Applying Artificial Intelligence Based on Fuzzy Logic for Improved Cognitive Wireless Data Transmission: Models and Techniques

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Abstract

Recently, the development of wireless network technologies has been advancing in several directions: increasing data transmission speed, enhancing user mobility, expanding the range of services offered, improving the utilization of the radio frequency spectrum, and enhancing the intelligence of network and subscriber equipment. In this research, a series of contradictions has emerged in the field of wireless network technologies, with the most acute being the contradiction between the growing demand for wireless communication services (on operational frequencies) and natural limitations of frequency resources, in addition to the contradiction between the expansions of the spectrum of services offered by wireless networks, increased quality requirements, and the use of traditional (outdated) management technologies. One effective method for resolving these contradictions is the application of artificial intelligence elements in wireless telecommunication systems. Thus, the development of technologies for building intelligent (cognitive) radio and cognitive wireless networks is a technological imperative of our time. The functions of artificial intelligence in prospective wireless systems and networks can be implemented in various ways. One of the modern approaches to implementing artificial intelligence functions in cognitive wireless network systems is the application of fuzzy logic and fuzzy processors. In this regard, the work focused on exploring the application of fuzzy logic in prospective cognitive wireless systems is considered relevant.

Keywords:

wireless network; cognitive wireless network; radio frequency spectrum; operational frequencies; natural limitations of frequency; quality requirements; artificial intelligence; data transmission.

1. Introduction

Fuzzy logic theory provides a way to model the uncertainty of natural language. In recent times, fuzzy logic has been applied to support intelligent and cognitive systems. The application of fuzzy logic allows for the easy consideration of multiple parameters for decision-making and does not require complex mathematical calculations. However, the most diverse and effective applications of cognitive functions are in wireless regional networks (IEEE 802.22 standard), wireless self-organizing networks (SON), and other types of wireless networks that utilize a variety of different operational parameters, both in terms of wireless broadcasting and the organization of transceivers within the network. A SON (Self-Organizing Network) is a peer-to-peer wireless data transmission network with a variable topology and the absence of a clear infrastructure, where each node can perform router functions and participate in packet data relay. Such a network must understand the application's tasks, and the application should be able to comprehend the network's capabilities at any given moment. This allows the network, through an understanding of the fundamental application requirements, to leverage new capabilities and dynamically select network protocols that satisfy these requirements.

The analysis indicates that the main directions of data transmission systems development include increasing speed, enhancing mobility, expanding coverage areas, and improving the intelligence of network and subscriber equipment. The evolution of the technical platform of wireless networks is also considered. At the current stage of network development, there is a transition to packet-switched systems, which include both channel-switching and packet-switching systems. In the next stage of development, key priorities will include expanding penetration areas and the ability to adapt to the environment and its influences. The ability of a wireless system to adapt to its environment is achieved through the application of cognitive technology at all levels of its architecture. In this step, a modified multi-level model for building cognitive wireless data transmission systems is proposed, featuring the introduction of an artificial intelligence plane that supports cognitive functions at all levels of the architecture.

The implementation of cognitive technology (cognitive radio systems and cognitive networks) will lead to an increase in the efficiency of radio frequency spectrum utilization, improvement in resource management, enhancement of communication quality, efficient access management, and the emergence of new types of services.

The term "cognitive" refers to the property of a communication device or network expressed in its ability to autonomously and dynamically change its topology, adjust operational parameters, redistribute network resources based on previously accumulated knowledge about the

Manuscript received December 5, 2023
Manuscript revised December 20, 2023
https://doi.org/10.22937/IJCSNS.2023.23.12.2

network's state, and adhere to user service policies. A promising direction in building cognitive systems involves technologies based on the use of fuzzy logic and artificial neural networks.

2. Research Methods and Related Works

In fact, it is dedicated to solving the problem of fuzzy adaptive control of the modulation scheme in an OFDM system. It is known that different signal modulation schemes are used at various distances from the transmitter node of a radio network, considering different levels of interference resilience. The task also takes into account the direction and speed of movement of nodes in the SON network relative to each other. The distance between the transmitter and receiver is determined by the received signal power, and the speed and direction of the change in distance correspondingly affect the signal power.

To address this issue, a relationship is established between the energy of the received signal and the data transmission speed. Based on this, different transmission speeds can be allocated in the coverage area of the radio network node. Adaptive modulation is employed to manage the transmission speed in the coverage area. Adaptive modulation in cognitive wireless self-organizing networks (C-SON) allows nodes to adapt the signal modulation scheme to the signal-to-noise ratio (SNR) in the radio channel. The choice of the modulation scheme for transmitting the next OFDM symbol is determined by the SNR estimation made by the receiver during the reception of the current OFDM symbol. Most existing methods for estimating the Signal-to-Noise Ratio (SNR) in an OFDM system are based on the analysis of a pilot signal sequence. Despite their effectiveness, these methods can be difficult or challenging to implement in certain cases. Additionally, a primary drawback of such methods is the need for transmitting a considerable amount of control information over the feedback channel from the receiver to the transmitter, which poses a significant limitation to their practical application.

3. Research Methodology

3.1 Method of channel adaptation

In this paper, a method of channel adaptation without auxiliary pilot signals is proposed for estimating the Signal-to-Noise Ratio (SNR) of QAM signals in Additive White Gaussian Noise (AWGN) channels. The modulation scheme is controlled based on the SNR estimation. Due to the non-uniform frequency response of the channel, there is non-uniform attenuation of different subcarriers in the OFDM transmission system. According to the SNR estimation in the transmitted OFDM symbol, subcarriers with low gain coefficients are disabled, and the power is evenly distributed among the remaining active subcarriers. The resulting power distribution at the transmitter will have the following form:

$$\begin{cases} P_i = \dfrac{P_t}{N_A} (i = 1 \div N_A), \\ P_i = 0 \; (i = N_A + 1 \div N) \end{cases}, \tag{1}$$

where Pt is the total power radiated by the OFDM system (assumed to be a constant value), Pi is the transmitted power of the signal on the i-th subcarrier,

$N_A \leq N$ is the number of active information subcarriers used for transmitting the current packet. When using a uniform distribution of bits over the A active subcarriers, the data transmission rate (the number of information bits B transmitted by the system in one time symbol duration Ts) can be determined as follows:

$$r(N_A, M, R) = \frac{B}{T_S} = \frac{R \cdot m \cdot N_A}{T_S} = \frac{R \cdot \log_2 M \cdot N_A}{T_S}, \tag{2}$$

where R is the code rate, m is the number of bits transmitted in one symbol of MQAM on one subcarrier, and M is the modulation order (M=4, 16, 64, 128). The probability of bit errors (pb) at the receiver of the OFDM communication system depends on the collective values of the Signal-to-Noise Ratio (SNR) on the active subcarriers. Taking into account bit interleaving, the probability of bit errors (pb) can be expressed as an averaged value (over NA active subcarriers) of the probabilities of bit errors:

$$p_b(N_A, M) = \frac{1}{N_A}\sum_{i=1}^{N_A} p_i = \frac{1}{N_A}\sum_{i=1}^{N_A} f_M(\gamma_i), \tag{3}$$

Where γ is the Signal-to-Noise Ratio (SNR), and $F_M(\gamma)$ is a monotonically decreasing function describing the relationship between the probability of bit errors and SNR for M-QAM.

$$f_M(\gamma) \approx \frac{2}{m}\left(1-\frac{1}{\sqrt{M}}\right).Q\left(\sqrt{\frac{3m\gamma}{2(M-1)}}\right) \tag{4}$$

As a result, the overall error probability due to the deactivation of fading subcarriers is significantly reduced, with only a slight loss in the system's bandwidth. However, potential bandwidth loss can be compensated for by employing high-order modulation on the remaining active subcarriers, which exhibit high SNR values. The structural diagram of the considered system is shown in Figure 1.

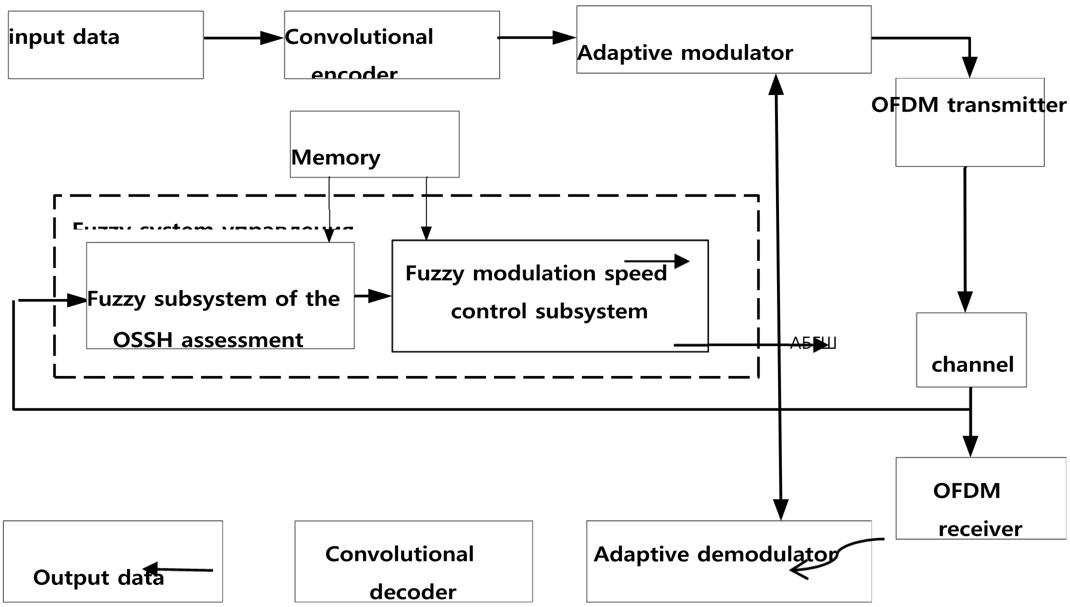


Figure 1. Structural diagram of a fuzzy control system with adaptive modulation

To implement the modulation scheme selection based on fuzzy logic, a model has been constructed in which the modulation speed (MS) and the values of SNR (Signal-to-Noise Ratio) γ are considered as fuzzy variables. The meaning of γ is presented as a linguistic variable, and its basic term set T_γ is defined as a set of possible values: T_γ = {"VL", "L", "M", "H", "VH"}, where "VL" stands for very low value, "L" for low value, "M" for medium value, "H" for high value, and "VH" for very high value. The value of γ is determined as a logical output obtained through the application of a given set of rules R1.

$$\gamma = R1(R_m, I_m, dR, dI) \tag{5}$$

where $R1$ is the rule base for determining the value of γ; R_m and I_m are linguistic variables representing the values of real components of the signal from memory; dR and dI, respectively, are linguistic variables representing changes in the real and imaginary components of the signal.

The possible values of linguistic variables m, R, I, dR, and dI are defined by a single term set T_d = {"*L*", "*M*", "*H*"}, where "*L*" stands for low value, "*M*" for medium value, and "*H*" for high value.

For the terms in T_{MS}, T_γ, and T_d, membership functions of triangular type are defined. The general form of membership functions (MF) for variables *dI, dR*, *I*, and *R* is shown in Fig. 2.

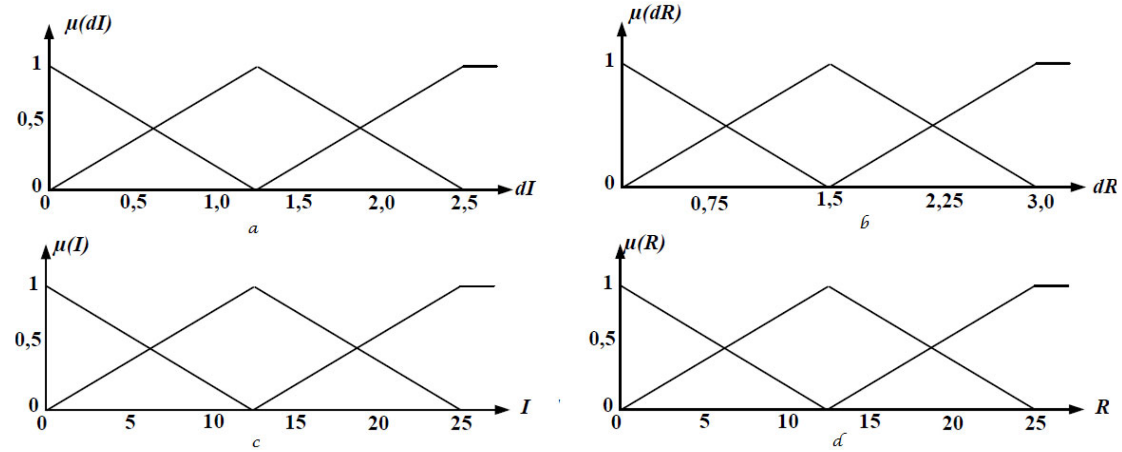


Fig. 2. Membership function: a – deviations of the imaginary component; b – deviations of the real component; c – imaginary component; d – real component.

The set of all rules is conveniently represented in the form of a table, where columns correspond to conditions of one parameter, rows correspond to conditions of another parameter, and at their intersections, and conclusions are recorded, corresponding to these conditions. The output of each implication rule R1 is the linguistic variable "γ", the set of values of which consists of five terms: "VL" - very low value, "L" - low value, "M" - medium value, "H" - high value, "VH" - very high value, with membership functions depicted in Fig. 3.

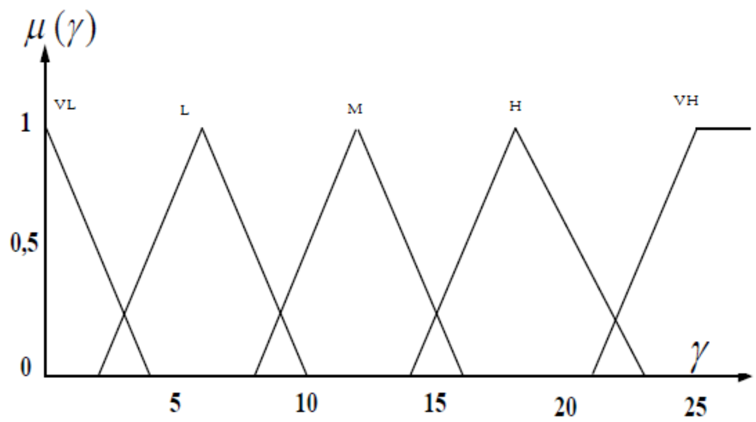


Fig. 3. Membership function: assessment SNR

The modulation speed MS is also represented as a linguistic variable, the basic term set of which, MS T, is defined as the set of possible values:

$$T_{MS} = \{4QAM, 16QAM, 64QAM, 128QAM\} \quad (6)$$

where 4QAM, …, 128QAM are designations of possible modulation schemes. The value of MS is determined as a logical output obtained by applying the set of specified rules R2.

$$MS = R2(\gamma, \Delta\gamma) \quad (7)$$

where R2 is the base of rules for selecting the value of MS; γ is the signal-to-noise ratio; Δγ is the change in signal-to-noise ratio Δγ "M" - small change, "C" - moderate change, "B" - large change, and the symbols "+" and "-" indicate positive or negative changes in SNR). The fuzzy inference rule base will consist of rules of the following types, Fig 4:

1. If *γ* is very high (VH) and *Δγ* is small (±*M*), then *MS* is 128QAM;
2. If *γ* is high (H) and *Δγ* is small (±*M*), then *MS* is 64QAM;
3. If *γ* is high (H) and *Δγ* is large positive (+*B*), then MS is 128QAM;
4. If *γ* is very high (VH) and *Δγ* is large negative (-*B*), then *MS* is 16QAM;
5. If *γ* is moderate (M) and *Δγ* is large positive (+*B*), then *MS* is 64QAM;
6. If *γ* is moderate (M) and *Δγ* is small (±*M*), then MS is 16QAM;
7. If *γ* is moderate (M) and *Δγ* is large negative (-*B*), then *MS* is 4QAM;
8. If *γ* is low (L) and Δγ is large positive (+*B*), then *MS* is 16QAM;
9. If *γ* is low (L) and *Δγ* is small (±*M*), then *MS* is 4QAM;
10. If *γ* is low (L) and *Δγ* is large negative (-*B*), then reject transmission.
11. If *γ* is very low (VL) and *Δγ* is small (±*M*), then reject transmission.

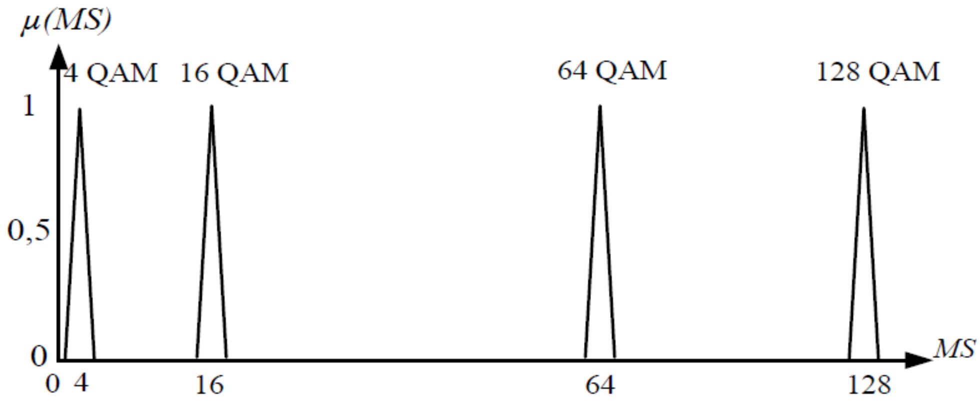


Figure 4. Modulation speed membership function

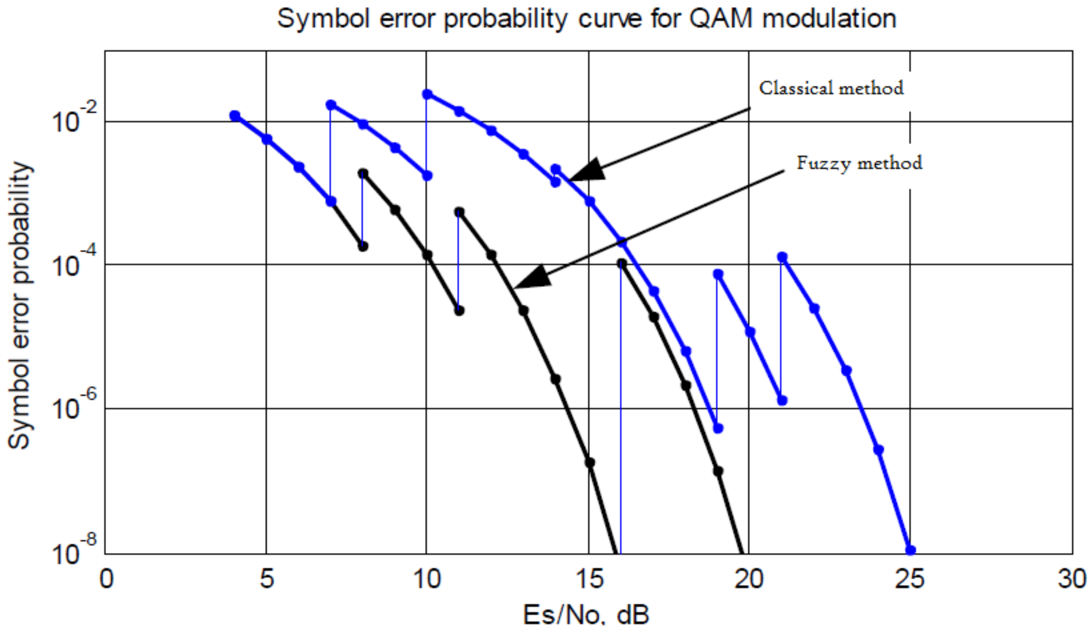


Fig. 5. Comparison of fuzzy and classical adaptive modulation

The fuzzy output itself can be formulated not only as "change the modulation" but also as "significantly reduce the transmitter power." In the second case, the defuzzification process, together with the knowledge base, determines what "significantly reduce" means in relation to the current power level and sends a command to the corresponding element of the power setting system to adjust the power to the specified level.

Figure 5 illustrates the effectiveness of the fuzzy speed control method in OFDM modulation compared to the classical method.

3.2 Multiple accesses to the data transmission environment

The problem of managing multiple accesses to the data transmission environment is considered in this study. From the perspective of channel access, the main problem is the possibility of conflicts arising from access to a shared resource. The mechanism of conflict occurrence involves the random simultaneous transmission of multiple packets over the shared channel, leading to packet overlap and distortion of the transmitted information. In this stage, an analysis of existing methods of multiple accesses in computer-based communication systems (CBCS) networks is conducted. Based on the analysis, it can be said that there is no perfect method for organizing access to the shared data transmission channel as of today. Therefore, one of the important issues in the field of quality of service provision in CBCS networks is the management of multiple accesses.

For further improvement of service quality and data transmission efficiency in Computer-Based Communication Systems (CBCS) networks, a method of fuzzy access control has been developed. This method enables more effective utilization of the channel bandwidth for various types of traffic and aims to limit the number of conflicts to prevent the possibility of overflow and blocking of low-priority streams. In developing the multiple access control method, a series of assumptions about the functioning of the communication channel and its access method are considered:

Assumption 1. The transmission time over the channel is divided into time slots. All time slots have the same duration, equal to the time it takes to transmit one packet.
Assumption 2. In each time slot, one of three events can occur:

$\theta_t = E$, If window w is empty, there is no transmission in the window.

S, If there is a successful transmission in window w, it is only the transmission of a single packet in the window.

C, If there is in window w collision, transmission more than one package in the window.

The sequence $\theta(t) = (\theta_1, \theta_2, \theta_t)$ represents the channel history at time t. It is assumed that by time t+1, all subscribers precisely know the channel's history.

Assumption 3. Each subscriber has a buffer for storing one packet. Each subscriber remembers the moment 'h' when their last new packet appeared and keeps the packet in memory until it is successfully transmitted. For the packet received by this subscriber at time 'h', the subscriber also remembers the sequence:

$$\nu^{(x)}(t) = \{\nu_1^{(x)}, \ldots \nu_t^{(x)}\} \quad (8)$$

where,

$\nu^{(x)}$ = 0, if this packet was not transmitted at time I,
1, if this packet was being transmitted at time i.

Assumption 4. Each subscriber in the system monitors the channel's state and assesses parameters such as θ (channel state), d (queue delay), and the degree of channel congestion change. They transmit this information to the input of a fuzzy controller, which, in accordance with a predefined rule base, evaluates the channel rating and sets the probability of packet transmission (P) in the window (w_t).

The figure 6 depicts a scheme of fuzzy access control by the subscriber. The subscriber continuously monitors and measures the channel's state in different time intervals τ_1, τ_2, and τ_n, where τ represents the cycle duration ($\tau = 8\Delta t$; $\Delta t = [t, t + 1]$ - the time interval required for transmitting one packet) before transmitting their packets.

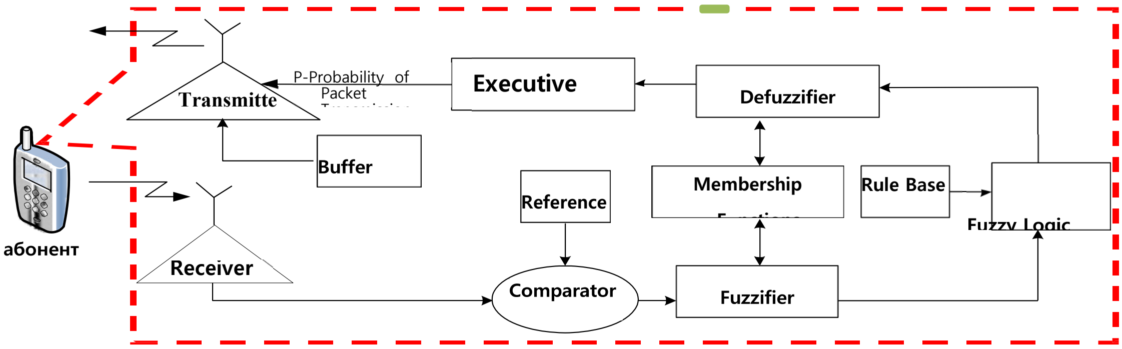


Fig. 6. Diagram of Fuzzy Subscriber Access Control

The results of measuring the channel's condition are sent to a comparator device, which determines the change in the channel's load (i.e., how the channel's condition at time τ_i has changed compared to the previous state at time τ_i-1). The comparator device also determines the channel's state value (the number of available slots at τ_i), the change in channel load, and the queue delay. These data are input to a fuzzy controller by the comparator device, which performs fuzzification on all values and then, according to a predefined rule base, executes a fuzzy inference operation. The result of the fuzzy inference is transmitted to a defuzzifier, which converts fuzzy values into crisp solutions. These crisp solutions are then input to the executive device. Based on the outcome of the fuzzy logic solution, the executive device sets the probability with which the incoming packet will be transmitted over the channel.

As input variables in our system:

The channel's state "X" is represented as a linguistic variable, and its base term set, denoted as T_X, is defined as the set of possible values:

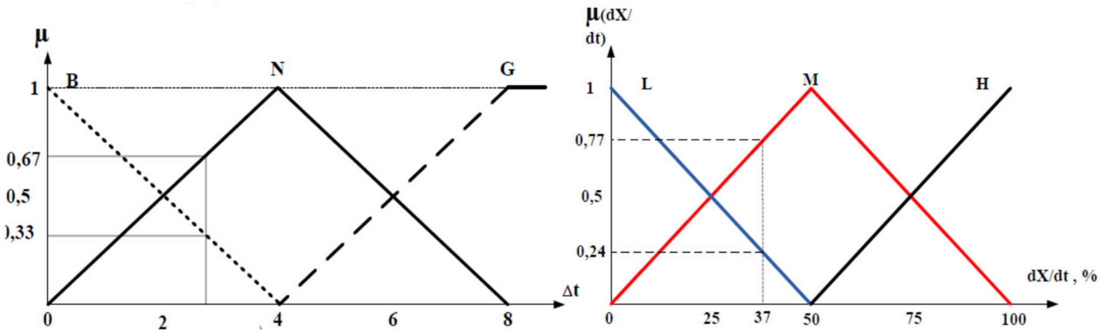
TX={"*B*","*N*","*G*"}, where:

- "*B*" represents a poor channel, indicating that the channel is loaded,
- "*N*" represents a channel in normal condition,
- "G" represents a good channel, indicating that the channel is not loaded.

The speed of change in the degree of channel load '*dX* / *dt*'. To transition to fuzzy variables of the speed of change in the degree of channel load, we will adopt the standard form of the membership function with terms:

$T_{dX/dt}$ = {"*L*", "*M*", "*H*"}, where "*L*" - low speed, "*M*" - medium speed, and "*H*" - high speed."

The queue delay 'd', which also has three terms: small (L), medium (M), and high (H).



a) b)

Fig. 7. Membership function: a - channel state; b - changes in the degree of channel load

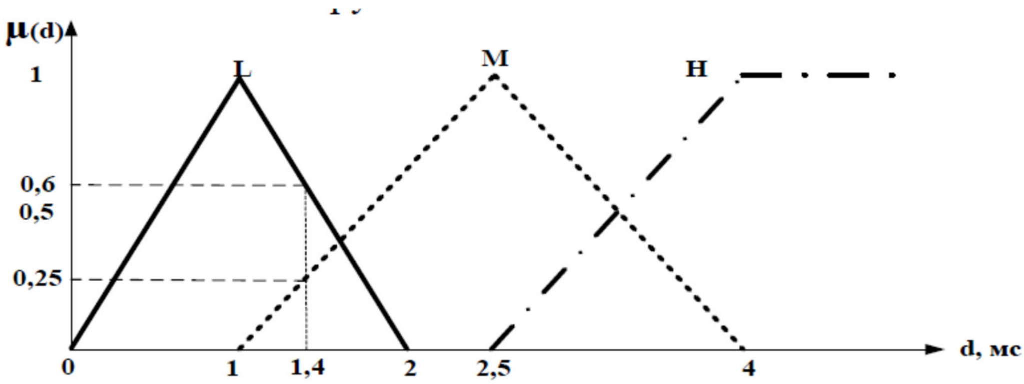


Fig. 7. Membership function of queue delay

The result of the fuzzy inference system will be determined by the fuzzy knowledge base, specifically by the production rules on which the fuzzy output is built. The output of each implication rule is the linguistic variable 'channel rating,' the set of values of which consists of five terms *T(R)*: very low (*VL*), low (*L*), medium (*M*), high (*H*), and very high (*VH*).

In the case under consideration, fuzzy rules are represented as:

- If the channel is in good condition (*G*), its load decreases compared to the previous state (*L*), and the queue delay is small (*L*), then the channel rating will be very high (*VH*). In terms of fuzzy variables, this rule can be expressed as follows:
  If X = G and dX/dt = L, and d = L, then R = VH.
- If the channel is in poor condition (*B*), its load increases compared to the previous state (*H*), and the queue delay is high (*H*), then the channel rating will be very low (*VL*). In terms of fuzzy variables, this rule can be expressed as follows:
  If X = B and dX/dt = H and *d = H, then R = VL.*

The overall rule base is presented in the following tables 1,2,3.

Table 1

Table 1

Queue delay (d) = low (L)			
Channel state (X)	Rate of change of channel state (dX/dt)		
	L	**M**	**H**
B	*L*	*L*	*L*
N	*H*	*H*	*H*
G	*VH*	*VH*	*H*

Table 2

Queue delay (d) = medium (M)			
Channel state (X)	Rate of change of channel state (dX/dt)		
	L	**M**	**H**
B	*L*	*L*	*VL*
N	*M*	*M*	*M*
G	*H*	*H*	*H*

Table 3

Queue delay (d) = high (H)			
Channel state (X)	Rate of change of channel state (dX/dt))		
	L	**M**	**H**
B	*VL*	*VL*	*VL*
N	*M*	*L*	*L*
G	*M*	*M*	*M*

The rule of fuzzy implication is defined by the Mamdani rule:

$$\mu_{B'}(R) = \max_{k=1...N}\{\min[\mu_{A_1^k}(X), \quad \mu_{A_2^k}(dX/dt), \quad \mu_{A_3^k}(d), \quad \mu_{B_1^k}(R)]\} \tag{9}$$

Where X , dX/dt , d, correspondingly, the input variables (channel state, rate of change in the degree of channel load, and queue delay).

A_1^K, A_2^K and A_3^K - their corresponding fuzzy sets, k=1, …, N – fuzzy inference rules, N – the number of fuzzy inference rules (N = 3*3*3 = 27, since each of the three linguistic variables can take three different values), R – the output variable (channel rating), B – its corresponding set.

In the example, let's assume that the number of available windows in τi during packet transmission was 3, the degree of channel load changed by 37% compared to the previous state, and the queue delay was 1.4 ms. In this case, as illustrated, the channel state has membership functions for the terms [B, N, G]. [$_B(X)$, $_N(X)$, $_G(X)$]=[0.33, 0.67, 0], correspondingly, the rate of change in the degree of channel load has membership functions [$_L(dX\ dt)$, $_N(dX\ dt)$, $_H(dX\ dt)$] equal to [0.24, 0.77, 0], and the queue delay has membership functions [$_L(d)$, $_N(d)$, $_H(d)$] = [0.6,0.25, 0].

To assess the channel rating with the given input data, a fuzzy system is modeled in the Matlab 7.4 environment, and the output shows that the channel rating is 55.8%.

3.3 Routing algorithm of fuzzy input

It is devoted to the development of a routing algorithm in the presence of fuzzy input data regarding the state of radio links in a cognitive wireless self-organizing network. So, a classification of routing protocols was conducted, and the operation of protocols used in cognitive radio networks (CBCS) was analyzed, along with the peculiarities of the functioning of CBCS themselves. The analysis results reveal that there is no unified routing method that satisfies QoS requirements and ensures optimization of all performance indicators in the network when dealing with fuzzy input data regarding the state of radio links.

For routing with quality of service prediction in cognitive radio networks (CBCS), the use of a routing method based on fuzzy logic is proposed. The utilization of fuzzy logic in this method allows for considering multiple parameters of node and communication channel states when selecting the optimal data transmission route in terms of service quality indicators. Importantly, this approach does not necessitate the construction of a precise mathematical model.

To explore potential data transmission routes, the reactive routing protocol FAODV (Fuzzy Ad-hoc On-demand Distance Vector) is considered. A reactive routing protocol was chosen due to its better scalability in large self-organizing networks. FAODV constructs routes using a "request-reply" cycle. Reactive methods do not require periodic updating of routing tables, preserving the bandwidth of the wireless environment and saving the energy reserves of mobile terminal batteries. Such protocols do not involve any unnecessary overhead when changes occur in the topology of the mobile network, especially when node movement is insignificant.

- At the first stage, a procedure is initiated to discover potential routes to the destination node, during which routing control packets also transmit parameters of the states of nodes and communication channels. After completing this procedure (based on a timer), the collected data are input to the fuzzy logic controller.
- In the second stage, a rating is calculated for each of the discovered routes. The state parameter values of each route are input to the fuzzy logic controller, which performs fuzzification of all values and then, in accordance with the established rule base, executes the fuzzy inference operation. The output of the controller provides a crisp (numerical) rating for each route. The route with the highest rating is considered optimal.
- On the third stage, after selecting the optimal route from the set of remaining discovered routes, two more routes with the highest ratings are chosen, and they become backup routes.
- After selecting the optimal route, the node records this route in the routing table for a specific period (caches the route). If a new connection request arrives and the destination address is present in the table, a new Route Request is not generated, and the data is sent via the previously stored route. Additionally, to ensure fault tolerance in case of node failures on the chosen route, two backup routes are selected in addition to the optimal route. They are chosen using the following algorithm:

  - The results of the route evaluation pass through a decision-making block where their ratings are computed. All routes are then recorded in a temporary table with their respective ratings.
  - Then, a pass is made through all the rows of the table, and routes are identified where the set of intermediate nodes does not intersect with the set of intermediate nodes of the selected optimal route. Thus, we find the set of non-overlapping routes. This is important because it reduces the probability that a node failure on the optimal route will affect the operation of the two backup routes.
  - From the set of marked routes, two routes with the highest ratings are selected, and they become the backup routes.
  - If the set of marked routes is empty, the procedure of selecting backup routes is repeated, but this time, routes that intersect with the one chosen at a node are marked.

During the information exchange process, a dynamic assessment of the working route is carried out. In the event of a decrease in its characteristics below a threshold value (determined by the application) due to increased node mobility, adverse weather conditions, or if a node or a portion of nodes leaves the route, the characteristics of the two remaining (backup) routes are refined, and the better one is selected. If among the remaining (backup) routes there is no suitable option in terms of quality, a repeated (three-stage) connection restoration process is initiated.

The following parameters of node and channel states were selected for the developed routing method: throughput, transmission delays, jitter of delays, load (size of the free queue), and the number of "hops" (node count). The network is represented as an undirected graph $G=(V,E)$, where V is the set of nodes, and E is the set of channels. Let's denote a cyclic route in G as r, which is a sequence of nodes. Define the state parameters for nodes and communication channels for each r-route.

The throughput of the entire route is considered to be the minimum throughput among all channels on the route r:

$$B(p) = \min_{i \in p}\{(B(v_i, v_{i+1})\}, \quad (10)$$

The packet transmission delay for all intermediate communication channels is summed up:

$$d(p) = \sum_{i=1}^{n-1} d(v_i, v_{i+1}), \quad (11)$$

The jitter of the entire route is considered as the maximum jitter among all channels on the route:

$$\Delta d(p) = \max_{i \in p}\{(\Delta d(v_i, v_{i+1})\}, \quad (12)$$

The load of the node's packet buffer is the relative load of packet buffers of nodes on the route is calculated as:

$$l = \sum_{i=1}^{n} l_i * \lambda_i . \quad (13)$$

Where l_i is the load of the buffer of the i-th node; $_i$-weighting coefficient of the load of the i-th node, i is the load coefficient of the i-th node; n is the number of nodes in the route.

The number of intermediate nodes. This parameter is additive, and its value is easy to compute, as the routing response contains a list of all intermediate nodes on the way to the destination node.

4. Results and discussions

As a result, after receiving the routing request response from the source node, the values of the listed parameters are extracted from the packet and fed into the input of the fuzzy logic controller. Each input parameter of the fuzzy controller is associated with a linguistic variable that has five terms: 'very low,' 'low,' 'medium,' 'high,' 'very high. The membership functions of linguistic variables (LV) are shown in Fig. 9 (conventional notations for LV: VL – 'very low,' L – 'low,' M – 'medium,' H – 'high,' VH – 'very high,' VM – 'very small,' VH – 'very large,' and so on)

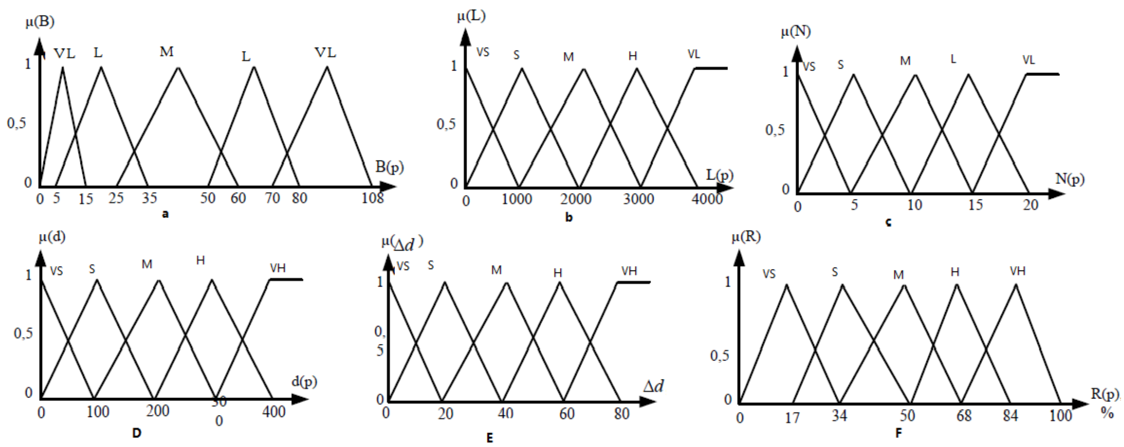
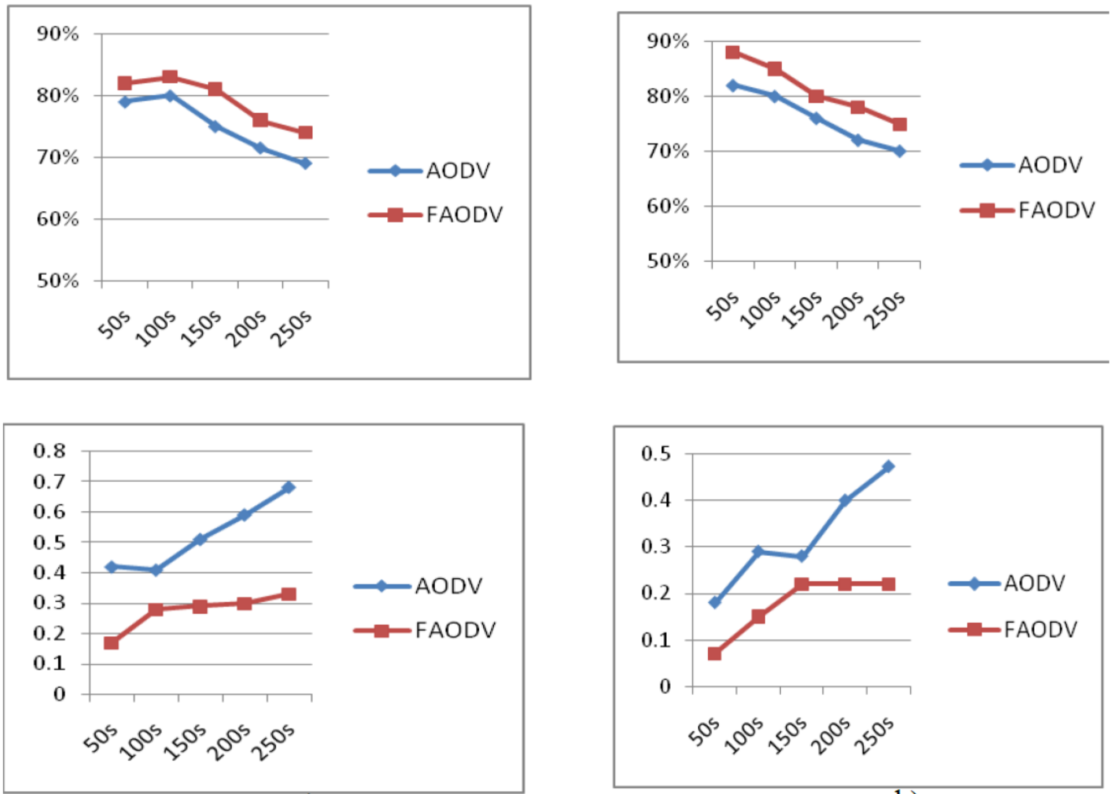


Fig. 9. Membership functions of linguistic variables: a – throughput; b – packet buffer load; c – number of hops; d – packet delay; e – jitter; f – route rating

Manuscript received December 5, 2023
Manuscript revised December 20, 2023
https://doi.org/10.22937/IJCSNS.2023.23.12.2

For comparison of the efficiency of the proposed routing method with existing methods based on two qualities of service criteria - the packet delivery ratio and the average packet transmission delay - the AODV routing protocol was chosen. This is because it is commonly used in practice, and there is a detailed description of its algorithm

The results of the modeling in Fig. 10 show that with a network node count of 10, the packet delivery rate increases to 5.07%, and the average packet delay on the route decreases by 49.517%. With 20 nodes, the packet delivery rate increases to 4.96%, and the packet delay on the route decreases by 45.32%.



a) b)

Fig. 10. Comparisons of the efficiency of the proposed routing algorithm with the classical AODV: a) number of nodes in the network 10; b) number of nodes 20.

Conclusion

The paper developed and investigated models and methods for applying fuzzy logic in cognitive wireless data transmission systems. The main findings can be summarized as follows:

1. Wireless data transmission networks are evolving towards the construction of prospective cognitive data transmission networks, where there is a broad utilization of artificial intelligence elements at all levels of the architecture.
2. Applying artificial intelligence based on fuzzy logic at the physical level enhances the quality of adaptive control of OFDM modulation.
3. The use of a fuzzy controller at the data link layer (MAC sub-layer) efficiently utilizes bandwidth and maintains high-quality service.
4. Applying fuzzy computations at the network level enhances the overall stability of the network operation.
5. The application of fuzzy logic is one of the promising technologies for building cognitive wireless networks.

Manuscript received December 5, 2023
Manuscript revised December 20, 2023
https://doi.org/10.22937/IJCSNS.2023.23.12.2

These results underscore the potential and effectiveness of employing fuzzy logic in improving the performance and manageability of cognitive wireless data transmission systems.

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