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APPLICATION OF THE DEEP Q-NETWORK MACHINE LEARNING METHOD IN AN ADAPTIVE ANTENNA SYSTEM WITH AN ARTIFICIAL INTELLIGENCE UNIT

The Deep Q-Network (DQN) machine learning method is analyzed. The possibility of applying the DQN machine learning method in an artificial intelligence module as part of an adaptive antenna system is shown in order to form a system of knowledge about the environment in which the adaptive antenna system operates. The algorithm for training a DQN agent is proposed and the proposed algorithm is implemented in the Python program code. As a result of the software implementation of the DQN algorithm, a knowledge system was obtained, which in the future will allow to realize the intelligent control of the radiation pattern petals of the adaptive antenna system.
Keywords: adaptive antenna system; artificial intelligence; machine learning; intelligent agent; artificial intelligence unit.

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ЗАСТОСУВАННЯ МЕТОДУ ГЛИБОКОГО МАШИННОГО НАВЧАННЯ Q-МЕРЕЖА В АДАПТИВНІЙ АНТЕННІЙ СИСТЕМІ З БЛОКОМ ШТУЧНОГО ІНТЕЛЕКТУ

У статті розглянуто можливості застосування методів глибокого машинного навчання для підвищення ефективності роботи адаптивних антенних систем сучасних безпроводових мереж. Основну увагу приділено методу глибокого підкріплювального навчання Deep Q-Network (DQN), який поєднує класичний алгоритм Q-learning із можливостями глибоких нейронних мереж. Проведено аналіз принципів функціонування методу DQN та його ключових компонентів, зокрема буфера відтворення досвіду (Replay Buffer), цільової нейронної мережі (Target Network), стратегії дослідження ε-greedy та механізму мінімізації функції втрат. Показано, що використання нейронної мережі для апроксимації функції цінності дій дозволяє інтелектуальному агенту приймати оптимальні рішення навіть у складних середовищах із великою кількістю можливих станів і дій.

У роботі запропоновано підхід до інтеграції методу DQN у модуль штучного інтелекту адаптивної антенної системи. Такий модуль може формувати систему знань про середовище функціонування радіомережі та забезпечувати інтелектуальне керування параметрами діаграми спрямованості антени. Розглянуто модель середовища у вигляді комірки безпроводової мережі, де точка доступу оснащена адаптивною антенною системою з блоком штучного інтелекту. У такій системі формування та динамічна зміна пелюсток діаграми спрямованості здійснюється з урахуванням переміщення абонентів у зоні радіопокриття. У рамках дослідження агент навчався знаходити оптимальні переходи між станами середовища, що моделює переміщення абонентів, з метою формування ефективної стратегії керування напрямками випромінювання.

Запропоновано алгоритм навчання агента на основі методу Deep Q-Network та реалізовано його у вигляді програмного коду мовою Python. За результатами програмної реалізації отримано зважений граф переходів між станами середовища, який інтерпретується як сформована система знань інтелектуального агента. Аналіз отриманих результатів показав, що метод DQN дозволяє визначати оптимальні та альтернативні маршрути переходів між станами з різними ймовірностями, що відкриває можливість прогнозування поведінки абонентів і більш точного керування напрямними характеристиками антенної системи.

Отримані результати свідчать про перспективність використання методів глибокого підкріплювального навчання у складі адаптивних антенних систем майбутніх безпроводових мереж, зокрема систем стандартів 5G та 6G. Запропонований підхід може бути використаний для реалізації концепції інтелектуальних антен, що здатні адаптуватися до змін середовища в режимі реального часу, оптимізувати використання радіочастотного спектра та підвищувати ефективність функціонування сучасних систем безпроводового зв'язку.

Ключові слова: адаптивна антенна система з модулем штучного інтелекту, діаграма спрямованості антени, штучний інтелект, машинне навчання, система безпроводового зв'язку.

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INTRODUCTION

Innovative approaches based on artificial intelligence/machine learning methods allow solving a number of urgent problems in the field of radio communications, including increasing the data transmission rate and ensuring the reliability of communication under conditions of high network load, optimizing the use of the frequency spectrum, reducing energy consumption, implementing the smart antenna concept [1, 2], etc.

The use of machine learning (ML), deep learning, and big data processing algorithms creates new opportunities for the further development of radio communication systems, in particular, antenna technology [3]. Modern radio communication systems put forward a number of requirements for the improvement of antenna technology, namely the need to ensure maximum energy efficiency and broadband [4], the ability to form a multi-lobe radiation pattern [3, 4], the ability to intelligently control individual radiation patterns in real time [1 – 3], the ability to allocate a separate radiation pattern for a specific subscriber terminal that is in motion [1 – 3]. These requirements for modern antenna technology can most likely be met by combining scientific achievements in the fields of antenna theory and artificial intelligence/machine learning, which will lead to the implementation of the “smart antenna” concept [3]. It is worth noting that the use of artificial intelligence methods to develop the antenna elements structure is already described [5, 6]. Also the possibility of using ML methods in order to optimize the parameters of antennas and adaptive antenna systems (AAS) is described in the literature. For example, in [3] the basic principles and achievements in the development of smart antennas is discussed as well as their application in various fields, such as wireless communications, satellite systems and networks, the Internet of Things is considered. Paper [3] also outlines future directions and evolution of smart antennas as key components of efficient and sustainable wireless communication systems. The research described in [7] shows that applying the ML algorithm of the Support Vector Machine method in AAS it is possible to provide intelligent control of the antenna system's radiation pattern. The paper [8] analyzes the existing classes of ML methods for the possibility of their use in AAS for the purpose of intelligent control of the radiation pattern. It was shown that the reinforcement learning can potentially be used by AAS to realize intelligent control of their own directional characteristics. In [9], improvement of the modern AAS scheme by integrating an artificial intelligence module into it is proposed. The diagram shows and describes the principle of interaction between the artificial intelligence module and the AAS. One of the methods of artificial intelligence/machine learning, the intelligent agent, is described and its mathematical model is presented. The possibility of applying the considered method in the cellular environment of a wireless communication network to improve the performance of an adaptive antenna system is shown. An example of the operation of an artificial intelligence unit as part of an AAS using the intelligent agent method is given. It is shown that using the ML method, an intelligent agent within a single wireless communication cell can create a certain knowledge system capable of understanding and learning taking into account the patterns of subscribers movement in the cell, and predicting the direction of a particular subscriber terminal movement. The resulting knowledge system is formed in the artificial intelligence unit which is included in the structural diagram of a modern AAS proposed in [9]. This knowledge system can potentially be used to more accurately control the directional pattern of an AAS.

Thus, the possibility of using ML methods to improve the concept of a smart antenna is substantiated in [3, 7 – 9]. In [8, 19], it is shown that reinforcement learning methods can potentially be combined with other ML methods, such as neural network methods, to increase the accuracy of controlling the directivity characteristics of an AAS. However, such a combination of ML methods to increase the efficiency of controlling the directivity characteristics of an adaptive antenna system has not been described in the literature. Therefore, the purpose of this paper is to propose an example of the operation of an artificial intelligence module as part of an adaptive antenna system using the deep Q-network ML method.

Deep Q-Network Method

The Deep Q-Network (DQN) method [10] is a method of deep reinforcement learning that combines traditional Q-learning methods [8 – 10] with the capabilities of deep neural networks. The traditional Q-learning method is described by the following mathematical model [9 – 11]:

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

In equation (1), s is the current state of an agent from a set of states $S(s_1, s_2, ...s_n)$, a is the current action of an agent in state s from a set of actions $A(a_1, a_2, ...a_n)$, α is a learning rate that can be set between 0 and 1, s' is a next state from a set of states $S(s_1, s_2, ...s_n)$, a' is a possible action of an agent from $A(a_1, a_2, ...a_n)$ in the state

s', λ is a discount factor that can also be set between 0 and 1, $R(s,a)$ is reward for transition between states, $\frac{\max}{a' \in A} Q(s',a')$ is a next action with maximum reward.

The DQN method uses a deep neural network to approximate a function that evaluates the utility of performing a certain action in a state [8, 10]. This allows the agent to make decisions even in complex environments with a large number of possible states and actions. Let's explain in more detail the work of the DQN method using the example of a graphical diagram of the learning process using the DQN algorithm (Fig. 1.1) [8, 10].

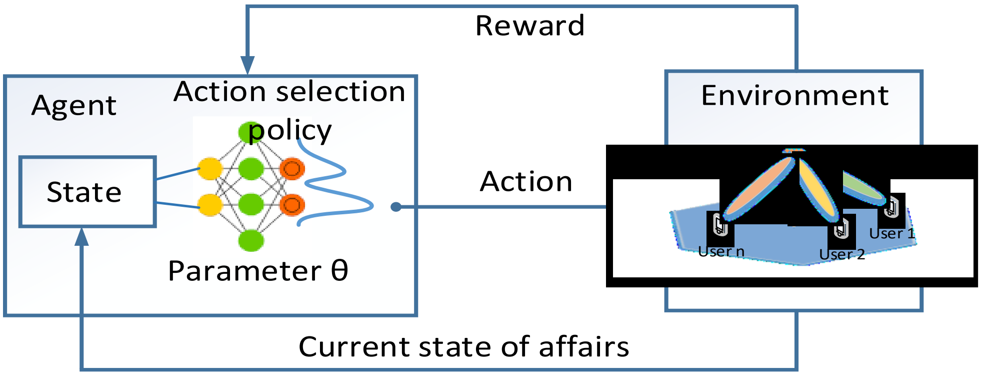

Fig. 1. Diagram of the learning process using the Deep Q-Network algorithm

Fig. 1.1 shows an agent acting in a certain environment, after the action is performed, the agent moves to a new state in the environment, and for the actions performed in the environment, the agent receives a reward. The maximum value of the reward determines the agent's transition to the optimal state. This principle is used to implement the algorithm of traditional Q-learning [8 – 10] which is described by expression (1.1). The DQN method includes in the above algorithm a deep neural network to approximate the function $Q(s,a)$. The task of the neural network is to analyze the set of target states and, accordingly, the set of actions and, as a result of the analysis select the optimal action for the agent to move to a new target state.

The analysis of the DQN method allows us to distinguish the following components [10, 11]: Replay Buffer, Target Network, ε-greedy strategy, minimization of the DQN loss function.

Replay Buffer is used to store past interactions of the agent with the environment (pairs of states, actions, rewards, and subsequent states). This allows for more efficient training of the neural network by reducing the correlation between successive data samples. Target Network is used to stabilize training. The parameters of the target network are updated by copying the parameters of the main network after a certain period of time reducing fluctuations in Q-value updates. The ε-greedy strategy is DQN uses an ε-greedy approach, where the agent chooses a random action with probability ε, and the best action according to the Q-value with probability (1 – ε). Minimization of the DQN loss function is the process of adjusting the weights of the DQN neural network in a way to reduce the discrepancy between the current Q-value estimates and the target Q-value, i.e. the loss function in the DQN is based on the difference between the current Q-value and the target Q-value. The minimization of the DQN loss function is described by the following expression [10, 11]:

$$L(\theta) = \mathrm{E}_{(s,a,r,s') \sim \mathrm{D}}\left[(y - Q(s,a;\theta))^2 \right], \tag{2}$$

where θ is the parameter (weight) of the main neural network, $Q(s,a;\theta)$ is the current estimate of the Q-value for the state and action , D is information from the playback buffer (random transitions), y is the target *Q*-value.

The target *Q*-value can be written using expression (1.1) taking into account the parameter of the target network θ^{-} as follows [8 – 11].

$$y = R(s,a) + \lambda \frac{\max}{a' \in A} Q(s',a';\theta^{-}), \tag{3}$$

where $\frac{\max}{a' \in A} Q(s',a';\theta^{-})$ is the next action with the maximum reward taking into account the target network parameter θ^{-}.

Thus, the process of training a neural network is reduced to updating the parameters of the target network θ^{-}.

For better understanding, we present the described learning process as an algorithm for training an agent using the deep Q-network method in Fig. 2.

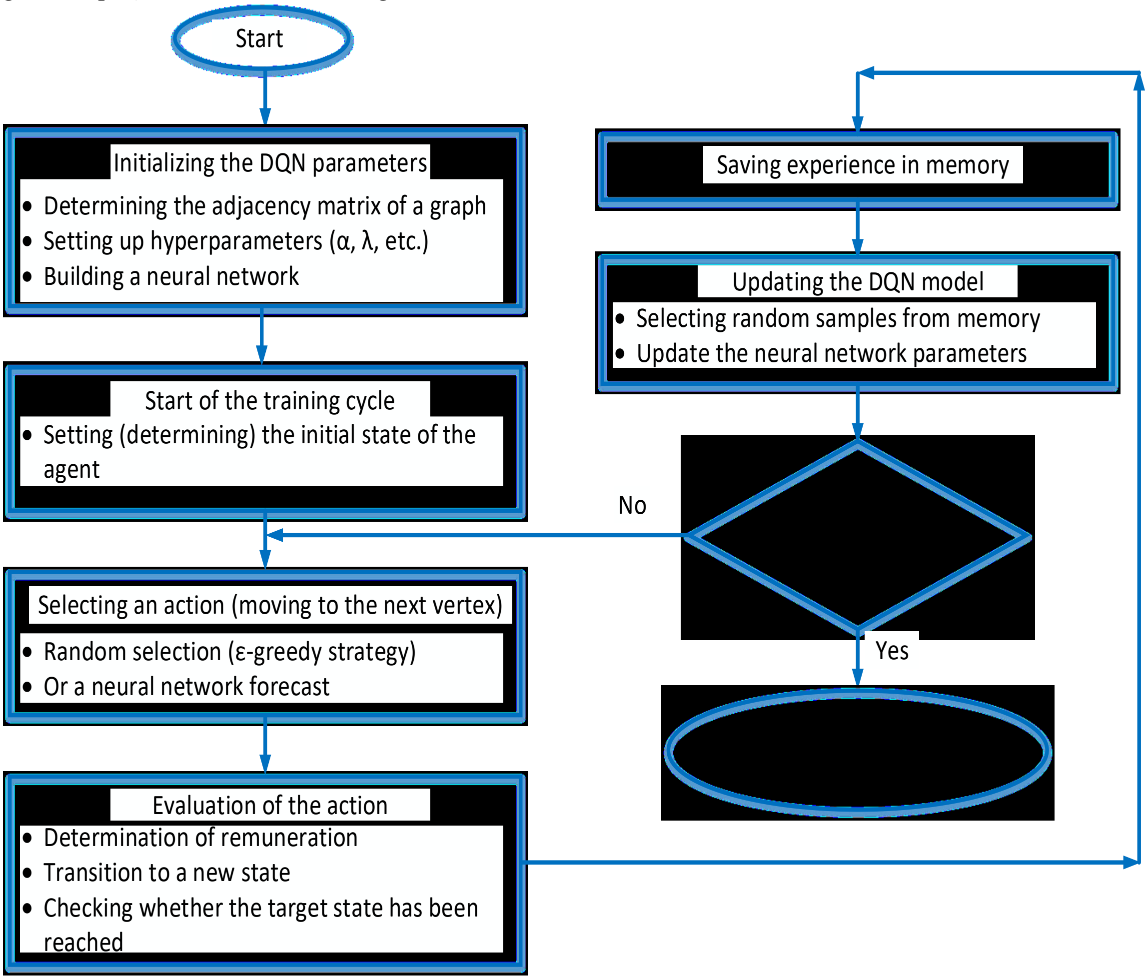

Fig. 2 Algorithm for training an agent using the Deep Q-Network method

Thus, this subsection analyzes the DQN ML method in detail. It is shown that the use of a neural network in DQN significantly improves the performance of the basic ML method of an intelligent agent.

Integration of the Deep Q-Network Machine Learning Method
into an Adaptive Antenna System with an Artificial Intelligence Unit

Let's consider a potentially possible variant of applying the DQN ML method in an adaptive antenna system with an artificial intelligence unit in order to form a certain knowledge system, on the basis of which it is possible to provide intelligent control of the antenna system's directivity characteristics. Note that the block diagram of an adaptive antenna system with an artificial intelligence unit was proposed and substantiated in [8, 9].

To substantiate the possibility of using the DQN ML method in adaptive antenna system with an artificial intelligence unit, let's look at Fig. 1.

We consider a cell of a cellular communication system as an environment where an intelligent agent operates. In the cell, an access point equipped with an AAS with an artificial intelligence unit works to realize the radio signal coverage area. The AAS with an artificial intelligence unit forms a multi-petal beamforming pattern where according to the 5G and 6G wireless network standards a beamforming petal is allocated individually for each subscriber and must change its directional angle in accordance with the direction of the subscriber movement within the radio coverage area of the cell [1]. Thus, in fact, the beamformer acts as an intelligent agent in the DQN ML method.

Let's take a closer look at the environment of a cell. Let it be a cell of an ultra-dense network [1] that implements a radio coverage area within one floor of an office building Fig. 3.

Fig. 3. shows the nine rooms of the office building. In the hall (room #3) an access point is installed that implements the cell of the ultra-dense radio network by allocating individual petals of AAS directional pattern for the corresponding subscribers.

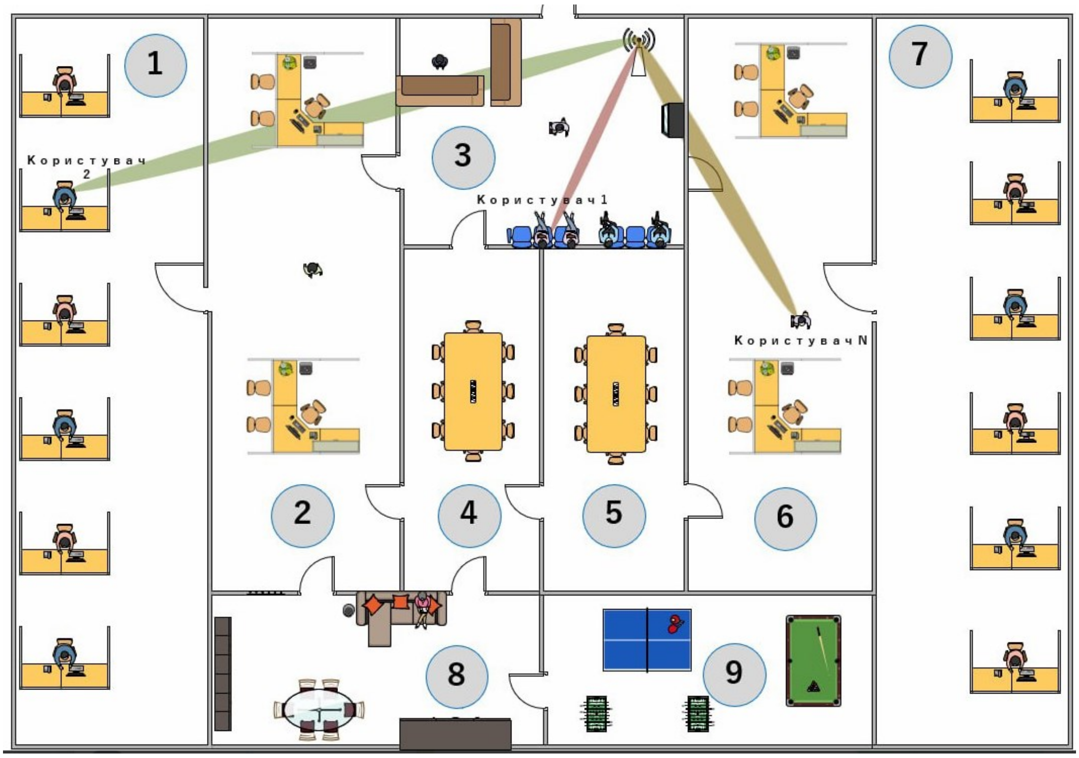

Fig. 3. Floor plan of an office building

So, for the environment described above we conduct a special case of training an intelligent agent in order to form a certain knowledge system on the basis of which it is possible to provide intelligent control of the antenna system's directivity characteristics.

Let's conduct training when the agent needs to find a way from room 3 (hall) to room 9 (rest room). Using the algorithm from Fig. 2 the training process in the form of a program code in Python is implemented [12].

The result of the agent training using the DQN algorithm is obtained in the form of a weighted color graph in Fig. 4.

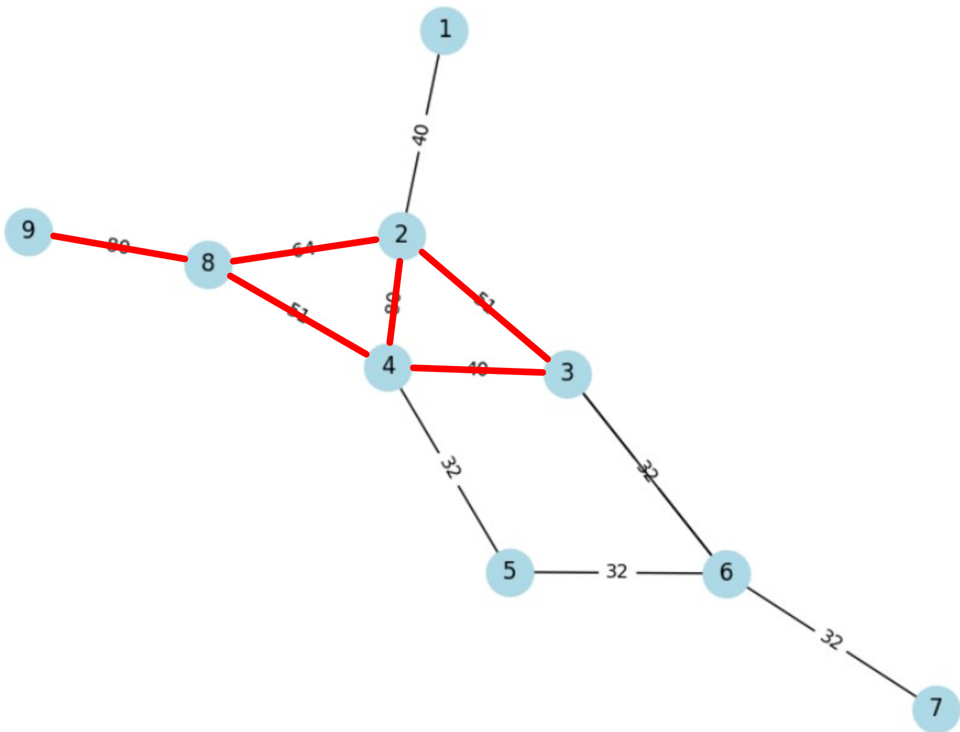

Fig. 4. The result of the agent training using the DQN algorithm

Fig. 4 shows a weighted color graph where the numbered vertices are the rooms in the plan of Fig. 3. Edges are the possibility of moving from one room to another. The values of the weights correspond to the values of the probabilities of the agent's transition from one room to another. The edges that are marked in red as a result of the DQN agent training are determined to be optimal for achieving the goal of moving the agent from room 3 to room 9. The graph shown in Fig. 4 is considered as the formed knowledge system of the DQN agent as a result of its training to determine the options for the agent's transition from room 3 to room 9.

Analysis of the graph in Fig. 4 allows us to conclude that as a result of the DQN agent training the optimal path for the agent's transition from vertex 3 to vertex 9 was determined.

The optimal path is from vertex 3 to vertex 2 (transition probability 51%), from vertex 2 to vertex 4 (transition probability 80%), from vertex 4 to vertex 8 (transition probability 64%), from vertex 8 to vertex 9 (transition probability 80%).

The closest alternative path has the following sequence of vertices: from vertex 3 to vertex 2 (transition probability 51%), from vertex 2 to vertex 8 (transition probability 64%), from vertex 8 to vertex 9 (transition probability 80%).

An interesting fact is that according to the results of training the DQN agent the closest alternative path has one less vertex than the optimal path which is determined in accordance with the higher values of the transition probability between the initial and target vertices.

CONCLUSION

Thus, this section analyzes in detail the DQN ML method. The possibility of applying the DQN ML method in an artificial intelligence module as part of an adaptive antenna system is shown in order to form a system of knowledge about the environment in which the adaptive antenna system operates. The algorithm for training a DQN agent is proposed and the proposed algorithm is implemented in the Python program code. As a result of the software implementation of the DQN algorithm a knowledge system was obtained which in the future will allow to realize the intelligent control of the radiation pattern petals of the adaptive antenna system.

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