Soft Computing Technique Based Call Admission Control Decision Mechanism

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Abstract. The decision Mechanism is the concluding phase of any decision making process. This paper discusses on the different methodologies available for implementing the decision mechanisms. The paper preambles with a brief description on set of conventional Multi criteria Decision Mechanisms (MCDM) like Analytical Hierarchy Process (AHP), Simple Additive weighting Method (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Grey Rational Analysis (GRA) along with benefits and limitations of each technique. The different intelligent/soft computing techniques that are widely used in decision making processes like fuzzy logic, neural networks are discussed and finally confines the discussions to the different neural network (NN) based decision support systems. The paper proposes a fuzzy neural network based architecture for call admission control decision mechanism in a heterogeneous wireless network environment.

Keywords: Analytical Hierarchy Process, TOPSIS, Grey Rational Analysis, Fuzzy neural networks.

1 Introduction

The MCDM system is an analytical technique that analyzes the complex problem of with contradicting constraints and assists in finding best possible solution by bringing all deciding factors together. The MCDM systems are extensively used in many fields

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like engineering and technology fields like environmental study, reliability of systems, study of social issues, financial analysis and analyzing political scenarios. The MCDM system will involve different conflicting interests in obtaining an optimal or near optimal solution to the multi constraint problem. The MCDM approach has been very widely used in the recent past for RRM mechanisms [1, 2]. The MCDM methods can be classified as conventional and evolutionary methods [3]. Some of the conventional methods used often are The Analytical Hierarchy Process (AHP), Simple Additive weighting Method (SAW) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Grey Rational Analysis(GRA). The evolutionary approaches are based on soft computing techniques like Genetic algorithms (GA), Fuzzy logic, Neural Networks (NN).

2 Conventional Decision Mechanisms

The Simple Additive weighting Method (SAW), Analytical Hierarchy Process (AHP), Grey Rational Analysis (GRA), and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are widely used conventional methods.

A. Simple Additive Weighting Method

SAW is undoubtedly the one of the best MCDM method. It is simple and easy to understand [4].In SAW the score is obtained from adding the contributions from each attribute The Normalization is applied to add two items with different measurement units as we will not be able to add two attribute values directly. In this method the overall score of an alternative is computed by multiplying the comparable rating for each attribute based on the importance of the weight assigned to the attribute and then summing these products over all attributes. [5].

Formally, score of an alternative in the SAW method can be expressed as

$$V(A_i) = V_i = \sum_{j=1}^{n} w_j v_j(x_{ij}), \quad i = 1,2,3 \ldots m \tag{1}$$

Where $V(A_i)$ is the value function of alternative A_i ; w_j and $v_j(.)$ are weights and value functions of attribute x_{ij} respectively. Through the normalization process, each incommensurable attribute becomes a pseudo-value function, which allows direct addition among attributes. The value of attribute A_i can, then, be rewritten as

$$V_i = \sum_{j=1}^{n} w_j r_{ij}, \quad i = 1,2,3 \ldots m \tag{2}$$

Where, r_{ij} is the comparable scale of x_{ij}, which can be calculated by normalization process [5].

The calculation of r_{ij} can be done using either linear normalization or vector normalization. In linear normalization, it adopts a simple procedure of dividing the rating of an attribute by its maximum value. The normalize value of the x_{ij} for a benefit attribute is given by

$$r_{ij} = \frac{x_{ij}}{x_j^{\max}} \quad i = 1,....m, \;\; j = 1,...n \tag{3}$$

For instance, if bandwidth and performance are benefit attributes of the network in CAC and need to have larger values then such networks are ideal for CAC. In case of cost attributes, lesser the cost more the weightage/preference to the network for CAC decision in the HWN environment. Hence for cost attributes the r_{ij} is calculated by:

$$r_{ij} = \frac{x_j^{\min}}{x_{ij}} \quad i = 1,....m, \;\; j = 1,...n \tag{4}$$

Finally, by applying the weight factors for individual attributes, the weighted average value V is calculated for each alternative.

B. AHP: Hierarchical SAW Method

AHP was developed by Saaty in 1980.This is the formalization of our intuitive understanding of a complex problem in a hierarchical structure.AHP develops a goal of hierarchy to solve the decision problem with a large number of attributes. It is best suited for finding optimal solution for complex decision making problems. In AHP the final objective of the problem is analyzed until the problem acquires a hierarchical structure. This step of structuring a problem as a hierarchy of multiple criteria is the first step of implementing the AHP.

A hierarchy should have at least three levels: focus or overall goal of the problem at the top, multiple criteria that define alternatives at middle and in this hierarchical structure the lowest level will have the alternative solutions of the problem found. The elements of each level of hierarchy are compared pair wise as far as the degree of preference of one against the other [6].The required comparison between the pair is realized via matrices. After comparison the next step is the assignment of preference for each pair of decision elements. The values assigned could be the Saaty numerical gradationvalues1,2,3,4,5,6,7,8,9,1/,2,1/3,1/4,1/5,1/6,1/7,1/8,1/9.The final stage of AHP is to compute the contribution of overall goal by aggregating the resulting weights vertically.

C. TOPSIS

The TOPSIS method was developed by Hwang and Yoon (1981). This method is based on the idea that the chosen alternative need to have the shortest distance from the ideal solution and the farthest distance from the negative ideal solution. The ideal solution is a theoretical solution for which all attribute values correspond to the maximum attribute values in the database comprising the satisfying solutions; the negative ideal solution is the hypothetical solution for which all attribute values correspond to the minimum attribute values in the database. TOPSIS thus gives a solution that is not only closest to the hypothetically best, that is also the farthest from the hypothetically worst [7]. TOPSIS then defines an index called similarity or relative closeness to the positive ideal solution and the remoteness from the negative ideal solution. Then it chooses an alternative with the maximum similarity to the positive ideal solution. TOPSIS assumes that each attribute takes either monotonically increasing or monotonically decreasing attribute. That is larger the attribute outcome greater the preference and this is applicable to benefit attributes for ex. Coverage, bandwidth etc.. But in case of the cost attributes lesser attribute more the preference.

D. Grey Rational Analysis

GRA builds the grey relationship between the individual elements of two series under comparison .The one of the two series used in GRA consists of best quality elements and the other series contains comparative elements. The less difference between these two series will help in drawing better comparison series. Taking the similarity and variability between two series is defined by Grey relational Coefficient (GRC).

There are 6 steps in implementing GRA[8].

Step 1 classifying the elements of series by three situations. The situations are larger-the –better, smaller-the-better and nominal the best
Step 2 defining upper bound, lower bound, and middle /moderate bounds of series elements
Step 3 Normalizing Individual entities
Step 4 defining the ideal series
Step 5 calculating the grey relational coefficient
Step 6 selecting the alternative with the largest grey relational coefficient

3 Intelligent Techniques in Decision Making

The application of intelligent/soft computing techniques has become wide spread for nonlinear time varying and complex problems that were posing a great challenge to researchers when they used the conventional methods. The partial list of soft computing techniques includes techniques such as such as Genetic algorithms, fuzzy logic systems, artificial neural networks and the hybrid systems like fuzzy neural networks have outperformed the conventional algorithmic methods. The advantages of these methods are many, which include most notably learning from experience, scalability, adaptability, moreover the ability to extract the rules without the detailed or accurate mathematical modeling. Soft Computing deals with data that is imprecise, data that are uncertain and partial correct to achieve controllability, robustness and low cost. All these features make the soft computing techniques the best candidates for solving the complex problems in any domain.

Intelligence is defined as the competence of understanding or the ability to perceive and comprehend meaning [9]. Majority of researchers immaterial of the field of research are attempting to design and develop intelligent systems and intelligent methods to solve complex problems. The term intelligent describes a system or method that is able to modify its action dynamically based on the ongoing events. These systems are adaptive and give the appearance of being intelligent as they change their behavior without the intervention of a user. The Intelligent systems can be classified into two categories: rule based techniques and non–rule based techniques [9]. The methods under rule-based methods include fuzzy logic and genetic algorithms. The non-rule based group comprises of techniques such as neural networks which aim to perceive and comprehend the significance of the data with which they are trained. Neural networks are best distinguished from other intelligent techniques in that they are non rule-based and can additionally be made stochastic so that the same action does not necessarily take place each time for the same input. This capability of stochastic behavior of neural network makes it to explore its environment more fully and potentially to arrive at a better solution than linear methods might allow.

The categorization of the intelligent techniques into rule-based and non-rule-based categories helps in understanding better how these systems work and where they may be applied. The rule based techniques will often have wider acceptance than the non-rule based methods. This is for the obvious reasons as it is fairly easy to understand how the rule-based intelligent system arrives at its solution and this can be used to analyze that this system will operate within definite set of input parameters.

A. Genetic Algorithms

The concept of GA originated in early 70s and was developed by Holland and his colleagues. The Genetic algorithms are based on the principles of evolution of natural genetics theory. As per the principles of evolution of natural genetics, the weak and unfit species within their environment are faced with extinction by natural selection. The strong ones have greater opportunity to pass their genes to future generation via reproduction. The notion of the GA is survival of the fittest, the individual who are fittest are likely to survive and have chance of passing their characteristics to next generation.

In GA terminology, a solution vector $x \in X$ is called an individual or a chromosome. The chromosomes are made of discrete units called Genes. Each of the gene controls one or more characteristics of chromosome. Initially Holland assumption of genes as binary numbers initially but in later implementation varied type of genes were introduced. In general, a chromosome is considered as a unique solution x in the solution space. This requires a method to map between the solution space and chromosomes. This mapping function is called as encoding.GA actually works with encoding of the problem and not the problem itself.

The GA operates with randomly initialized population which is formed by a group of chromosomes. As the search progress with the filter solutions, the population finally converges to a single solution. The crossover and mutation are the two operators used to find new solution from the existing solutions.

The parent chromosomes are combined together to form new chromosomes called offspring in crossover operation. The parents are selected among existing chromosomes in the group of chromosomes by giving preference for the fitness of the chromosome so that offspring is expected to inherit a good gene. By repeated application of crossover operation, the percentages of genes of good chromosomes are expected to increase in the population, which leads to an overall good solution. The mutation operator introduces random changes in characteristics of chromosomes. Mutation process is normally applied at the gene level. In typical implementation of GA, the mutation rate is very small which may be less than 1%. Therefore, the new chromosomes produced by mutation will not be very different from the original ones. The purpose of mutation operation is to reintroduce genetic diversity back into the population, and to overcome local optimal solution.

Among the various artificial intelligence techniques, GAs has been widely used in optimization tasks, including numerical optimization and combinatorial optimization problems as well as admission control in wireless systems. Its ability for parallel searching and fast evaluation distinguish itself from other decision and optimization algorithms. In parallel searching, a distributed GAs (DGA) is well known to be a smarter search algorithm compared to traditional GAs. In order to solve the CAC problem, several GA based approaches have been proposed for specific wireless network architectures [10][11]. Although these schemes are promising, they do not specifically consider admission control policies as a means to provide a unified scheme for maximum network utilization, minimum handoff latency and QoS.

B. Fuzzy Logic

The concept of Fuzzy logic has been extensively applied in characterizing the behavior of nonlinear systems. The nonlinear behavior of the system can be effectively captured and represented by a set of Fuzzy rules [12]. In other words fuzzy logic can be viewed as a theory for dealing with uncertainty about complex systems, and as an approximation theory. Many engineering and scientific applications including time series are not only nonlinear but also non-stationary. Such applications cannot be represented by simple fuzzy rules, because fixed number of rules can describe time invariant systems only and cannot take in to account the non-stationary behavior. Recently, a new set of Fuzzy rules have been defined to predict the difference of consecutive values of non-stationary time series [13].

Fuzzifier is the first step in the Fuzzy Logic (FL) and control decision making system. The objective of this process is to assign, for each input linguistic variable, a value between 0 and 1 corresponding to the degree of membership of this input to a given Fuzzy Subset or Term. The fuzzifier transforms the crisp inputs into degrees of match with linguistic values. A Fuzzy Subset is a linguistic subjective representation of the input variable. The linguistic variables are denoted by LVi. The fuzzification is performed by the fuzzifier and is the process that transforms crisp data into fuzzy sets. A fuzzy set is characterized by a membership function μF which takes values in the interval [0, 1], namely, $\mu F: U \rightarrow [0, 1]$. Thus, a fuzzy set may be represented as a set of ordered pairs of a generic element u and its grade of membership function $F = \{(u, \mu F(u)) | u \in U\}$ [14].

The Inference engine and fuzzy rule base is the second step of the fuzzy logic and control decision making system .In a FC, the dynamic behavior of the system is characterized by a set of linguistic rules based on expert knowledge. The expert knowledge is expressed in If-Else form:

Since the antecedent and the consequent parts of these IF–THEN rules are associated with fuzzy concepts, they are called fuzzy inference rules or fuzzy control rules. Several linguistic variables might be involved in the antecedents and conclusions of these rules, thus providing a convenient way for expressing control/decision policies and simplifying complex decision problems. The total of the fuzzy inference rules forms the fuzzy rule base, the inference engine is the control mechanism that applies fuzzy control rules contained in the fuzzy rule base.

Defuzzification is the next step in the FL based decision control system .The defuzzification process is executed by the defuzzifier and consists of the transformation of the outputs of the inference process, which are so far fuzzy sets, into non-fuzzy (crisp) control value. The defuzzification method considered is the center-of-area method [15].

The advantages of fuzzy logic approach [16] are easy to understand and build a predictor for any desired accuracy with a simple set of fuzzy rules, no need of mathematical model for estimation and fast estimation of future values due to the less computational demand. The limitation of fuzzy logic approach is that it works on single step prediction and it does not have learning capability. In general the methods based on fuzzy logic are cumbersome to use, which requires exercise knowledge and user involvement in order to make decision rules .This makes fuzzy logic solutions applicable and more convenient when the problem dimension is very small. Bringing in the learning abilities of neural networks to fuzzy logic systems may provide a more promising fuzzy logic approach.

C. Neural Networks

Neural networks have large number of highly interconnected processing elements called ‘node’. These nodes demonstrate the ability to learn and generalize from training patterns or data. The neural networks are low-level computational elements that exhibit good performance when they deal with sensory data. They can be applied to the situation where there is sufficient observation data available. The NN method is used in any problem related to control, prediction and classification. NNs are able to gain this popularity because of the commanding capacity they have in modeling exceptionally complex nonlinear functions. NNs have a biggest advantage in terms of easy to use which is based on training-prediction cycles. Training the NN plays crucial role in the system usage of NNs. The training pattern that contains a predefined set of inputs and expected outputs is used to train the NN. Next, in prediction cycle, the outputs are supplied to the user based on the input values. To make NNs to behave like a physical system or predict or control the training set used in the training cycle shall consist of enough information representing all the valid cases [17-19]. NNs are flexible soft computing frameworks for modeling a broad range of nonlinear problems [20]. One significant advantage of the neural network based approach over other classes of nonlinear models is that NNs are universal approximation tools that can approximate large class of functions with a high degree of accuracy [21]. This approximation power of NN model comes from several parallel processing elements, called as ‘neurons’. No prior assumption of the model form is required in the model building process. Instead, the network model is largely determined by characteristics of the data.

The benefits of neural network approach [22] are as follows. First, the NN Prediction accuracy is much superior to conventional approaches. Second, NN Model can be used for single and Multi-step forecasting. Third, they are capable of learning the system and demands low computation structures. The limitations of NN approach are: The optimal choice of number of layers and number of neurons in each layer is a heuristic process and it requires expertise in the field of NNs for a model designer. Deciding of the weights to the non-cyclic links will determine the accuracy of forecasting. However, deciding the appropriate weights to the link is once again a heuristic process.

D. Recurrent Neural Networks

The Recurrent Neural Network (RNN) architecture can be classified into fully interconnected nets, partially connected nets and Locally Recurrent & Globally Feed-forward (LRGF) nets [23]. The recurrent neural networks (RNNs) have superior capabilities than the feed forward neural networks [24][25]. Since a recurrent neuron has an internal feedback loop to capture the dynamic response of a system without external feedback through delays. The RNNs have the ability to deal with time-varying input or output through their own natural temporal operation [24]. In addition to all these , the RNNs have dynamic mapping and demonstrate good control performance in the presence of un-modeled dynamics, parameter variations, and external disturbances [24][26]. Since, a recurrent neuron has the internal feedback loop to capture the dynamic response of the system without external feedback through delays; the RNNs have superior capabilities than the non-recurrent feed forward neural networks [27].

E. Radial Basis Function Networks

A fuzzy system maps an input fuzzy set into an output fizzy set. The characteristics of this mapping are governed by fuzzy rules in the fuzzy system. One of the important design issues of fuzzy systems construction a set of fuzzy rules which plays vital role in the system performance of the fuzzy systems. Where the construction of rules can be implemented using either manual or automatic rule generation. The manual approach becomes more difficult if the required number of rules increases or if there is lack of domain knowledge which may is not easily available .This not only limits applications of fuzzy systems, but also forces system designers to spend tough time to fine tune fuzzy rules abstracted from the knowledge of domain experts.

These difficulties motivate researchers to automate the process of fuzzy rule extraction**.** The basic idea behind the automatic design approaches is to estimate fuzzy rules through learning from input and output sample data. The functional equivalence between radial basis function networks and fuzzy systems with some restrictions was shown in [28]. The Radial Basis Function Network (RBFN) proposed in [29]is a type of neural networks which employ local receptive fields to perform function mappings, demonstrated that RBFNs and their usefulness in a variety of applications including classification, prediction, and system modeling.

The RBFN has a faster convergence property than a multilayer Perceptron (MLP) because of its simple structure and simple learning process. Additionally, the RBFN has a similar feature to the fuzzy system. First, the output value is calculated using the weighted sum method. Then, the number of nodes in the hidden layer of the RBFN is same as the number of if–then rules in the fuzzy system. Finally, the receptive field functions of the RBFN are similar to the membership functions of the premise part in the fuzzy system. Therefore, the RBFN is very useful to be applied to time variant systems [30] [31].

The implementation of RBFN bases for recurrent RBFN based FNN improves the accuracy of the approximation function. Based on the architecture of the conventional RBFN, the Recurrent Radial Basis Function network (RRBFN) have input looped neurons with sigmoid activation functions. These looped neurons represent the dynamic memory of the RRBF, and the Gaussian neurons represent the static one. The dynamic memory enables the networks to learn temporal patterns without an input buffer to hold the recent elements of an input sequence. The recurrent or dynamic aspect is obtained by cascading looped neurons on the first layer. This layer represents the dynamic memory of the RRBF network that permits to learn temporal data. The RRBFN architecture is able to learn temporal sequences and RRBFN network is based on the advantages of Radial Basis Function networks in terms of training process time.

4 Intelligent Methods in CAC Decision Mechanisms

Fuzzy logic based CAC is excellent in dealing with real world imprecision and has a greater ability to adapt itself to dynamic, imprecise and burst traffic environments. But Fuzzy logic is incompetent in learning capabilities needed to automatically construct its rule structure and membership functions which is mandatory to achieve optimal performance.

Neural network based CAC provides learning and adaptation capabilities which reduce the estimation error of conventional CAC and achieve performance similar to that of a fuzzy logic based call admission controller. However, for obvious reasons it is difficult to incorporate the knowledge embodied in conventional methods into the design of neural networks. From the above discussion it is clear that the fuzzy logic is easy to understand and uses simple linguistic terms and if-then rules and NNs are smart enough to learn the system characteristics. Therefore the Fuzzy Neural Networks (FNN) combines the benefit of both NNs and fuzzy systems to solve the CAC problem. This research work proposes an ICACM based on Fuzzy Neural Call Admission Control (FNCAC) developed using RRBFN to handle the complex problem of CAC in HWNs supporting multimedia traffic. The advantages of RRBFN have already been discussed in the previous chapter. FNCAC is a hybrid model and it is a combination of fuzzy logic and NN that succeeds in absorbing the benefits of all the three approaches discussed i.e. Conventional, Fuzzy logic and NN based CAC while minimizing their drawbacks for HWNs for supporting multimedia traffic.

5 FNCAC Controller for ICACM

The fuzzy neural call admission control (FNCAC)of the intelligent call admission controller mechanism (ICACM) utilizes the learning capability of the NN to reduce decision errors of conventional CAC policies that is generally resulted from modeling, approximation, and unpredictable traffic fluctuations of the system. FNCAC also employs the rule structure of the fuzzy logic controller which is easy to learn and requires less learning time and prevents operating errors. Further, the neural fuzzy network is a simple structured network which needs proper selection of input variables and design the rule structure for the FNCAC scheme so that it not only provides a robust framework to mimic experts' knowledge embodied in existing traffic admission control techniques but also constructs an intelligent computational algorithm for CAC.

The FNCAC controller with its other processors for HWNs is as shown in Figure 1. The peripheral processors are traffic estimator of the incoming traffic, and a network resource estimator of the HWN environment. The network character estimator will provide the information about the available network resources in the system. The Incoming traffic requirement estimator collects the incoming traffic requirements like BER, required bandwidth/data rate of the incoming traffic/user request through the network resource manager. The network resource manager plays an important role in Resource provisioning.

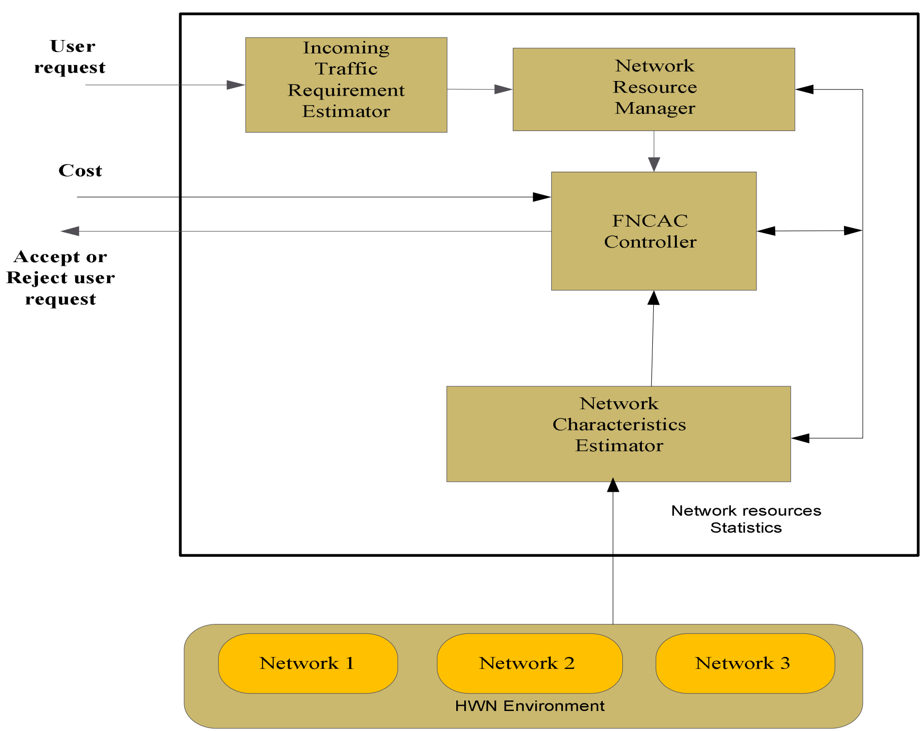

Fig. 1. Architecture of FNCAC based ICACM

The FNCAC also takes price as one of the input. The FNCAC will take the decision of admitting/ rejecting the user request based on the user QoS requirements and networks resource constraints and the economic input like cost which will act as bias. The FNCAC based ICACM meets the interest of the network service provider by increasing the radio resource utilization which results in increased revenue. It improves the user's satisfaction by enhanced QoS provisioning and overall network stability.

The proposed ICACM particularly use the feed forward neural networks which has the ability to map any nonlinear and non-stationary function to an arbitrary degree of accuracy. One such popular feed-forward network is the Radial Basis Function Network(RBFN).

It is a single hidden layer feed-forward network. Each node in the hidden layer has a parameter vector called as Centre. These centres are used to compare with network input and produce radically symmetrical response. These responses are scaled by connection weights of the output layer and then produce network output, where Gaussian basis function is used and is represented as

$$\hat{y} = \sum_{i=1}^{n} w_i \exp\left(-\frac{\left\| y - \mu_i \right\|}{2\sigma_i} \right) \tag{5}$$

Recurrent Radial Basis Function Network is a class of Locally Recurrent and Globally Feed-Forward(LRGF) RNN. In LRGF network the recurrent/self-connection is either in the input layer or in the output layer. RRBFN is having recurrent connection at the input layer. Where i is the dimension of the influence field of hidden layer neuron, y and i are input and prototype vector respectively.

The proposed architecture of RRBFN based FNCAC for ICACM is shown in Figure 2. The FNCAC takes the characteristics of the three different networks for the study and the requirements of the incoming traffic are taken as inputs. The cost is considered as the bias input. The NN based Call admission control involves training and testing of RRBFN based CAC controller.

6 Validation of FNCAC

The training and testing samples are randomly picked from the sample size of 3000. The second phase of simulation is training and testing of the RRBF network. The RRBF network has 500 neurons in input layer with sigmiodal activation function with recurrent connection the range of recurrent weights are -1 to +1, the hidden RBF layer has 375 neurons with RBF activation and output layer has single neuron with linear activation. Input weights are in the range of - 0.40 to + 0.40, recurrent weights are in the range of - 0.6 to +0.6. All the layers except input layer neurons have radial activation function.

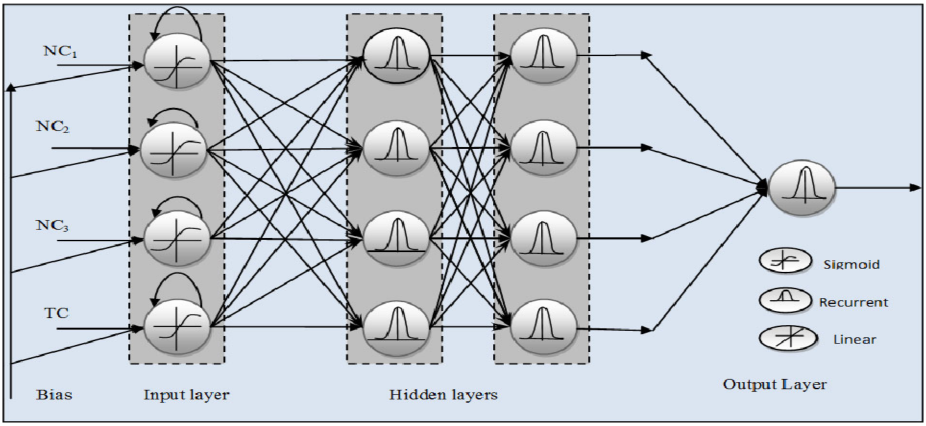

Fig. 2. Architecture of RRBFN based FNCAC for ICACM

The set of experiments were conducted with varying the aggregate traffic and individual traffic of the network and the call blocking probability of Fuzzy neural technique was compared with the conventional CAC and Fuzzy based CAC.

The performance of RRBFN based FNCAC system for next generation networks is compared and validated with the performance of fuzzy based CAC and conventional Guard channel based CAC. The Performance of FNCAC model in an heterogeneous RATs supporting multimedia traffic is studied pitching upon the call blocking probability by varying the utilization rate of the aggregate traffic and the individual traffic and is indicated in Figure 3.

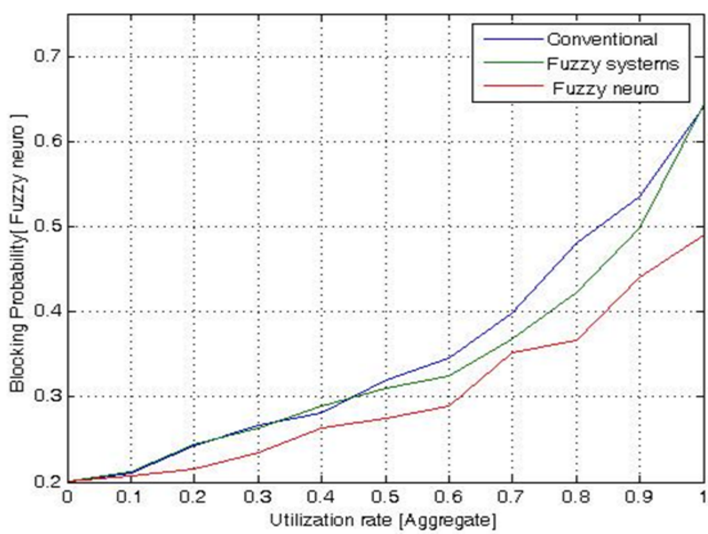

Fig. 3. Call blocking probability of FNCAC for the aggregate traffic

The simulation study conducted records the following observations.

The concept of minimizing the call blocking probability is an optimization technique to provide fair QoS to the set of users in the wireless network and there is a need of intelligent call admission control strategy in the admission control mechanism to make the decision of accepting are rejecting a call, keeping the blocking probability minimal in an HWNs was clearly indicative.

The increase in the utilization rate of the aggregate traffic in the network increases the call blocking probability of the system. The important observation made from the Simulation results reveal that the FNCAC scheme achieves superior system utilization and high learning speed while keeping the QoS contract, compared with the conventional CAC and fuzzy logic based CAC scheme.

7 Conclusion

The analysis made in the work makes RBFN-based FNN is the right tool for implementing the CAC decision in this study. In addition, the structure and the parameter learning phases are preformed concurrently and on line in the Recurrent RBFN based NN makes RRBFN the better choice for CAC Mechanism. The soft computing techniques based decision making system is widely implemented. In our future work we are planning to implement the soft computing based decision mechanism radio resource management techniques in fourth generation networks.

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