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Research Article

A Hybrid Approach to Call Admission Control in 5G Networks

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Artificial intelligence is employed for solving complex scientific, technical, and practical problems. Such artificial intelligence techniques as neural networks, fuzzy systems, and genetic and evolutionary algorithms are widely used for communication systems management, optimization, and prediction. Artificial intelligence approach provides optimized results in a challenging task of call admission control, handover, routing, and traffic prediction in cellular networks. 5G mobile communications are designed as heterogeneous networks, whose important requirement is accommodating great numbers of users and the quality of service satisfaction. Call admission control plays a significant role in providing the desired quality of service. An effective call admission control algorithm is needed for optimizing the cellular network system. Many call admission control schemes have been proposed. The paper proposes a methodology for developing a genetic neurofuzzy controller for call admission in 5G networks. Performance of the proposed admission control is evaluated through computer simulation.

1. Introduction

Nowadays telecommunication operators face new challenges. The fifth generation mobile networks should provide new outstanding attributes such as higher mobility, higher traffic demands, and higher levels of the quality of service.

Call admission control offers an effective way to avoid network traffic congestion thus providing a guaranteed quality of service. A call admission control algorithm provides a decision whether a call should be accepted into a network or dropped. An efficient call admission control scheme can improve the call blocking and call dropping probabilities and overall system utilization [1–3].

Employing up-to-date techniques such as artificial intelligence in 5G network gives more capability to handle traffic. Artificial intelligence can be used in case of network overloading and to support decision-making. Thus 5G with artificial intelligence can satisfy the expected needs along with the new technical challenges [4].

Artificial intelligence-based techniques [5, 6] have replaced conventional techniques in different engineering applications and are widely used in telecommunication networks [7–9].

Using artificial intelligence technique for call admission control was proposed in [10]. According to [11], applying the fuzzy systems provides reducing the call rejection and a higher quality of service. Papers [12–14] have examined application of the fuzzy logic in control systems. An algorithm based on neural networks for decision of call admission has been proposed in [15]. Its results have substantiated solving the call admission control problem with the neural network approach. But better results could be obtained by using a hybrid approach, proposed in [16]. In [17] genetic algorithms have been proposed to be applied for optimization of the call admission problem that led to better user's satisfaction [18].

Thus, using neural networks, fuzzy systems, and genetic algorithms may provide solving the call rejection problem. A better method can be derived when combining these three techniques. That is because the combination overcomes limitations of one technique and produces a relevant result for improving the quality of service [19]. Using artificial intelligence in 5G networks has been investigated in [20–22].

The authors propose to apply in 5G mobile networks a genetic neurofuzzy controller with two input linguistic variables and one output linguistic variable. The controller manages call acceptance or rejection thus allowing congestion avoidance. The authors have already suggested the fuzzy controller in [23] and the neurofuzzy controller in [24]. This paper considers results of a further investigation.

The objective of this paper is a genetic neurofuzzy controller for call admission control in 5G mobile networks.

The paper is organized as follows. In the Materials and Methods, the first subsection introduces linguistic variables and membership functions for a fuzzy controller; the second subsection describes structure of the controller and its operation; the third subsection considers genetic optimization of the controller. The fourth subsection presents simulation in Matlab. The last section provides conclusions.

2. Materials and Methods

2.1. Fuzzy Controller. Fuzzy systems simulate human reasoning and are applied for characterizing behaviour of nonlinear systems. Fuzzy approach may be employed when there is no mathematical model of the process.

Let us consider a mobile system formed by a number of operators sharing their Radio Access Networks in order to ensure users' satisfaction. Therefore, when a user arrives to the system and his call cannot be admitted, it is transferred to another operator to avoid the rejection.

For developing a fuzzy controller its linguistic variables, their terms, and membership functions should be defined. Input variables of the fuzzy controller describe all the possible states of a process controlled and its output variable describes all possible controlling actions. Then, a rule base should be assigned consisting of a set of IF-THEN rules to describe controlled states. To evaluate operability of the fuzzy controller a simulation is performed.

Input linguistic variables of the access fuzzy controller are the effective capacity (E) and offered cell load (O); its output variable is the probability for call acceptation, rejection, or transfer (P). The architecture of the fuzzy controller is shown in Figure 1.

A fuzzy controller transforms input variables to membership function values, evaluates a fuzzy output according to a rule base, and then converts the fuzzy output to a crisp one.

The proposed fuzzy controller is to be converted into an adaptive neurofuzzy inference system (ANFIS), suitable for operating under uncertain conditions. For updating the rule base a genetic algorithm is to be used. The architecture of the genetic neurofuzzy controller is shown in Figure 2.

The linguistic variable of the effective capacity E is defined with terms "low," "medium," and "high":

$$T(E) = \{Low(L), Medium(M), High(H)\}. \tag{1}$$

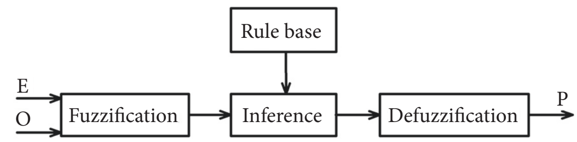

Figure 1: Architecture of the fuzzy controller.

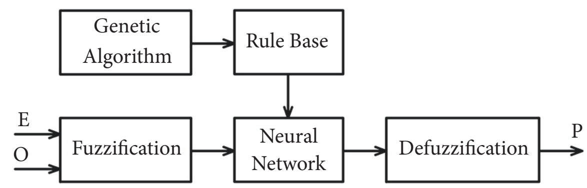

Figure 2: Architecture of the genetic neurofuzzy controller.

The linguistic variable of the offered load O is defined with terms "low," "medium," and "high":

$$T(O) = \{Low(L), Medium(M), High(H)\}. \tag{2}$$

The linguistic variable of the call acceptation P is defined with terms "transfer," "reject," and "accept":

$$T(P) = \{Transfer(T), Reject(R), Accept(A)\}. \tag{3}$$

"Reject" means the call will be blocked. "Accept" means the call will be admitted to the system. "Transfer" means the call will be transferred to the other operator.

Figures 3 and 4 present input variable membership functions, which are of trapezoid type and defined as

$$\mu(x) = \begin{cases} 0 & if\ x \le a_1\ or\ x \ge a_4, \\ \dfrac{(x-a_1)}{(a_2-a_1)} & if\ x \in (a_1, a_2], \\ 1 & f\ x \in (a_2, a_3), \\ \dfrac{(a_4-x)}{(a_4-a_3)} & if\ x \in (a_3, a_4). \end{cases} \tag{4}$$

Figure 5 illustrates output variable membership functions, which are singletons and defined as

$$\mu(x) = \begin{cases} 0 & if\ x \ne m, \\ 1 & if\ x = m. \end{cases} \tag{5}$$

The suggested fuzzy controller operates according to the rule base consisting of nine rules. Input and output values are specified in Table 1.

The fuzzy controller operates as follows.

Each input variable gets a corresponding fuzzy value:

$$\begin{gathered} E \longrightarrow E_L, E_M, E_H; \\ O \longrightarrow O_L, O_M, O_H. \end{gathered} \tag{6}$$

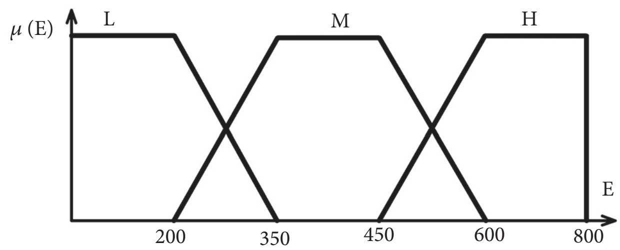

Figure 3: Membership functions for the effective capacity. Definition of the membership functions: L: low; M: medium; H: High.

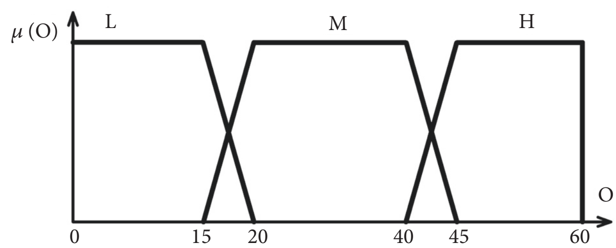

Figure 4: Membership functions for the offered cell load. Definition of the membership functions: L: low; M: medium; H: High.

Table 1: Fuzzy rule table denoting the output P values according to the input E and O values.

E		O	
	L	M	H
L	R	T	T
M	A	R	T
H	A	A	R

The minimum operations are performed:

$$\begin{aligned} w_1 &= \min\left[E_L, O_L\right]; \\ w_2 &= \min\left[E_L, O_M\right]; \\ w_3 &= \min\left[E_L, O_H\right]; \\ w_4 &= \min\left[E_M, O_L\right]; \\ w_5 &= \min\left[E_M, O_M\right]; \\ w_6 &= \min\left[E_M, O_H\right]; \\ w_7 &= \min\left[E_H, O_L\right]; \\ w_8 &= \min\left[E_H, O_M\right]; \\ w_9 &= \min\left[E_H, O_H\right]. \end{aligned} \tag{7}$$

The crisp value is obtained:

$$P = \frac{\sum_{i=1}^{9} w_i \cdot P_i}{\sum_{i=1}^{9} w_i}. \tag{8}$$

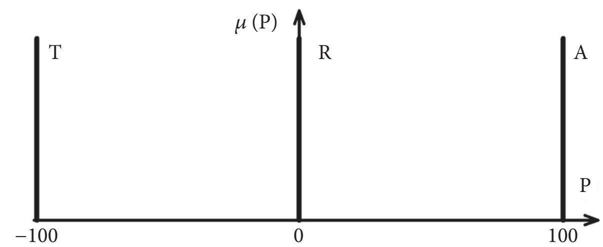

Figure 5: Membership functions for the call acceptance. Definition of the membership functions: T: transfer; R: reject; A: accept.

2.2. Neural Network. Neural networks consist of interconnected artificial neurons. They are able to acquire, store, and employ expert knowledge and can learn new patterns. Neural networks are applied for such problems as optimization, classification, pattern matching, function approximation, and data clustering.

For improving the operability of the fuzzy controller, it is converted into a neurofuzzy controller. For this aim an adaptive neurofuzzy inference system (ANFIS) was chosen. It is a neural network operating like a fuzzy system under uncertain conditions, combining both fuzzy logic and neural networks principles. ANFIS is capable of approximating functions. Its advantage is combining fuzzy reasoning with learning capabilities when solving a problem.

Figure 6 presents a block diagram of the neurofuzzy controller.

The access neurofuzzy controller has fuzzy rules of the form:

$$\begin{aligned} &\text{If } a = A_m \\ &\text{and } b = B_n \\ &\text{then } c = C_p. \end{aligned} \tag{9}$$

$$m = 1, 2, 3; \; n = 1, 2, 3; \; p = 1, 2, 3.$$

The output of each node in layer 1 is the membership degree of input:

$$\begin{aligned} Y_{1j} &= \mu A_j(a) \quad \text{for } j = 1, 2, 3; \\ Y_{1j} &= \mu B_{j-3}(b) \quad \text{for } j = 4, 5, 6. \end{aligned} \tag{10}$$

The output of each node in layer 2 is the weighting factor of the fuzzy rule:

$$Y_{2i} = w_i = \mu A_m(a) \cdot \mu B_n(b), \quad i = 1 \ldots 9. \tag{11}$$

The output of each node in layer 3 is the ratio of the firing strength of the fuzzy rule to the total value of all firing strengths:

$$Y_{3i} = n_i = \frac{w_i}{(w_1 + w_2 + \ldots + w_9)}. \tag{12}$$

The output of each node in layer 4 is multiplication of the normalized output with the node function:

$$Y_{4i} = n_i f_i. \tag{13}$$

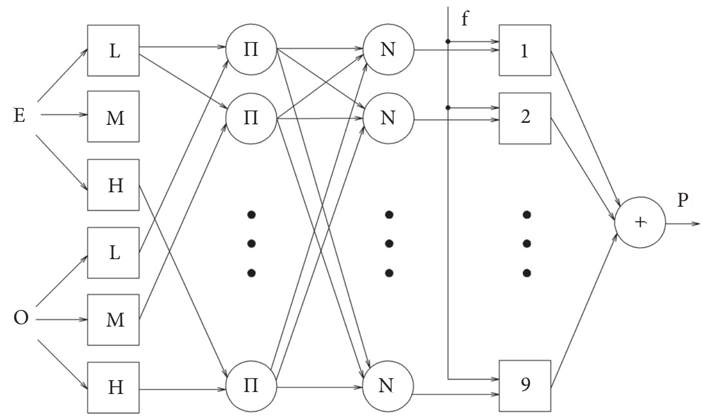

Figure 6: Block diagram of the neurofuzzy controller. Each neuron in first layer is used to fuzzify received crisp inputs. Nine neurons in second layer correspond to a fuzzy rule. Neurons in the third layer are used for the normalization of the values. The fourth layer is the defuzzification one. The single neuron in fifth layer represents an output of the neurofuzzy system.

Table 2: Encoding values.

	E	O	P	
L	00	00	00	T
M	01	01	01	R
H	11	11	11	A

The output of layer 5 gives the output of the controller:

$$Y_5 = n_1 c_1 + n_2 c_2 + \ldots + n_9 c_9. \quad (14)$$

2.3. Genetic Algorithm. Genetic algorithms provide an accurate and fast solution for optimization problems. They act according to processes of selection, mutation, crossover, and reproduction. They are able to optimize both continuous and discrete variables. So, a genetic algorithm is employed for updating the rule base.

A chromosome represents a solution encoded into genes. Here, a gene corresponds to a linguistic variable value. Table 2 shows encoding the fuzzy rules into chromosomes. The term "Low" of the input linguistic variables is specified as "00." The term "Medium" of the input linguistic variables is specified as "01." The term "High" of the input linguistic variables is specified as "11." The term "Transfer" of the output variable is specified as "00." The term "Reject" of the output variable is specified as "01." The term "Accept" of the output linguistic variable is specified as "11."

Here, each fuzzy rule is defined by a set of 5 genes that identify fuzzy sets for each of two input and output variables.

Chromosome for the 1-st fuzzy rule looks so

$$\boxed{0 \mid 0 \mid 0 \mid 0 \mid 0 \mid 1} \quad (15)$$

Chromosome for the 9-th fuzzy rule looks so

$$\boxed{1 \mid 1 \mid 1 \mid 1 \mid 0 \mid 1} \quad (16)$$

The fitness function is

$$F = \frac{1}{\varepsilon + RMSE}, \quad (17)$$

where RMSE (root mean square error) is an objective function, showing the error value between the actual output and the predicted output

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_{real} - P_{pred}\right)^2}, \quad (18)$$

where n is a number of observations.

The genetic algorithm is as follows:

(1) Generate random population of chromosomes

(2) Evaluate the fitness values of every chromosome

(3) Select two parent chromosomes according to their fitness value

(4) Crossover the parents chromosomes to form child chromosomes

(5) Mutate the child chromosomes

(6) If the end condition is satisfied, finish; else go to step (2)

2.4. Simulation. The authors have used the Matlab program to confirm the operability of the proposed neurofuzzy controller. Figure 7 illustrates the simulated in Matlab fuzzy controller. Two input variables and one output variable were specified. The rule base was assigned. To check the operability of the fuzzy controller we set the input values and run the simulation to obtain the output value.

Let the effective capacity E=253 and offered load O=15. According to Figure 8, we get the probability for call acceptation P=35.5%.

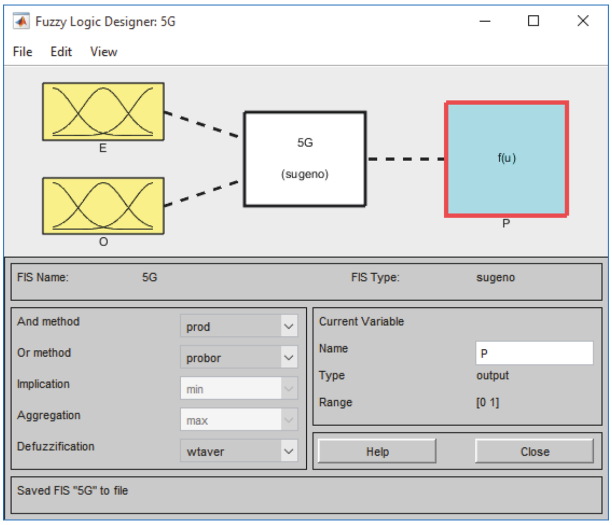

FIGURE 7: Fuzzy controller in Matlab. The fuzzy controller is of Sugeno-type for converting into ANFIS.

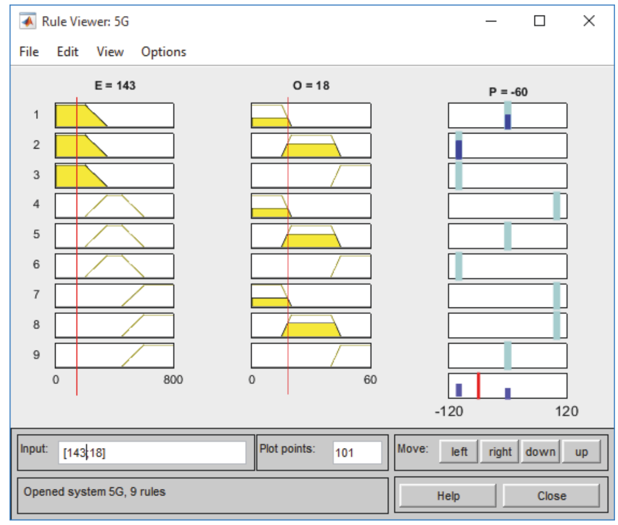

FIGURE 9: Simulation results. Probability for call acceptation is -60%. It means the call is likely to be transferred to another operator.

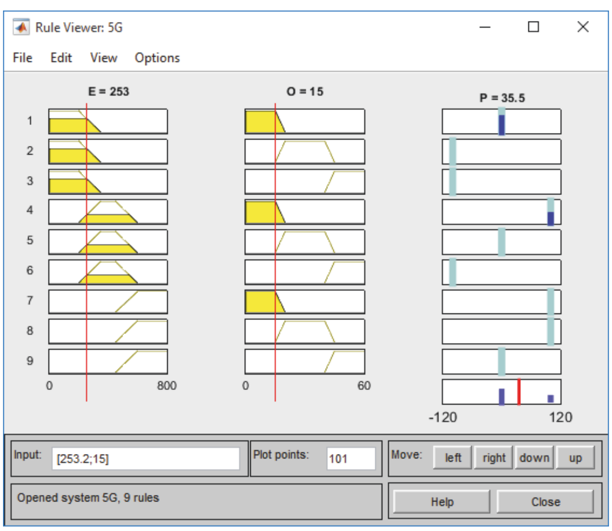

FIGURE 8: Simulation results. Probability for call acceptation is 35.5%. It means the call is likely to be passed to the system.

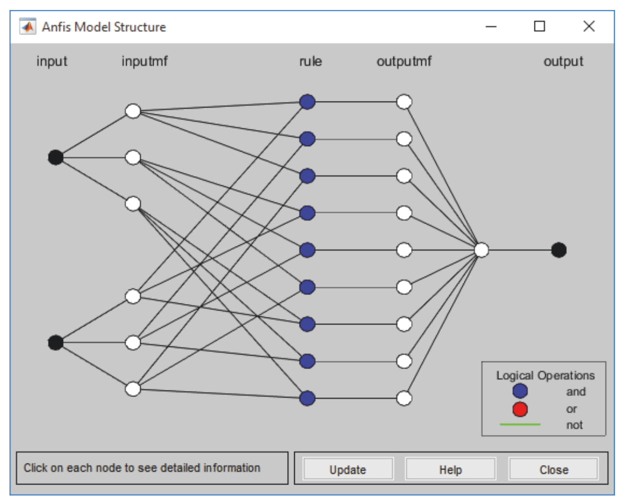

FIGURE 10: Structure of the proposed neurofuzzy controller in Matlab software, all nodes in five layers and links between them are shown.

Let the effective capacity E=143 and offered load O=18. According to Figure 9, we get the probability for call acceptation P=-60%.

Figure 10 presents the structure of the neurofuzzy controller.

Figure 11 illustrates data applied for training the neurofuzzy controller.

Figure 12 shows the training error.

The simulation employed the hybrid learning rule combining the gradient rule and the least squares estimate. Error tolerance was 0. The number of iterations was 10. The input value membership functions after the training process were of a trapezoidal type.

3. Conclusions

The next generation wireless networks are more complex and dynamic, possessing many design challenges for the network planning and management.

This paper considers the artificial intelligence based methodology for designing the controller for call admission in 5G networks to support their quality of service.

To give a better solution to the optimization problem, the suggested controller is built combining a fuzzy system with an artificial neural network and genetic algorithm. Artificial neural networks learn the network behaviour and make accurate predictions, estimating when a call to be admitted in a changing situation. Fuzzy systems deal with uncertainty; at the call admission schemes they can reduce the number of rejected calls, thus increasing the quality of

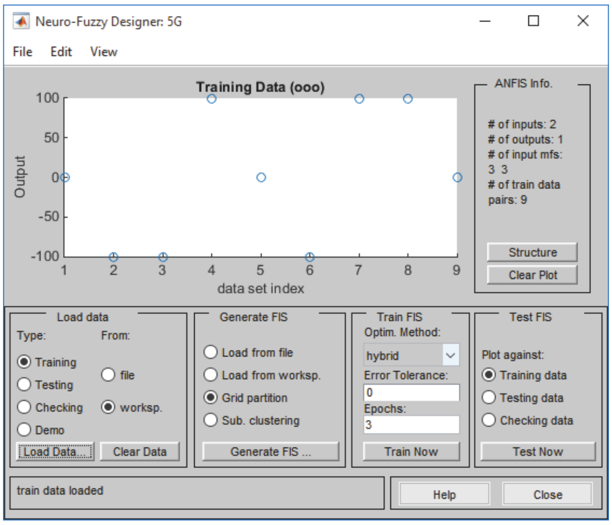

Figure 11: Training data. Nine desired output values and corresponding input values were specified as an array. The x-axis shows number of the array's row. The y-axis shows desired output value.

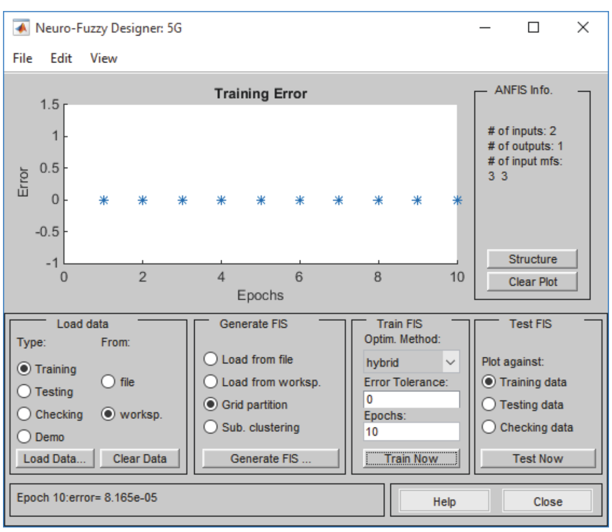

Figure 12: Training error. It equals 0 meaning the training was successful.

service. Genetic algorithms can optimize given values and provide the resource reservation and guaranteed services for calls.

The proposed fuzzy controller was converted into the neurofuzzy system. The genetic algorithm was proposed for improving the rule base. The simulation results sustain that the considered genetic neurofuzzy controller can be employed in 5G mobile networks. The proposed approach can increase the quality of service by decreasing the call blocking probability of the new incoming calls in a network.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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