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APPLICATION OF ARTIFICIAL INTELLIGENCE METHOD IN ADAPTIVE ANTENNA SYSTEM

Introduction

The rapid development of modern telecommunications is leading to the evolution of communication technology generations from 5G [1] to 6G [2 – 4]. One of the main components of 5G and 6G telecommunication networks are radio networks [1 – 4], and obviously the quality of their functioning directly depends on the antenna technologies and antenna systems used. When designing antenna systems for 5G and 6G networks, the main issue is the full implementation of so-called "smart antennas" [5, 6] that can meet the requirements of modern radio networks. The physical implementation of a smart antenna is based on modern interpretations of phased antenna arrays [5, 6], e.g. UM-MIMO antennas are expected to be used in 6G radio networks [7, 8]. The analysis of papers [1 – 8] allows to determine the main requirements for antenna systems in the scope of application of 6G networks, namely, antennas should provide, first, maximum energy efficiency and broadband [5, 6], second, the ability to form a multi-beam radiation pattern [5, 6, 8], then, the possibility of controlling individual beams of the radiation pattern in real time [1, 5, 6, 9], and the possibility of selecting a separate beam of the radiation pattern a specific mobile user equipment (UE) (UE group) [1, 6, 8, 9].

Thus, according to the above mentioned study of modern antenna systems, one of the important challenges is the analysis of the possibility of real-time control (with minimal time delays) of a separate beam of the radiation pattern for a specific mobile UE (UE group).

Methods of controlling the radiation pattern of an antenna array by changing the amplitude-phase characteristics at the feed points of the antenna array elements are well described in the literature [5, 6, 9, 10]. However, it is not described how the antenna adaptive processor [6, 10] that controls the antenna system should understand and learn, taking into account the UE movement patterns within the cell, and predict the direction of the specific UE movement to ensure proper radiation pattern control.

Therefore, the purpose of this paper is to propose a method that provides the antenna system with an understanding and prediction of the UE movement patterns within the cell and, based on the received knowledge, potentially allows the antenna radiation pattern to be controlled in real time (with minimal time delays).

Integration of an artificial intelligence unit into the block diagram of an adaptive antenna system

To achieve the goal described in this article, it is necessary to solve the problem of training the antenna system (array) to understand and predict the direction of movement of a given subscriber within the cell, i.e. to make the array truly "smart". This task can be achieved by integrating artificial intelligence algorithms and systems into the process of controlling the antenna array pattern.

Analyzing the literature [5, 6, 10, 11] allows us to draw the following block diagram of a modern adaptive antenna system. The block diagram shown in Fig. 1 consists of an antenna array containing four antenna elements, each antenna element is connected to a phase shifter that provides a change in the phase characteristics of the signal emitted by a particular antenna element of the array.

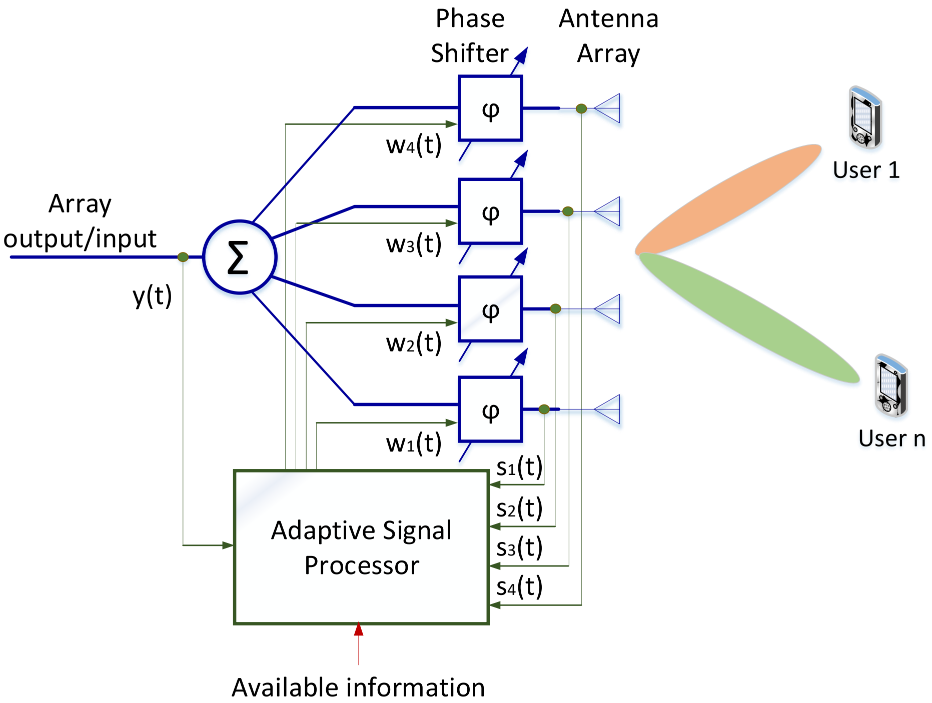

Fig. 1. Block diagram of an adaptive antenna system [5, 6, 10, 11]

The change in phase characteristics occurs in accordance with the adjustable complex weights formed by the adaptive signal processor – a vector of complex weights [10]

$$w(t) = [w_1(t), w_2(t), w_3(t), w_4(t)]^T \tag{1}$$

where T means transpose [10]. The adaptive signal processor is a structural unit that controls the antenna array pattern by means of control signals (1) that it generates on the basis of some collected information, namely

- the complex signal vector (voltage matrix) formed on the antenna elements of the antenna array [10]

$$s(t) = [s_1(t), s_2(t), s_3(t), s_4(t)]^T ; \tag{2}$$

- the feedback signal [10]

$$y(t) = s^T(t)w(t); \tag{3}$$

- "available information" [11] – other information that is necessary for the formation of the signal (1), for example, in mobile communication systems, this may be information about the coordinates of subscriber terminals in the operator's network, etc.

At the next stage, we integrate the artificial intelligence unit (AIU) [12] into the structure shown in Fig. 1.

In Fig. 2, the AIU is added to the block diagram of the adaptive antenna system [5, 6, 10, 11], which interacts with the communication system core through an interface and receives available information, and also has interfaces through which it interacts with the adaptive signal processor.

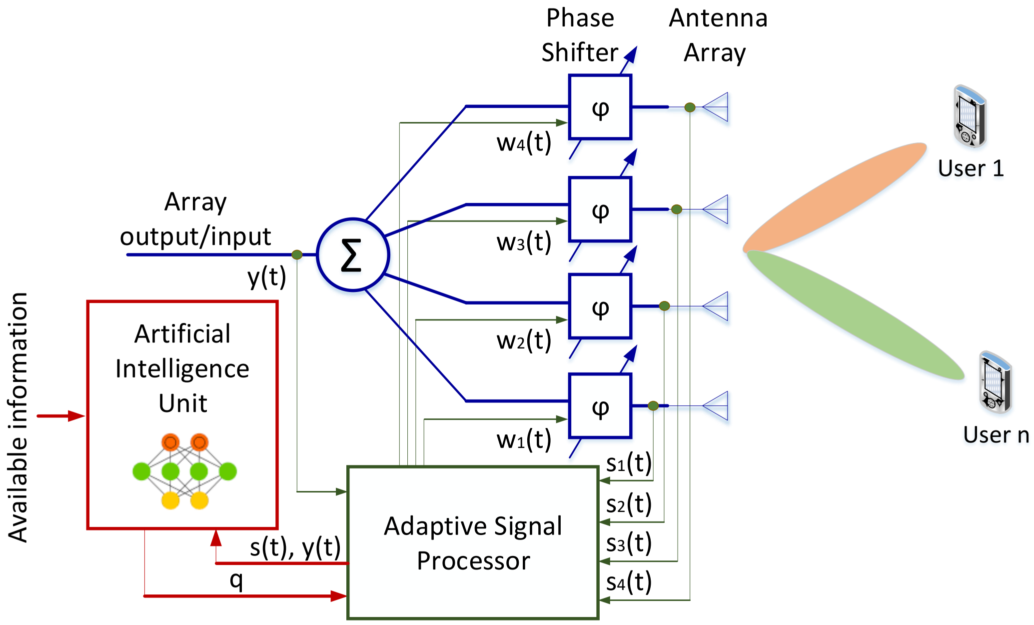

Fig. 2. Block diagram of an adaptive antenna system with AIU

The AIU receives data from the communication system core and data from the Adaptive Signal Processor, for example, (2) and (3), and processes them using one of the machine learning algorithms. As a result of the machine learning algorithm, the AIU forms a certain knowledge system about the environment in which the antenna array operates. The adaptive signal processor, in turn, uses the knowledge system formed in the AIU (receives the coefficients q) to more accurately control the antenna array pattern. In this case, we can write expression (1) in the following form

$$w(t)' = q[w_1(t), w_2(t), w_3(t), w_4(t)]^T . \tag{4}$$

In expression (4) $w(t)'$ denotes the vector of complex weights (control signal for the adaptive antenna array) that takes into account the coefficient q generated by the AIU based on the machine learning algorithm.

It should be noted that the value q can be represented in different forms, depending on the knowledge system (data structure) formed by the AIU, q can express some coefficients, or it can be represented by some signal constructions, etc.

At the next stage of this paper, we will consider one of the artificial intelligence methods that can be applied in AIU.

Artificial intelligence method for adaptive antenna system

To form a knowledge system for an adaptive antenna system that can understand, learn, and also predict the UE movement patterns within the cell is proposed to use one of the methods of artificial intelligence, an intelligent agent [13 – 18].

In AI, an intelligent agent is an entity that observes and acts on an environment [13, 17]. When machine learning algorithms are applied to intelligent agents, their behavior becomes rational and their actions are always aimed at achieving a goal. In this context, intelligent agents act with the rudiments of thinking like human thinking or intellectually developed beings [13 – 18]. As a result of learning, intelligent agents can generate an answer when there is no ready solution, perform a cognitive selection of objective conditions essential for action, perform a generalized, indirect reflection of reality, search for and discover significantly new things, identify and achieve intermediate goals [13 – 15].

The machine learning process can be implemented using the reinforcement learning of intelligent agents [13 – 18]. Consider the process of reinforcement learning based on Q-learning technique. In this technique, an intelligent agent must learn the environment in which it acts and find the best possible actions to reach the end point from the initial one. After reaching the goal, the agent receives a certain reward in the form of accumulated points [13 – 18]. The final goal of the agent is to receive maximum rewards and learn optimal policy for the given Markov decision process, which means to develop a behavioral model of optimal action in the specified environment. The basis of Q-learning is the so-called quality function (Q-function), which can be defined using [14 – 18]

$$Q(s,a) = (1-\alpha)Q(s,a) + \alpha\left[R(s,a) + \lambda \frac{\max}{a' \in A} Q(s',a')\right]. \tag{5}$$

In equation (1),
s is the current state of an agent from a set of states $S(s_1, s_2, \dots s_n)$,
a is the current action of an agent in state s from a set of actions $A(a_1, a_2, \dots a_n)$,
α is a learning rate that can be set between 0 and 1,
s' is a next state from a set of states $S(s_1, s_2, \dots s_n)$,
a' is a possible action of an agent from $A(a_1, a_2, \dots a_n)$ in the state s',
λ is a discount factor that can also be set between 0 and 1 (recommended 0,8 [14, 18]),
$R(s,a)$ is reward for transition between states,
$\frac{\max}{a' \in A} Q(s',a')$ is a next action with maximum reward.
If α =1 [14, 18], equation (1) can be rewritten as

$$Q(s,a) = R(s,a) + \lambda \frac{\max}{a' \in A} Q(s',a') . \tag{6}$$

The process of learning an intelligent agent operating in an environment that is a mobile communication cell can be illustrated by the diagram in Fig. 3 [16].

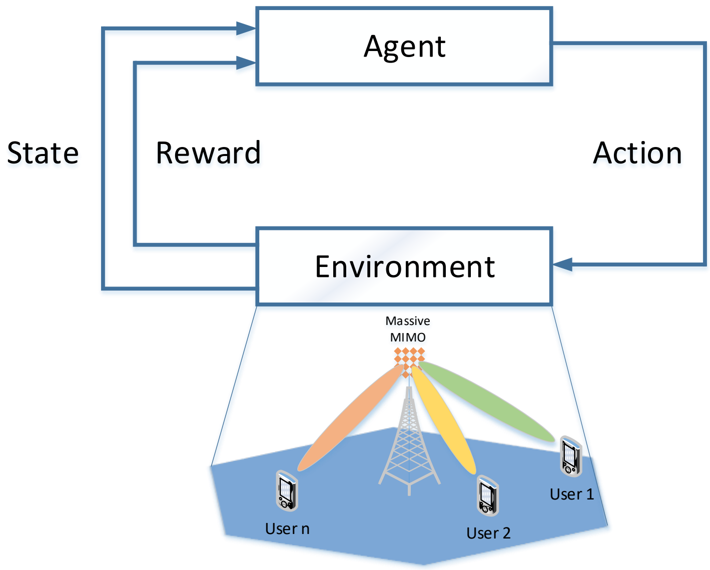

Fig. 3. Diagram of Q-learning

At the next stage of this paper, we will consider in detail an environment that is a cell of a mobile communication system in which an intelligent agent operates.

Mobile communication cell as intelligent agent application environment

Consider a cell of the mobile communication system operating in the conditions of urban development as an application environment of the intelligent agent. In the center of the cell, the access point/base transceiver station (BTS) equipment is located with the adaptive antenna system, which forms a multibeam radiation pattern capable of changing the radiation direction angle of a single beam of the radiation pattern in the horizontal and vertical planes. Thus, the intelligent agent will operate in a non-homogeneous, limited circular BTS coverage area, an urban development environment with a fixed grid of streets and placement of buildings. Within the BTS coverage area, subscribers (UEs) move continuously along the street grid. The challenge for an intelligent agent is to learn the movement patterns of subscribers on the street grid and perform Q-learning to develop a behavioral model that allows the adaptive antenna system to optimally control the directional radiation characteristics of each beam of the radiation pattern. The final model of the agent's behavior as a result of Q-learning will enable the antenna system to control the radiation pattern in real time, resulting in the optimal distribution of the BTS energy resource to the subscribers within the coverage area.

There are several patterns of movement of subscribers that can be identified during a certain time interval, for example, a day, in any cell of a cellular network. Such patterns depend on the social nature of life in the area where the cell is implemented. In this paper we consider one of the possible patterns, namely the movement of students (potential subscribers of a cellular network) between a university and a student campus.

Fig. 4 shows a cell of a mobile communication system as a geometry of a specific environment.

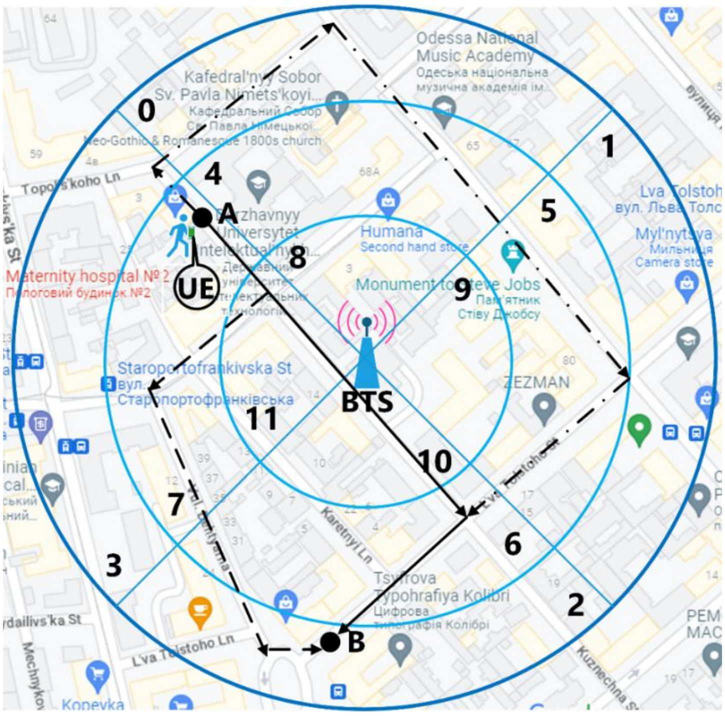

Fig. 4. Cell of a mobile communication system

Fig. 4 shows the map of the urban area where the BTS equipment is located. The coverage area of the specified access point is bounded by the circle with the largest radius of 0,22 km. Within the specified circle, the coverage area is divided into 12 conventional sectors numbered from 0 to 11. Sector 7 at point A shows a subscriber with UE. There is also a university near point A where many students (potential subscribers) study. Point B is on a student campus. The subscriber aims to move along the grid of city streets from point A (sector 7) to point B (sector 2).

Thus, within the considered cell, we can postulate the subscriber movement pattern between the university and the student campus at a certain time of day. It is this pattern that the intelligent agent must understand, learn and develop a behavioral model that allows the adaptive antenna system to operate optimally in this environment.

So, Figure 4 shows three possible routes of the subscriber's movement. The first route is marked with a solid line and runs from sector 7 through sectors 11, 10, and 6 to sector 2. The second route is marked with a dashed line, and it passes through sectors 7, 11, 7, 6, 2, and the third route is marked with a dash-dotted line - sectors 7, 3, 0, 4, 5, 6, 2.

Q-learning of intelligent agent

Now, we formally demonstrate the application of Q-learning of an intelligent agent during the movement of a subscriber from point A to point B in Fig. 1 (in our case, the subscriber is an intelligent agent).

Numbered sectors and a grid of streets connecting them make it possible to describe the states in which the agent (subscriber) can be located, for example, state 0 – stay in sector 0, state 1 – stay in sector 1, and so on. The movement of the agent (subscriber) during the transition from one state to another (from one sector to another along the corresponding streets) is shown in the form of a graph in Fig. 5. The structure of the graph reflects the grid of streets (Fig. 4) and determines the possibility of the agent moving from one sector to another.

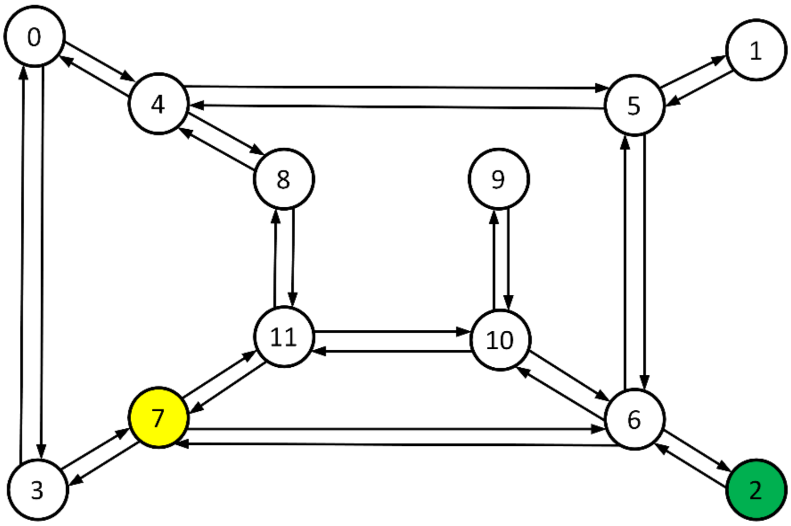

Fig. 5. Graph of possible agent states and actions

According to the graph in Fig. 5 we create a table of rewards – matrix R [13, 14, 18]. In this matrix, according to the Q-learning algorithm [13, 14, 18] the value -1 means the absence of a connection between the vertices of the graph and, accordingly, the impossibility of a direct transition of the agent (subscriber) between these vertices (sectors in Fig. 4), the value 0 means the ability of the agent to move directly between the vertices of the graph (there is the street connecting two sectors, Fig. 4), and the value 100 means an instant reward for the transition of the agent to the target vertex of the graph (subscriber has reached the target point B in sector 2, Fig.4).

Table 1

–	Action												
State	–	0	1	2	3	4	5	6	7	8	9	10	11
	0	-1	-1	-1	0	0	-1	-1	-1	-1	-1	-1	-1
	1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1
	2	-1	-1	100	-1	-1	-1	0	-1	-1	-1	-1	-1
	3	0	-1	-1	-1	-1	-1	-1	0	-1	-1	-1	-1
	4	0	-1	-1	-1	-1	0	-1	-1	0	-1	-1	-1
	5	-1	0	-1	-1	0	-1	0	-1	-1	-1	-1	-1
	6	-1	-1	100	-1	-1	0	-1	0	-1	-1	0	-1
	7	-1	-1	-1	0	-1	-1	0	-1	-1	-1	-1	0
	8	-1	-1	-1	-1	0	-1	-1	-1	-1	-1	-1	0
	9	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	0	-1
	10	-1	-1	-1	-1	-1	-1	0	-1	-1	0	-1	0
	11	-1	-1	-1	-1	-1	-1	-1	0	0	-1	0	-1

In the next stage, according to the Q-learning algorithm [13, 14, 18], we create a matrix Q – the so-called "memory" matrix of an intelligent agent. At the initial stage, the matrix Q is initialized with zero that is the memory of the intelligent agent does not contain any information. Further, as a result of training the matrix Q is gradually filled out, thus forming certain knowledge of an intelligent agent [13, 14, 18].

Consider the first step of filling out the Q matrix using expression (2), as well as the initial data of Fig. 4, Fig. 5, and matrix *R* – calculate the element Q(6,2):

$$Q(6,2) = R(6,2) + 0{,}8\max(Q(2,6)) = 100 + 0{,}8\max(0) = 100.$$

As a result, the element Q(6,2) of the matrix Q gets the value 100. Now we can perform the second step – calculate the element Q(10,6):

$$Q(10,6) = R(10,6) + 0{,}8\max(Q(6,2), Q(6,5), Q(6,7), Q(6,10)) = 0 + 0{,}8\max(100,0,0,0) = 80.$$

Based on the calculated elements Q(6,2) and Q(10,6), we perform the corresponding calculations of the remaining elements of matrix Q in the same way, and present the results in Table 2.

Table 2

–	Action												
State	–	0	1	2	3	4	5	6	7	8	9	10	11
	0	0	0	0	26	41	0	0	0	0	0	0	0
	1	0	0	0	0	0	64	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0	0	0
	3	33	0	0	0	0	0	0	64	0	0	0	0
	4	33	0	0	0	0	64	0	0	33	0	0	0
	5	0	41	0	0	41	0	80	0	0	0	0	0
	6	0	0	100	0	0	64	0	64	0	0	64	0
	7	0	0	0	26	0	0	80	0	0	0	0	41
	8	0	0	0	0	41	0	0	0	0	0	0	41
	9	0	0	0	0	0	0	0	0	0	0	64	0
	10	0	0	0	0	0	0	80	0	0	41	0	41
	11	0	0	0	0	0	0	0	0	33	0	64	0

The results of the calculations given in the matrix Q are displayed on the graph (Fig. 6) as weighting coefficients for the transitions between the vertices of the graph.

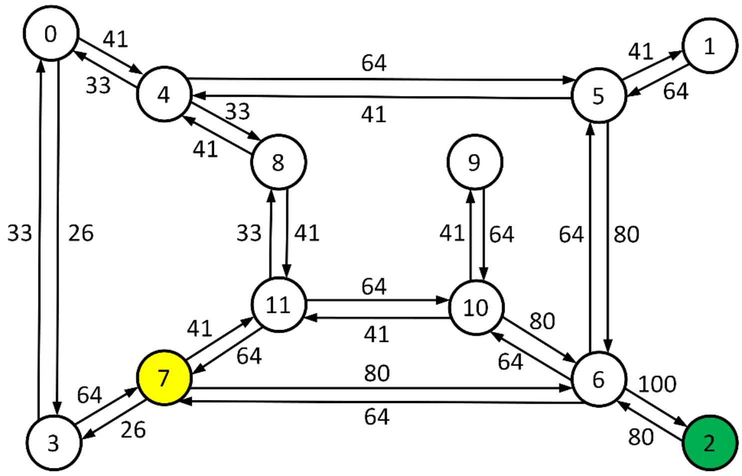

Fig. 6. Graph of possible states and actions of an agent when overcoming the path from vertex 7 to vertex 2

Weighting coefficients for transitions (Fig. 6) shows the probability of transition of an agent from one state to another, where the initial state of the agent is 7 and the target state is 2.

Thus, the results obtained in Table 2 and Figure 6 for an agent (subscriber of a cellular network) reflect the movement pattern of the subscriber within a cellular network between the university and the student campus. The obtained results can be used by the antenna controller for beam control of the adaptive antenna system radiation pattern assigned to a subscriber in real time or with minimum latency. Note that the obtained weighting coefficients are relevant both for a single subscriber and for each subscriber of the group on the considered routes, since each subscriber has an individual beam.

Accordingly, using the AI method, the intelligent agent telecommunication system can study the subscriber movement pattern within a cell and, based on the obtained pattern, forms a knowledge system as a Q-matrix. Then the antenna controller of an antenna system of a cell uses the received knowledge matrix Q to effectively control the beams of the radiation pattern, since matrix Q allows to predict the direction of the subscriber movement within the cell.

It should also be noted that in order to reduce the number of calculations when forming the Q-matrix, a relatively small number of sectors (states) in the cell is considered in order to demonstrate the possibility of using the Intelligence Agent method to form a knowledge system on the basis of which the antenna system radiation pattern can be controlled. Increasing the number of sectors in a cell leads to a more detailed analysis of the pattern of subscriber movement in the cell and, as a result, increases the accuracy of the antenna system pattern control. Improving the accuracy of antenna pattern management leads to improved energy efficiency. The idea is that the energy radiated by the antenna system is not arbitrarily distributed in space (and thus suffers additional space losses) within the base station service sector, but is focused in a certain narrow sector of space (a radiation pattern petal) for a particular subscriber [5, 6, 10, 11].

Conclusions

Therefore, in this paper the requirements for adaptive antenna systems in current and future fifth (5G) and sixth (6G) generation wireless networks were analyzed. The block diagram of a modern adaptive antenna system was considered, and in order to improve this block diagram the integration of an artificial intelligence unit into it was proposed. One example of the operation of an artificial intelligence unit as part of an adaptive antenna system was proposed using the intelligent agent method of artificial intelligence. It is shown that using the intelligent agent method it is possible to create a knowledge system capable of understanding and learning, taking into account the patterns of movement of subscribers in the cell, and predicting the direction of movement of a particular user equipment (group of user equipment). The resulting knowledge system is formed in an artificial intelligence unit and can potentially be used by the adaptive signal processor to more accurately control the radiation pattern of the antenna system, which allows to realize the functions of a smart antenna and control the dedicated beam of the antenna system's radiation pattern in real time or with minimal time delay. Thus, the objective of this paper was achieved.

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