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NEUROAGENT MODEL OF DECISION-MAKING

The neuroagent model of decision-making in the conditions of uncertainty is investigated. Adaptive methods of an artificial neural network learning without the teacher are considered. The algorithm and program model of neuroagent decision-making are developed. Efficiency of neuroagent decision-making has been confirmed by results of computer experiment. Influences of parameters of model on the neuroagent learning rate are investigated.

Keywords – decision making, uncertainty conditions, neuroagent model, adaptive method.

Introduction in a problem of decision-making in the conditions of uncertainty

In an everyday life and at performance of the official duties people consider and decisions which provide the solving of various problems, achievement of those or other purposes, for example, minimisation of efforts or expenses of resources or minimisation time at performance of works, profit maximisation, maintenance of intellectual, cultural and career growth, maintenance of health, psychological balance etc.

Decision-making is a process of a rational or intuitive choice of alternative variants of the actions which purpose are achievements of current result or the result kept away in time [1–5]. The list of possible variants is caused by environment and area of employment of the person which makes the decision. So, activity of the scientist is connected with the analysis of variants of the decision of a problem, work of the teacher – with a choice of a way of presentation of a matter, and work of the doctor – with a choice of strategy of treatment of the patient.

The rational choice of alternative decisions consists of such stages [6]:

1) A problem situation analysis;
2) Identification of a problem and a purpose formulation;
3) Search of the necessary information;
4) Formation of alternatives;
5) Formation of criteria for estimation of alternatives;
6) Carrying out of estimation of alternatives;
7) A choice of the best alternative;
8) Alternative realisation;
9) Development of criteria for monitoring of implementation of the alternative decision;
10) Monitoring of performance of a variant of the decision;
11) Estimation of results.

The decision-making system (DMS) consists of control object (or decision applications) and persons who makes the decision. It is considered that in structure of DMS available feedback for estimation of efficiency of the accepted decisions and updating of strategy of decision-making during the future moments of time. Such approach to construction of DMS is called as optimising [7]. Unlike the situational approach when the decision make at once on the basis of the input data, in the optimising approach the decision is specified through a feedback link.

The choice of variants of decisions in the task-oriented information systems and control systems, as a rule, is carried out in the conditions of uncertainty [8, 9]. Uncertainty is understood as a situation when there is not enough information for adequate decision-making or results of decision-making are unknown a priori. Uncertainty of DMS can be caused discrepancy or incompleteness of the input data, stochastic the nature of external influences, absence of adequate mathematical model, an indefiniteness of the formulated purpose, the human factor etc. In the conditions of uncertainty risks of generation of inefficient decisions with negative economic, technical and social consequences increase. To uncertainty of decision-making systems can be partially compensated application of various methods of an artificial intellect [10–12].

For DMS effectiveness maintenance construction of model of the person which makes the decision (DMP), and its use at a predesign stage or for development of recommendations during decision-making process is important. The system which realises such model, is called as decision-making support system (DMSS) [12–15].

Construction of modern DMSS in the conditions of uncertainty is carried out by application of methods and artificial intelligence techniques on the basis of the agent-oriented methodology [16–19]. The intellectual agent of decision-making (DMA) is model of DMP, independent system of making of decisions with artificial intellect elements. The agent co-operates with DMP as a consulting subsystem of decision-making.

Application of modern methods and artificial intelligence techniques to designing of DMS which function in the conditions of uncertainty of the information, is a perspective direction of increase of efficiency of decision-making processes and managements [13].

Life cycle of DMA includes: a decision choice, supervision of reaction of environment, processing of reaction for adaptive formation of strategy of decision-making. Observing conditions of system and processing current prizes, the agent should find such way of decision-making which would provide maximisation of its average gains in time. For this purpose it should contain the mechanism for integrated storing of reactions of environment and on its basis of adaptive development of variants of decisions.

At uncertainty of operating conditions of system to construction of intellectual DMA apply methods on the basis of automatons with variable structure, of stochastic games, of rules of indistinct logic, of bayesian networks of trust, of markovian hidden networks, of artificial neural networks and other adaptive methods [9, 13, 20–22].

For maintenance of high efficiency of DMS and possibilities of parallel processing of the information use artificial neural networks [23–27] which consist of set of neurons and communications between them. For reception of necessary structure of communications between neurons the neuronet learning procedure is used, in a course what one communications amplify, and others – are weakened.

DMS, realised on the basis of the device of artificial neural networks, is called as neuroagent decision-making. Neuroagent decision-making process can occur in an independent mode of DMS functioning or in an interactive mode of neuroagent interaction with DMP.

Neural networks realise "soft" calculations on the sample of processes which proceed in a brain of the person. Owing to modern knowledge of the organisation and brain functions, similarity of a neuronet with a brain consists that the information which arrives in neuronets from environment, is used for storing and learning of a network by means of a synaptic communications correcting between neurons.

Neural networks are used as model of objects with unknown characteristics. Except problems of support of decision-making, they are applied to the decision of problems of classification and recognition of objects, by approximations of functions on its limited set of values, forecasting of sequences, filtering of the noisy data, compression of the information, substantial information search, construction of associative memory, control of dynamic objects etc.

Use of neural networks provides such advantages:

1) Nonlinearity – neural networks allow to receive nonlinear dependence of a target signal on the input signal;

2) Adaptability – neural networks have ability to adapt the synaptic weights to environment changes;

3) Plasticity and failure tolerance – neural networks keep the information in distributed on all communications of a neural network a kind and failure one or several of neurons does not lead to system refusal as a whole;

4) Universality – neural networks do not require special programming as they solve various problems of processing of the information on identical algorithms of learning of neurons.

Artificial neuronets have more than semicentenial history of research: from W.S. McCulloch and W.H. Pitts neural model [28], from F. Rosenblatt perceptron [29] – to creation modern neurocomputers [30], electronic devices with functions which model work of a live brain. Despite it, the question of application of neural networks for optimising decision-making in the conditions of uncertainty in DMS with feedback is insufficiently studied on the present.

Construction of neuroagent model of optimising decision-making in the conditions of uncertainty with ability to accumulate experience of decision-making and selflearning at the cost of adaptive reorganisation of synaptic communications between neurons is the purpose of this work.

Statement of a problem of decision-making in the conditions of uncertainty

DMS in the conditions of uncertainty is described by a tuple (U, ξ, DM), where $U = \{u[1], u[2], ..., u[N]\}$ is a set of discrete variants of decisions, $\xi(u) \sim Z(v(u), d(u))$ is an estimation of quality of the made decision $u \in U$ which is a random variable with a priori unknown distribution, an expected payoff $v(u) = E\{\xi(u)\}$ and the limited dispersion $d(u) < \infty$, DM is a method of decision-making which consists in a choice of one of variants of decisions $u \in U$.

Let DMS resolves a repeated choice of variants of decisions the intellectual agent during time moments $t = 1, 2, ...$. After a choice of a variant $u_t = DM(\xi_{t-1}) \in U$ the agent receives a random current prize $\xi_t(u_t)$.

The received current prizes of agents are averaged in time for estimation of efficiency of decision-making process:

$$\Xi_t(\{u_t\}) = t^{-1} \sum_{\tau=1}^{t} \xi_\tau . \qquad (1)$$

The purpose of the agent is maximisation of function of average prizes:

$$\underline{\lim}_{t \to \infty} \Xi_t \to \max_u . \qquad (2)$$

So, on the basis of supervision of current prizes ξ_t the agent should choose current decisions $u_t = u \in U$ so that with time course $t = 1, 2, ...$ to provide maximisation of criterion function (1).

Neuroagent method of the problem solving

Known adaptive methods of generating of sequences, $\{u_t\}$, $t = 1, 2, ...$ for maximisation of average prizes are based on dynamic distributions of random variables [31]. Unlike them, we will consider a neuroagent decision-making method. The structure of neuroagent decision-making systems is represented on Fig. 1.

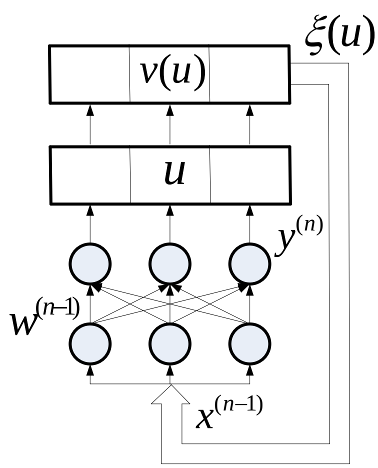

Fig. 1. Structure of neuroagent DMS

The model of the environment of decision-making is set by a vector of mathematical expectations of random prizes v. The quantity of elements of a vector equals to quantity of variants of decisions: $N = |U|$. On an input of environment value of a variant of the decision $u \in U$ arrives. An output of environment is corresponding value of current prizes $\xi(u)$.

Let the neuroagent is set by an artificial network with $n=2$ neuron layers. The quantity of elements of each layer is identical, equal to quantity of variants of decisions N. On an neuroagent input the vector of the parameters $x^{(n-1)}$ calculated on the basis of outputs $\xi(u)$ of environment injections. The vector of parameters $y^{(n)}$ on which basis variants of decisions $u \in U$ are defined is outputs of neuroagent. Weights $w^{(n-1)}$ designate size of synaptic communications between neurons. Positive values of weights correspond raising, and negative correspond to brake synapses. Zero value of weights means absence of communication between neurons.

Neuroagent functioning is carried out on one of adaptive algorithms of learning without the teacher, for example, Hebb's algorithm, Kohonen's algorithm or another [27]. Learning without the teacher, or self-learning, by the nature is the closest to the biological prototype – a brain. Self-learning is not guided by presence of correct neuronet outputs. The algorithm of self-learning independently finds out internal structure of the input data, reconstructing weights of synaptic communications so that relatives (under some metrics) sets of input signals have caused close enough initial sets of signals. Actually, the process of neuroagent self-learning solves a problem of the data clustering, finding out statistical properties of educational sets and grouping similar initial sets in clusters. Submitting on an input of learnt neuronet a vector from the set class, we will receive characteristic for this class a target vector. The target vector obviously is not known. Its formation is caused by structure of educational sample, random distribution of initial values of weights of communications between neurons and a combination firing neurons a target layer of neuronet.

The choice of variants of decisions $u \in U$ is carried out by the determined or stochastic method.

The determined method consists in definition of variants of decisions on the basis of the maximum values of outputs $y_t^{(n)}$:

$$u_t = \left(u[i] \middle| i = \arg\max_{j=1..N} y_t^{(n)}[j] \right). \tag{3}$$

Application of this method can lead to that some from neurons will not take participation in learning.

Unlike previous, the stochastic method expands a freedom in neuroagent choosing. For this purpose the auxiliary vector of conditional probabilities of a choice of variants of decisions a method of projecting of a vector of outputs $y_t^{(n)}$ on a N - dimensional unit ε -simplex is under construction:

$$p(u_t \mid u_\tau, \xi_\tau, \tau = 1,2,...,t-1) = \pi_\varepsilon^N \{y_t^{(n)}\}, \tag{4}$$

where π_ε^N is a projector on unit ε -simplex $S_\varepsilon^N \subseteq S^N$ [31]. The parameter ε regulates speed of expansion of ε - simplex S_ε^N to an unit simplex S^N and can be used as the additional factor of management of convergence of a neuroagent decision-making method.

The received vector of probabilities is used for construction of empirical distribution of discrete random variables on which basis the choice of variants of decisions is carried out:

$$u_t = \left\{ u[i] \middle| i = \arg\left(\min_i \sum_{j=1}^{i} p_t(u_t[j]) > \omega \right), i = 1..N \right\}, \tag{5}$$

where $\omega \in [0, 1]$ is a real random number with uniform distribution.

Value of a random variable with unknown distribution Z which is interpreted as a current prize of the agent is reaction of the environment of decision-making to the chosen variant:

$$\xi(u_t) \sim Z(v(u_t), d(u_t)),$$

where $v(u_t)$ is a mathematical expectation, $d(u_t)$ is a dispersion.

The received current prize $\xi_t(u_t)$ moves on inputs of neuroagent

$$x^{(n-1)} = e\xi(u_t), \tag{6}$$

where $e=(1\,|\,\forall u\in U)$ is the vector, which all elements equal to unit; $\chi()\in\{0,1\}$ is a display function of event.

On requirement normalisation of elements of a vector, $x^{(n-1)}$ for example, the such is carried out:

$$x^{(n-1)}=e\xi(u_t)/\,|\,\xi_{\max}\,|,$$

where $\xi_{\max}$ is the maximum value of current prizes. Normalisation can lead to reduction of quantity of the steps necessary for neuroagent learning.

Total inputs $x^{(n)}$ of a layer with number n are calculated on the basis of $y^{(n-1)}$ layer neuron outputs with number $(n-1)$:

$$x^{(n)}[j]=\sum_{i=1}^{N}w_t^{(n-1)}[i,j]y^{(n-1)}[i],\ \ j=1..N, \tag{7}$$

where $w_t^{(n-1)}[N,N]$ is a matrix of weights of communications between neuronet nodes, calculated at the moment of time t. Here $w_t^{(n-1)}[i,j]$ designates communication weight between node i of a layer $(n-1)$ and node j of a layer n.

For calculation of neuroagent outputs $y^{(n)}$ a transfer function $\varphi()$ of neuron is used:

$$y^{(n)}[j]=\varphi(x^{(n)}[j]), \tag{8}$$

where $j=1..N$.

Depending on a solved problem and a kind of neuronet transfer function $\varphi()$ can be threshold, linear with saturation, sigmoid, sinusoidal, radially-symmetric etc. [27].

More often for modelling of an artificial neural network use the linear

$$y_t^{(n)}[j]=\begin{cases}0, & if\ \ x_t^{(n)}[j]\le\theta,\\ \eta(x_t^{(n)}[j]-\theta), & if\ \ x_t^{(n)}[j]>\theta,\end{cases} \tag{9}$$

and bipolar sigma

$$y_t^{(n)}[j]=-0.5+1/(1+e^{-\eta(x_t^{(n)}[j]-\theta)}) \tag{10}$$

transfer functions. The parameter $\eta>0$ sets a tangent of angle of an inclination of a straight line for linear transfer function and level of a steepness for sigma transfer function. The parameter $\theta\ge0$ defines an activation threshold of neuron.

Learning of neuroagent is carried out by change of weights $w_t^{(n-1)}$ of synaptic communications between neurons. Recalculation of weights of communications is carried out with use of a Hebb's signal method, a Kohonen's method or other method of learning without the teacher.

Learning by a Hebb's method leads to strengthening of communications between firing neurons:

$$w_t^{(n-1)}[i,j]=w_{t-1}^{(n-1)}[i,j]+\gamma_t(y_{t-1}^{(n-1)}[i]*y_{t-1}^{(n)}[j]),\ \ i=1..N,\ \ j=1..N. \tag{11}$$

Neurons for which value of a total input $x^{(n)}$ exceeds an activation threshold θ are called as firing.

Learning with use of a Hebb's differential method leads to strengthening of communications between those neurons which outputs have changed more all:

$$w_t^{(n-1)}[i,j]=w_{t-1}^{(n-1)}[i,j]+\gamma_t\left(y_t^{(n-1)}[i]-y_{t-1}^{(n-1)}[i]\right)*\left(y_t^{(n)}[j]-y_{t-1}^{(n)}[j]\right),\ i=1..N,\ \ j=1..N. \tag{12}$$

Learning of a network by a Kohonen's method is based on the competition mechanism which essence consists in difference minimisation between input signals of the neuron-winner which arrive from neuron outputs the previous layer, and its weight factors of synapses:

$$w_t^{(n-1)}[i,k]=w_{t-1}^{(n-1)}[i,k]+\gamma_t(y_{t-1}^{(n-1)}[i]-w_{t-1}^{(n-1)}[i,k]),\ i=1..N, \tag{13}$$

where k is an index of the neuron-winner.

Unlike a Hebb's method in which simultaneously can be fired a few neurons of one layer, in a Kohonen's method neurons one layer compete among themselves for the right of activation [23]. This rule is known in the literature from machine learning under the name „the winner takes away all".

In a Kohonen's method reorganisation of weights of communications is carried out only for the neuron-winner. The winner is that neuron, which value of synapses are as much as possible similar for an input image.

Definition of the neuron-winner is carried out by distance calculation between vectors $y_{t-1}^{(n)}$ and $w_{t-1}^{(n-1)}$:

$$D_{t-1}[j] = \sqrt{\sum_{i=1}^{N} \left(y_{t-1}^{(n-1)}[i] - w_{t-1}^{(n-1)}[i,j] \right)^2}, \quad j = 1..N.$$

Wins the neuron with the least distance:

$$k = index \min_{j=1..N} (D_{t-1}[j]).$$

Other way of definition of the neuron-winner consists in maximisation of outputs $y_{t-1}^{(n)}$ of neurons a layer n according to (3). In this case the index of the neuron-winner is a serial number of the chosen variant of the decision u_{t-1}:

$$k = index(u[j] \,|\, \chi(u[j] = u_{t-1}),\ j = 1..N). \tag{14}$$

In space of vectors of weights of elements round the neuron-winner the learning radius R can be set:

$$r_t[j] = \left\| w_t^{(n-1)}[k] - w_t^{(n-1)}[j] \right\|, \quad j = 1..N,$$

where $w_t^{(n-1)}[k]$ is a vector of weights of the neuron-winner; $\|*\|$ is an Euclidean norm of a vector.

Everyone neuron, the distance from which vector of weights to a vector of weights of the neuron-winner is less radius of learning ($r_t[j] < R$), takes part in recalculation of synapse weights. Weights of neurons which are outside of learning radius, do not change. The learning radius decreases in time so that in the end of learning process only one neuron-winner could carry out updating of weights of communications.

Parameters γ_t in (11) – (13) and ε_t in (4) define speed of neuroagent learning. For maintenance of convergence of process of neuroagent learning these parameters are set as positive monotonously descending sizes:

$$\gamma_t = \gamma_0 / t^{\alpha}, \quad \varepsilon_t = \varepsilon_0 / t^{\beta}, \tag{15}$$

where $\gamma_0, \alpha > 0$; $\varepsilon_0, \beta > 0$.

The choice of variants of decisions proceeds to achievement of the set quantity of steps $t_{\max}$, or to performance of a condition of accuracy of learning:

$$\delta_t = \left\| w_t^{(n-1)} - w_{t-1}^{(n-1)} \right\| < \varepsilon, \tag{16}$$

where ε is an accuracy of neuroagent learning which is defined by Euclidean norm of change of weights of communications between neurons for two consecutive moments of time.

Quality of DMS is estimated by the value of function of average prizes reached in the course of optimisation Ξ_t (1) and an error of a choice of an optimum variant of decision-making.

As the optimum we will consider a variant of decision-making with the maximum value of a mathematical expectation of a prize:

$$u^* = \arg v(u^*),$$

where $v(u^*) = \max_{u \in U} v(u)$.

The error of a choice of an optimum variant of the decision can be defined on a deviation $\Delta(\Xi_t)$ of value of function of average prizes from predicted optimum value or an error $\Delta(p_t)$ of probability of a choice of an optimum variant of decision-making.

The deviation of value of function of average prizes from predicted optimum value is calculated so:

$$\Delta(\Xi_t) = |\,\Xi_t - v(u^*)\,| \,. \tag{17}$$

The error of probability of a choice of an optimum variant of the decision averaged in time is calculated so:

$$\Delta(p_t) = \frac{1}{t}\sum_{\tau=1}^{t}\left\| p_\tau - e^* \right\| , \tag{18}$$

where e^* is an unit vector-indicator of an optimum variant of the decision.

Vector elements e^* are defined so:

$$e^*[i] = \begin{cases} 0, \; if \;\; i \neq \arg\max\limits_{j=1..N} v[j] \\ 1, \; if \;\; i = \arg\max\limits_{j=1..N} v[j] \end{cases}, \; i = 1..N \,. \tag{19}$$

For simplification of research of convergence of algorithm of neuroagent learning we will assume that a variant of the optimum decision is unique, i.e.:

$$h = v(u^*) - \max_{u \in U, u \neq u^*} v(u) > 0 \,. \tag{20}$$

Kohonen's algorithm of neuroagent functioning

1. To set initial values of parameters:

$t = 0$ – the initial moment of time;

N – quantity of variants of decisions;

$U = \{u[1], u[2], ..., u[N]\}$ – set of variants of decisions;

$v = (v_1, v_2, ..., v_N)$ – vector of mathematical expectations of prizes;

$d = (d_1, d_2, ..., d_N)$ – vector of dispersions of prizes;

$w_0^{(n-1)}[N, N]$ – matrix of initial weights of communications between nodes of neuronets;

η, θ – parameters of transfer function of neuron;

γ_0 – parameter of a step of neuron learning;

$\alpha \in [0,1]$ – order of a step of neuron learning;

ε_0 – parameter an ε -simplex;

β – order of speed of expansion of ε -simplex;

$t_{\max}$ – maximum quantity of steps of a method;

ε – accuracy of learning.

2. To execute the determined choice of a variant of the decision u_t according to (3), or a stochastic choice according to (4) – (5).

3. To receive value of current prizes, as a random variable with normal distribution $\xi(u_t) \sim Normal(v(u_t), d(u_t))$. The is normal-distributed prizes are estimated on the help of the sum of random variables $\omega \in [0,1]$ with uniform distribution:

$$\xi(u_t) = v(u_t) + \sqrt{d(u_t)}\left(\sum_{j=1}^{12} \omega_t[j] - 6\right).$$

4. To calculate neuroagent inputs $x^{(n-1)}$ according to (6) and corresponding neuron outputs $y^{(n-1)}$ a layer $(n-1)$ according to (8). As transfer function linear function (9) is chosen.

5. To calculate total neuron inputs $x^{(n)}$ (7) and corresponding neuron outputs $y^{(n)}$ (8) for a layer n.

6. To calculate value of parameter γ_t according to (15).

7. To define an index k of the neuron-winner according to (14).

8. To calculate weights of communications for the neuron-winner, $w_t^{(n-1)}[j,k]$, $j=1..N$ according to (13).

9. To calculate characteristics of quality of decision-making Ξ_t (1), $\Delta(\Xi_t)$ (17) and $\Delta(p_t)$ (18).

10. To set the next moment of time $t:=t+1$.

11. If $t<t_{\max}$ then go to a step 2, differently – the end.

Results of computer modelling

Work-status of neuroagent models which is defined by its possibility to be learned to choose optimum variants of the decision, are confirmed by results of computer experiment.

On Fig. 2 in logarithmic scale diagrams of function of average prizes Ξ_t and errors $\Delta(\Xi_t)$ and a $\Delta(p_t)$ choice of an optimum variant of management for environment with normally distributed prizes $\xi(u)$ $\forall u \in U$ with mathematical expectations $v=(0,3;0,9;0,1;0,5)$ and dispersions $d=(0,01;0,01;0,01;0,01)$ are represented. The neuroagent receives current random prizes as reactions of environment for a choice of one of $N=|U|=4$ variants of decisions.

Initial values of weights of communications $w_0^{(n-1)}$ between neurons are the random variables in regular intervals distributed in an interval [0; 1]. Results are received for algorithm of neuroagent learning (13) with parameters: $\gamma=1$; $\alpha=0,1$; $\varepsilon=0,999/N$; $\beta=1$.

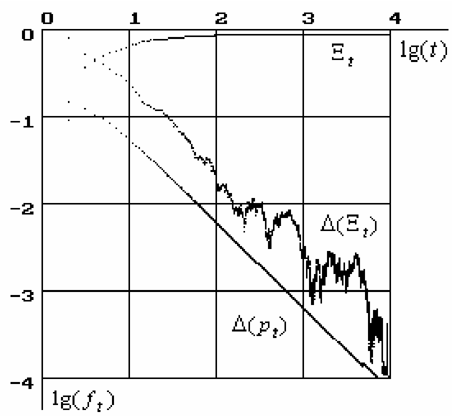

Fig. 2. Neuroagent learning characteristics

Growth Ξ_t to value $v(u^*)$ and corresponding reduction $\Delta(\Xi_t)$ and $\Delta(p_t)$ in time testify to convergence of a neuroagent decision-making method in sense of performance of criterion function (2). Decrease diagrams of functions $\Delta(\Xi_t)$ also $\Delta(p_t)$ shows that the neuroagent method (13) learns to choose an optimum variant of the decision with the greatest value of a mathematical expectation of a prize.

Let's study dependence of time of neuroagent learning from algorithm key parameters. Learning time we will define as a minimum quantity of the steps necessary for neuroagent learning with accuracy $\varepsilon>0$:

$$t_{out}=(t=t_{\min} \mid \delta_t<\varepsilon),$$

where current accuracy of learning δ_t is estimated according to (16).

For algorithm with a random choice of variants of decisions it is necessary to execute averaging of time of neuroagent learning for different sequences of random variables:

$$\overline{t}=\frac{1}{k_{\exp}}\sum_{j=1}^{k_{\exp}} t_{out}[j],$$

where $k_{\exp}$ is a quantity of experiments.

The average quantity of steps of learning $\overline{t}$ depends on parameters of algorithm of neuroagent learning and parameters of the environment of decision-making.

The diagram of dependence of average time $\overline{t}$ of neuroagent learning from parameter α is represented on Fig. 3 in logarithmic scale. The parameter $\alpha \in (0,1]$ defines an order of monotonous decrease of size $\gamma_t > 0$ (15) which regulates speed of neuroagent learning. With value α increase the value γ_t decreases. Results are received for environment of decision-making with parameters, $N = |U| = 4$, $v = (0,3; 0,9; 0,1; 0,5)$ and $d = (0,01; 0,01; 0,01; 0,01)$.

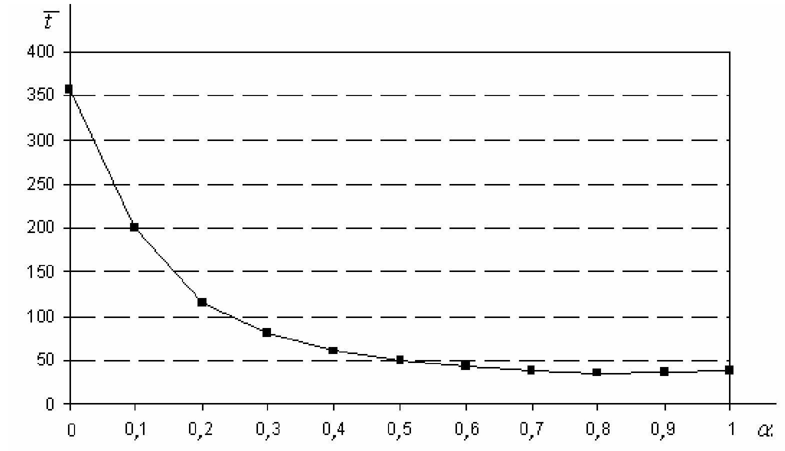

Fig. 3. Influence of parameter α for the period of neuroagent learning

Accuracy of neuroagent learning equals $\varepsilon = 10^{-3}$. The data is averaged on $k_{\exp} = 100$ experiments. In all experiments learning with the set accuracy provides correct localisation of an optimum variant of the decision which is defined by a condition (19).

Apparently from results of modelling, the parameter increase α leads to reduction of average quantity of steps $\overline{t}$ of neuroagent learning.

Dependence of average quantity of steps $\overline{t}$ of neuroagent learning from a dispersion d of the stochastic environment (a dispersion of estimations of variants of decisions) is presented on Fig. 4.

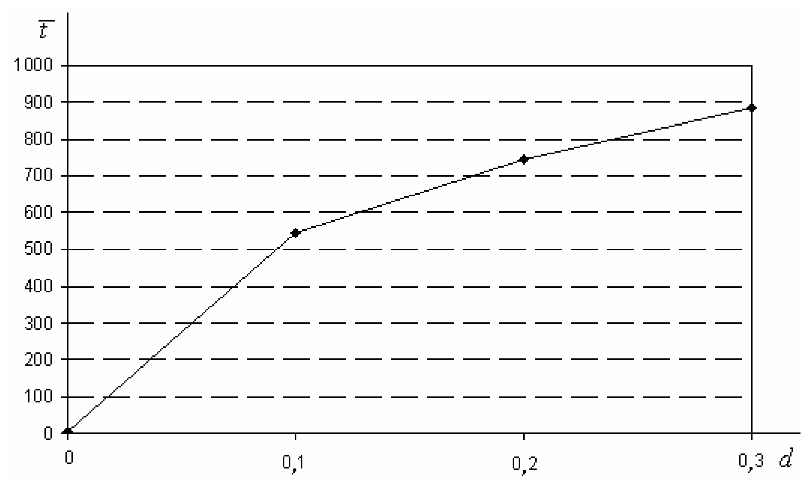

Fig. 4. Influence of a dispersion of estimations of variants of decisions for the period of neuroagent learning

With dispersion growth the average quantity of the steps necessary for neuroagent learning increases. It is necessary to notice that excessive growth of a dispersion can lead to wrong definition of an optimum variant of the decision.

Influence of quantity of variants $N = |U|$ of decision-making on speed of neuroagent learning is represented on Fig. 5. The decision-making environment is set by parameters:

$$v(u) = 0{,}1 \ u \in U, \ u \neq u^*;$$
$$v(u^*) = 0{,}9;$$
$$d(u) = 0{,}01 \ \forall u \in U.$$

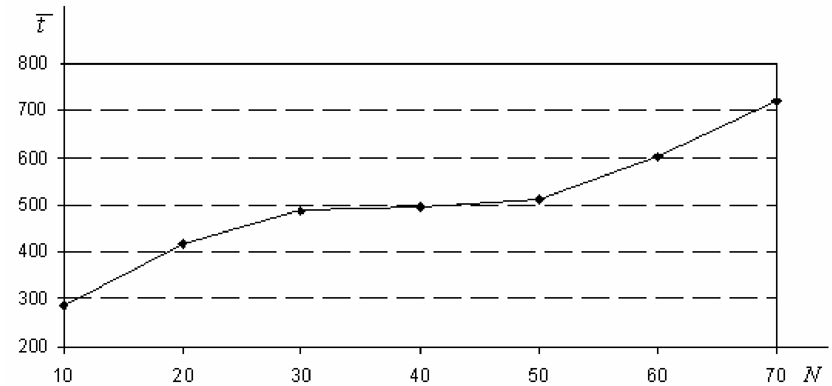

Fig. 5. Dependence of time of neuroagent learning from quantity of variants of decisions

Growth of quantity of variants of decision-making leads to reduction of convergence rate of algorithm of neuroagent learning.

It is experimentally established that convergence of a method depends on size h of an interval of difference of mathematical expectations of prizes (20).

The diagrams of function $\Delta(p_t)$ received for different values of parametre h, are represented on Fig. 6. The random environment of decision-making is set by parameters:

$$N = |U| = 4;$$
$$v(u) = 0{,}1 \ u \in U, \ u \neq u^*;$$
$$v(u^*) = v(u) + k * 0{,}1, \ k = 1, 2, \ldots;$$
$$d(u) = 0{,}01 \ \forall u \in U.$$

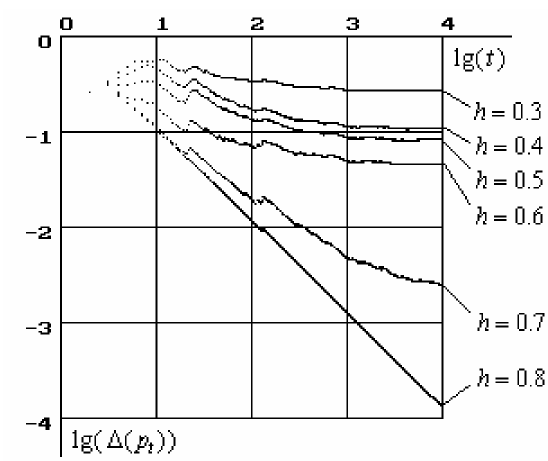

Fig. 6. Dependence of speed of neuroagent learning from an interval of difference of estimations of variants of decisions

Apparently on Fig. 6, with increase h the convergence of neuroagent method improves that appears in growth of probability of definition of optimum value $v(u^*)$ and, accordingly, decrease $\Delta(p_t)$ at repetitions of computer experiment.

The order of a neuroagent decision-making method can be estimated convergence rate on value of a steepness of the diagram of function $\Delta(p_t)$ which can be calculated as a tangent of angle of linear approximation of function $\Delta(p_t)$ with time axis in logarithmic scale. Growth of a steepness of diagrams $\Delta(p_t)$ testifies to speed increase of neuroagent learning.

Conclusions

In this article the new neuroagent model and a method of adaptive decision-making in the conditions of stochastic uncertainty, based on an artificial neural network with feedback with learning without the teacher are offered. The current variant of the decision gets out on the basis of neuronet outputs in the determined or stochastic way. The determined choice is based on definition of the maximum value of a neuroagent outputs. The stochastic choice provides definition of probabilities of a choice of variants of decisions by a method of optimum projecting of neuroagent outputs on an unit simplex. After a choice of a variant of the decision reaction of the environment of decision-making as value of a current neuroagent prize is defined. The current prize on a feedback link goes on inputs of two-layer neuronet. Further there is a neuroagent learning by updating of weights of communications between neurons to the help to one of algorithms of learning without the teacher. Learning process repeats in real time till the moment of stabilisation of weights of communications between neurons with the set accuracy. The learning course is directed on maximisation of neuroagent average prizes.

The developed program model confirms convergence an adaptive neuroagent decision-making method (13). Efficiency of a method is estimated by means of characteristic functions of average prizes and errors of a choice of an optimum variant of management. Convergence of a neuroagent method depends on quantity of variants of decisions and correlation of parameters of a method and the decision-making environment. Result of growth of quantity of variants of decisions or dispersions of their estimations are reduction of convergence rate of a neuroagent method. Expansion of an interval of difference of expected payoff leads to improvement of convergence rate of process of neuroagent learning.

Reliability of the received results is confirmed by repeatability of values of the calculated characteristics of a neuroagent method of decision-making for different sequences of random variables.

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