASNFC-MC Controller

3) Layer 3 (Rule base Layer): Each neuron in this layer corresponds to a single fuzzy rule. A fuzzy rule neuron receives inputs from the fuzzification neurons that represent fuzzy sets in the rule antecedents. In a neuro-fuzzy system, intersection can be implemented by the product operator. The rule base (total possible rules = $3^4 = 81$) for ASNFC-MC is shown in table II.

TABLE II. Rule Base for ASNFC-MC

Rule No.	IF				THEN			
	P_{nv}	P_{nvi}	P_{hd}	P_{hr}	N	R	U_{nv}	U_{nvi}
1	L	L	L	L	L	L	L	M
2	L	L	L	M	L	L	L	L
3	L	L	L	H	L	H	L	L
4	L	L	M	L	M	L	L	L
5	L	L	M	M	M	M	L	L
6	L	L	M	H	M	H	L	L
7	L	L	H	L	H	M	L	L
8	L	L	H	M	H	M	L	L
9	L	L	H	H	H	H	L	L
10	L	M	L	L	L	M	L	M
11	L	M	L	M	L	M	L	M
12	L	M	L	H	L	H	L	M
13	L	M	M	L	M	L	L	M
14	L	M	M	M	M	L	L	M
15	L	M	M	H	M	M	L	M
16	L	M	H	L	H	L	L	L
17	L	M	H	M	H	M	L	M

18	L	M	H	H	H	M	L	M
19	L	H	L	L	L	L	L	M
20	L	H	L	M	L	M	L	H
21	L	H	L	H	L	H	L	H
22	L	H	M	L	M	M	L	H
23	L	H	M	M	M	M	L	H
24	L	H	M	H	M	H	L	H
25	L	H	H	L	H	L	L	M
26	L	H	H	M	H	M	L	M
27	L	H	H	H	H	L	L	M
28	M	L	L	L	L	M	M	L
29	M	L	L	M	L	M	M	L
30	M	L	L	H	L	M	M	L
31	M	L	M	L	M	L	M	L
32	M	L	M	M	M	M	M	L
33	M	L	M	H	M	H	M	L
34	M	L	H	L	H	L	M	M
35	M	L	H	M	H	M	M	M
36	M	L	H	H	H	H	M	M
37	M	M	L	L	L	M	M	L
38	M	M	L	M	L	M	M	L
39	M	M	L	H	L	H	M	M
40	M	M	M	L	M	L	M	M
41	M	M	M	M	M	M	M	M
42	M	M	M	H	M	M	M	L
43	M	M	H	L	M	L	M	M
44	M	M	H	M	H	M	M	M
45	M	M	H	H	M	H	M	L
46	M	H	L	L	L	M	M	H
47	M	H	L	M	L	M	M	H
48	M	H	L	H	L	M	M	H
49	M	H	M	L	M	L	M	H
50	M	H	M	M	M	L	M	H
51	M	H	M	H	M	H	M	H
52	M	H	H	L	M	L	M	H
53	M	H	H	M	M	L	M	M
54	M	H	H	H	H	H	M	M
55	H	L	L	L	L	L	M	M
56	H	L	L	M	L	M	M	M
57	H	L	L	H	L	H	H	M
58	H	L	M	L	M	L	H	M
59	H	L	M	M	M	M	H	L
60	H	L	M	H	M	M	H	L
61	H	L	H	L	H	L	H	M
62	H	L	H	M	H	M	H	L
63	H	L	H	H	H	L	H	L
64	H	M	L	L	L	M	H	L
65	H	M	L	M	L	M	H	M
66	H	M	L	H	L	H	H	M
67	H	M	M	L	M	L	H	M
68	H	M	M	M	M	M	H	L
69	H	M	M	H	M	H	H	L
70	H	M	H	L	H	M	H	L
71	H	M	H	M	H	M	H	M
72	H	M	H	H	H	M	H	M
73	H	H	L	L	M	L	H	M
74	H	H	L	M	L	M	H	M
75	H	H	L	H	L	H	H	M
76	H	H	M	L	M	L	H	M
77	H	H	M	M	M	L	H	M
78	H	H	M	H	M	H	H	H
79	H	H	H	L	H	L	H	H
80	H	H	H	M	H	H	H	H
81	H	H	H	H	H	H	H	H

4) Layer 4 (Output membership Layer): Neurons in this layer represent fuzzy sets used in the consequent of fuzzy rules. Neurons in this layer have two operating modes: down- up and up-down. The down-up operating mode is used to determine integrated firing strength of fuzzy rules applicable to that input. The output linguistic variables used are: handoff data call queue capacity 'N' (0 to 30) = {Low (L), Medium (M), High (H)}, handoff real-time call queue capacity 'R' (0 to 20) = {Low (L), Medium (M), High (H)}, new voice call threshold 'Unv' (0 to 10) = {Low (L), Medium (M), High (H)}and new video call threshold 'Unvi' (0 to 10) = {Low (L), Medium (M), High (H)}. The value of 'N' and 'R' is function of the soft handoff threshold parameters T_ADD and T_DROP. The up-down operating mode is used during training of the system by giving them the output data set (Ň,Ř,Ũnv and Ũnvi). Depending on the error, between current output and desired output, the weights are adjusted between Layers 3-4.

5) Layer 5 (Defuzzification Layer): Each neuron in this layer represents a single output of the neuro-fuzzy system. It takes the output fuzzy sets clipped by the respective integrated firing strengths and combines them into a single fuzzy set. This neuro-fuzzy system applies standard defuzzification methods, ie the CoG technique.

Training of ASNFC-MC:

The membership functions for input and output parameters along with the rule base have already been described in the previous chapter. A total of 81 rules have been developed depending on different combinations of input-output linguistic parameters. The training of the neuro-fuzzy controller is done by providing input-output data set as done for ASNFC CAC model. The data set for training of the proposed model is taken from the analytical models defined in research papers [6]. For the training of the proposed neuro-fuzzy controller training data set shown in table III is used and U_{nv},U_{nvi} and U_{dn} is taken to be 12 each.

TABLE III. Training Dataset for ASNFC Model

Traffic		Handoff Traffic		N	R	P_{nv}	P_{nvi}	P_{hd}	P_{hr}
RT	NRT	RT	NRT						
10	10	5	5	6	2	0.005	0.002	0.001	0.001
20	10	10	5	4	4	0.008	0.006	0.001	0.002
30	20	10	10	8	2	0.012	0.011	0.002	0.003
40	20	20	10	6	2	0.013	0.012	0.004	0.004
50	30	20	10	4	2	0.016	0.014	0.006	0.009
10	30	5	15	8	4	0.003	0.002	0.008	0.003
20	40	5	20	6	4	0.005	0.004	0.01	0.002
30	40	15	15	6	2	0.008	0.006	0.02	0.005
40	50	20	20	4	2	0.014	0.01	0.03	0.008

50	50	20	25	8	2	0.03	0.025	0.045	0.01
10	30	5	15	6	4	0.019	0.019	0.05	0.02
20	40	10	20	8	4	0.032	0.029	0.042	0.008
30	40	10	10	8	2	0.045	0.04	0.05	0.023
40	50	20	25	4	4	0.072	0.066	0.06	0.045
50	50	25	20	8	2	0.09	0.082	0.043	0.035

When input and output linguistic values are applied during training, the system automatically generates a complete set of fuzzy IF-THEN rules. The initial weights between Layer 3 and Layer 4 are all set to value 1.0. The modified rule base for the trained ASNFC model along with final weights is visualized in Table IV.

TABLE IV. Rule Base for ASNFC-MC Model After Training

No	IF				THEN				Wt
	P_{nv}	P_{nvi}	P_{hd}	P_{hr}	N	R	U_{nv}	U_{nvi}	
6	L	L	M	H	M	H	L	L	0.68
8	L	L	H	M	H	M	L	L	0.6
10	L	M	L	L	L	M	L	M	0.8
13	L	M	M	L	M	L	L	M	0.9
16	L	M	H	L	H	L	L	L	0.56
19	L	H	L	L	L	L	L	M	0.2
25	L	H	H	L	H	L	L	M	0.7
29	M	L	L	M	L	M	M	L	0.3
36	M	L	H	H	H	H	M	M	0.9
41	M	M	M	M	M	M	M	M	0.67
46	M	H	L	L	L	M	M	H	0.24
52	M	H	H	L	M	L	M	H	0.64
55	H	L	L	L	L	L	M	M	0.8
57	H	L	L	H	L	H	H	M	0.48
61	H	L	H	L	H	L	H	M	0.97
66	H	M	L	H	L	H	H	M	0.3
73	H	H	L	L	M	L	H	M	0.58
75	H	H	L	H	L	H	H	M	0.4
81	H	H	H	H	H	H	H	H	0.9

4. Results and Discussions

The ASNFC-MC model after training is simulated using MATLAB to obtain different performance measure parameters. The obtained results are then compared with Class based priority scheme [6]. In Class based Priority Scheme, each type of traffic has its own cutoff threshold. The scheme supports any number of classes of traffic, each of which can have its own QoS requirements in terms of number of channels needed, length of the connections and cutoff priority employed. The proposed scheme uses finite buffering for both new calls and handoff calls. During simulation some of parameters are kept constant i.e M=64, $U_{nv}=U_{dn}=U_{nvi}=12$, N=6 and R=4.

The forced termination probability of real time and non-real time calls is visualized in Figure.4 and Figure.5 respectively. Both figures give an illustration that it is lower in case of ASNFC-MC scheme. Neuro-fuzzy model can dynamically varies the queue size for real and non-real time handoff calls. Due to this in case of incoming higher traffic rate, more calls can be handled. This leads to lesser forced termination of calls.

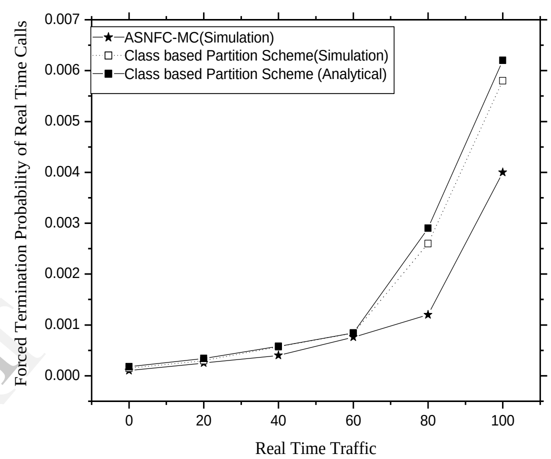

Figure 4. Forced termination probability of real time calls v/s Real time traffic

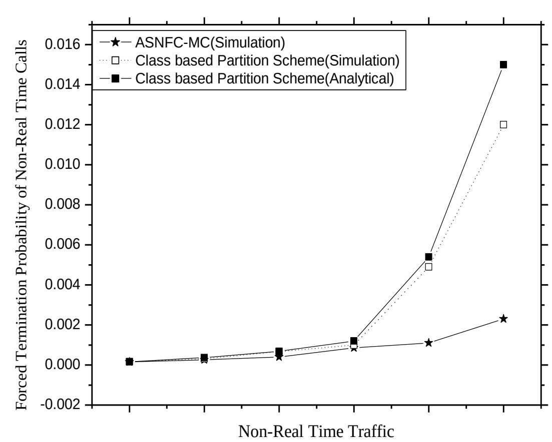

Figure 5. Forced termination probability of Non-real time calls v/s Non-Real time traffic

The percentage channel utilization by the two schemes is visualized in Figure.6. As the ASNFC-MC algorithm makes dynamical fuzzy decision of the threshold values, so it provides better cell utilization for same values of incoming traffic.

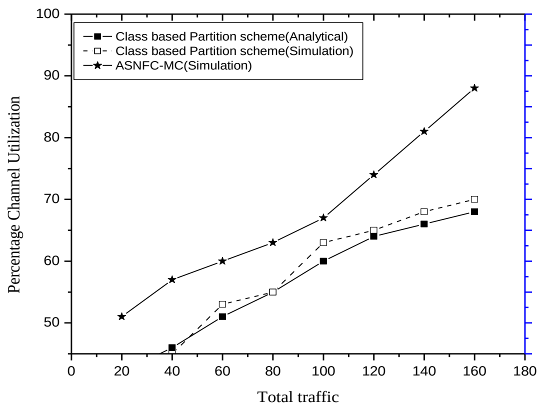

Figure 6. Percentage channel utilization v/s total traffic

5. Conclusion

On analysis and simulation, the results showed that the Neuro-fuzzy model due to its adaptable nature of adjusting the soft handoff coverage region offer better results for for forced termination probability of real and non-real time calls and percentage channel utilization.

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