Formation of the predicted training parameters in the form of a discrete information stream

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Abstract. In work process of training in the form of a discrete information stream is considered. On each of stages of the considered process portions of the training information and quality of their assimilation are analysed. Individual characteristics and reaction trained for every portion of information on appropriate sections are defined. The control algorithm of training with the predicted number of control checks of the trainee who allows to define what operating influence is considered it is necessary to create for the trainee. On the basis of this algorithm the vector of probabilities of ignorance of elements of the training information is received. As a result of the conducted researches the algorithm on formation of the predicted training parameters is developed. In work the task of comparison of duration of training received experimentally with predicted on the basis of it is solved the conclusion is drawn on efficiency of formation of the predicted training parameters.

1. Introduction
During training process consideration as the system including all stages: knowledge acquisition, digestion of material and control check, it has been revealed that this process is carried out under the operating influence which is natural for presenting in the form of a discrete information stream.

At each stage of this process the trainee receives portions of information \( u_k \), \( k = 1, 2, \ldots, N \) which are in turn presented in the form of the renumbered elements on every portion of information:

\[
u_k = \left( m_{k-1} + 1, m_{k-1} + 2, \ldots, m_k \right),
\]

where \( m_k \) – the quantity of the elements of a portion of information given on \( k \) a training session, defined according to (1)

\[
m_k = \max_{i = \text{Gen}} \left\{ m^* : t_i \geq f \cdot \sum_{i = \text{Gen}} p_i \left( t_i^* \right) \right\},
\]

where \( f \) – the average time of learning of an element of a portion of information at his first presentation to the trainee; \( m \) – total of elements of a portion of information on all this process.
For check of level of knowledge of the trainee testing in certain timepoints \( t^j_i, j = 1,2,\ldots,l \) is held provided that time of testing of each trainee doesn't exceed time allocated for studying of a portion of information: \( t^j_i \leq t^k_i \).

In this process of training the number of measurements \( s^* \) is set on the basis of the calculated dimension of a strange attractor. It is considered that studying of a portion of information in timepoint \( t^j_i, j = 1,2,\ldots \) on \( k \) a stage he acquires all volume of information and, therefore, the probability of ignorance is equal to zero.

\[
p^k_i \left( t^k_i \right) = 0. \tag{3}
\]

The probability of ignorance \( P^k_i \) in timepoint \( t^k_i, j = 1,2,\ldots \) a stage is defined on \( k \) on the basis of exponential dependence [7-9].

\[
P^k_i = \left( p^k_i, p^k_2, \ldots, p^k_m \right), \tag{4}
\]

where

\[
p^k_i = 1 - \exp\left[ -\alpha^k_i t^k_i \right], \quad i = 1,2,\ldots,m_i, \quad k = 1,2,\ldots,N, \tag{5}
\]

where

\[
t^{k+1}_i = \begin{cases} 
\Delta t_i, & i \in u_k; \\
\Delta t_i + \Delta t_i, & i \notin u_k, 
\end{cases} \tag{6}
\]

Considering the fact that over time information obtained by the trainee is forgotten over time, this process is formalized by the expression given below:

\[
\alpha^k_i = \begin{cases} 
\alpha^k_i, & i \notin \bigcup_{j=1}^k u_j; \\
\gamma_1 \alpha^k_i, r^k_i = 0 & i \in \bigcup_{j=1}^k u_j; \\
\gamma_2 \alpha^k_i, r^k_i = 1 & i \in \bigcup_{j=1}^k u_j,
\end{cases} \tag{7}
\]

where \( \alpha^k, \gamma_1, \gamma_2 \) – individual characteristics of a condition of the trainee or parameters of adaptation, \( r^k_i \) – the reaction of \( k \) of a portion of information trained for influence defined according to a ratio (8) in the form of answers to control questions (testings):

\[
r^k_i = \begin{cases} 
0, & \text{if the trainee has given the correct answer;} \\
1, & \text{otherwise.} 
\end{cases} \tag{8}
\]

Definition of reaction of the trainee, on every portion of information and also definition of individual characteristics will allow to improve all indicators on each trainee.

2. Theoretical part

Being based on above the given reasonings, the level of ignorance of a portion of information is defined by expression:

\[
Q^k_j = \sum_{i=1}^{m_i} p^k_i q_i, \tag{9}
\]
and

\[
\alpha^{i+1}_j = \begin{cases} 
\gamma_i \alpha^i_j, r^i_j = 0; \\
\gamma_i \alpha^i_j, r^i_j = 1, i = 1, 2, \ldots, l.
\end{cases}
\]  

(10)

\[
t^{i+1}_j = \Delta t_j.
\]

(11)

Naturally function of quality of training needs to be defined as average value of levels of ignorance on \(k\) a training session.

\[
Q = \frac{1}{l} \sum_{i=1}^{l} Q^k_i.
\]

(12)

In actual practice considering that individual abilities of each trainee aren't identical delivery of the portions of the training information (PTI), it can't be acquired by each trainee completely. In this regard an important role in the course of training will play the number of measurements of level of ignorance \(Q_j\), information on which defines a condition of an object of management.

Considering that in our case process of training begins after giving of the first PTI, the vector of external influences of \(S\) is identical \(u_i\). The control algorithm of training with the predicted number of control checks of the trainee defines what operating influence (a portion of information) needs to be created for the trainee.

We will in more detail consider a control algorithm of training with the predicted number of control checks of the trainee:

1. With use of testing the examination of the trainee of a portion of the training information \(u_i\) as a result of which the set \(R_i = \{r^k_1, r^k_2, \ldots, r^k_n\}\) where are defined by a ratio \(r^k_i\) (8) is formed is carried out.

2. Using expressions in formulas (7), (10) adaptation of parameters of an object of management is made.

3. Based on a formula (5) with attraction of expressions (6)-(7), (10)-(11) the vector of probabilities of ignorance of EDI is calculated \(P_i\).

4. Using formulas (11-12) values \(Q^k_i\) and function of quality of training of \(Q\) are defined.

5. Process of \(k\) of a grade level comes to an end if the criterion of quality of training \(Q \leq \sigma\) is carried out. Further to the trainee moves following PTI \(u_{i+1}\) according to points 1-5 of an algorithm.

If the criterion of quality of training, then is not executed if \(j < s^*\) (\(s^*\) – assessment of quantity of variables of function of quality received on the basis of a method of computation of correlative dimensionality on time series of observations) PTI \(u_i\) again are given to the trainee for a study according to points 1-5 of an algorithm.

Training achievement of the goal reflects a condition of an object with use of a control algorithm of training more precisely with the predicted number of control checks of the trainee which basis temporary ranks are doesn't use model of change of a condition of an object of management which because of variety and accident of factors can reflect a real condition of an object not absolutely precisely. Therefore, more exact assessment \(s^*\), allows to adapt more effectively the synthesized system on the properties to optimum system.

We will consider in more detail process of management of training with the predicted number of control checks of the trainee [6, 9, 14]. When receiving PTI \(r^k_i\) the trainee, his knowledge will be characterized by some random variable \(\lambda^k_i \in [0, 1]\) having the following distribution:

\[
P(\lambda^k_i = 1) = p^i_k;
\]

(13)
\[ P(\lambda_k = 0) = 1 - p_i^k, \quad i = 1, 2, \ldots, m_k. \] (14)

Considering expression (5) it is possible to tell that the vector \( P_k \) unambiguously is defined by vectors:

\[ \alpha^k = (\alpha^k_1, \alpha^k_2, \ldots, \alpha^k_m); \] (15)

\[ t^k = (t^k_1, t^k_2, \ldots, t^k_m). \] (16)

Therefore, in \( 2m_k \) – measured Euclidean space vector function \( f : R^{2m_k} \to R^m \), such is defined that

\[ P_k = f(\alpha^k, t^k). \] (17)

Based on (11) function determining the level of ignorance it is presented in the form of a scalar product: \( Q_j = (P_k, q) \) where \( q = (q_1, q_2, \ldots, q_m) \in R^m \), is a coordinate vector which are defined prior to training.

Proceeding from above stated, in \( 2m_k \) – measured Euclidean space vector function, such is defined \( h : R^{2m_k} \to R^l \) that

\[ Q_j = (f(\alpha^k, t^k), q) = h(\alpha^k, t^k). \] (18)

Based on the analysis of expressions (15)-(18) we draw a conclusion that in timepoint \( t^k_j \) process of management of training can be described two casual \( m_k \) – measured vectors \( \alpha^k \) and \( t^k \).

3. Practical part. Obtaining experimental values of individual characteristics

Ratios (17)-(18) with use \( \zeta_k = (\alpha^k, t^k) \) it is possible to write down in a look:

\[ P_k = f(\zeta_k) \]

\[ Q_j = h(\zeta_k). \] (19)

For a further research of management of training we will consider a vector \( \chi_k = (\chi^k_1, \chi^k_2, \ldots, \chi^k_m) \) with components:

\[ \chi^k_i = \begin{cases} 1, & i \in k \cup u_j; \\ 0, & i \notin k \cup u_j. \end{cases} \] (20)

We will assume that \( \omega = ( (\alpha^1, t^1), (\alpha^2, t^2), \ldots, (\alpha^m, t^m) ) \) – a training trajectory for the specific pupil from \( \Omega \) – a set of all possible trajectories of century \( R^{2m} \). Considering (7) we receive that random variables \( \alpha^{k+1}_i \) have conditional distribution of probabilities:

\[ P\left( \alpha^{k+1}_i = \alpha^k_i \left| \alpha^k_i, t^k_i \right. \right) = 1 - \chi^k_i; \]

\[ P\left( \alpha^{k+1}_i = \gamma_i \alpha^k_i \left| \alpha^k_i, t^k_i \right. \right) = (1 - p^k_i) \chi^k_i; \] (21)

\[ P\left( \alpha^{k+1}_i = \gamma_i \alpha^k_i \left| \alpha^k_i, t^k_i \right. \right) = p^k_i \chi^k_i, \quad i = 1, 2, \ldots, m. \]
Expression (19) shows that on \((k+1)\) – the \(m\) a training session \(\alpha^{k+1}\) completely is defined by a vector 
\(\zeta_k = (\alpha^k, t^k)\) and doesn't depend on number of a session \(k\). To define a vector we will consider that the period between sessions is constant and equal \(\Delta t\). Therefore, expression (6) will take a form:

\[
t^{k+1}_i = \begin{cases} 
\Delta t, & i \in u_k \\
\Delta t + \Delta t, & i \notin u_k
\end{cases}
\]

\(i = 1, 2, \ldots, m.\) (22)

And expression (22) will take a form:

\[
t^{k+1}_i = \Delta t + (1 - \chi^i)^2 t^i - z(i, t^i).
\] (23)

Therefore, and on \((k+1)\) – the \(m\) a step, and on \(k\)-m a step, \(\zeta_{k+1}\) is defined \(\zeta_k\), \(P_{k+1}\) and \(Q^{k+1} = \frac{1}{l} \sum_{j=1}^{l} Q^{k+1}_j\) it means, as is defined by realization \(\zeta_k\) and doesn't depend on \(k\). It allows to draw the following conclusion. The probability of any state on \(k\)-m a step depends on a state previous, but doesn't depend on a way of transition from a state to a state. We will define conditional population means of parameters and functions of process of training \(\zeta_k = (\alpha^k, t^k)\) at \(k\) a step of functions \(P_i\) and \(Q^k\).

Using expressions (14) and (23) we will receive:

\[
M (\alpha^{k+1} | \zeta_k) = \alpha^t (1 - \chi^i)^2 + \gamma, \alpha^t (1 - p^i)^2 \chi^i + \gamma, \alpha^t p^i \chi^i = \alpha^t (1 - \chi^i (1 - \gamma_i) - \chi^i (\gamma_1 - \gamma_2) p^i) .
\] (24)

Considering that under a condition \(\zeta_k\) time \(t^{k+1}\) is the determined size, we will receive:

\[
M (\alpha^{k+1} t^{k+1} | \zeta_k) = \Delta t (\alpha^t (1 - \chi^i (1 - \gamma_i) - \chi^i (\gamma_1 - \gamma_2) p^i) + (1 - \chi^i) \alpha^t t^i).
\] (25)

Considering (5) and (7) we will receive

\[
M (p^t | \zeta_k) = M \left( 1 - \exp \left[ -\alpha^t t^{k+1} \right] \right) = 1 - \left( 1 - p^i \right) \exp \left[ -t^{k+1} \left( \alpha^t + \chi^i \gamma_i \right) \right] - p^i \exp \left[ -t^{k+1} \left( \alpha^t (1 - \chi^i) + \chi^i \gamma_i \right) \right].
\] (26)

Considering (19) and (26), we receive

\[
M(Q^t | \zeta_k) = \sum_{l=1}^{m} q, M (p_l^{k+1} | \zeta_k) = \sum_{i=1}^{l} q, - \sum_{i=1}^{m} q, \left[ (1 - p^i) \exp \left[ -t^{k+1} \left( \alpha^t + \chi^i \gamma_i \right) \right] - p^i \exp \left[ -t^{k+1} \left( \alpha^t (1 - \chi^i) + \chi^i \gamma_i \right) \right] \right],
\] (27)

where \(t^{k+1}\) is determined by a formula (25).

We define (27) for \(\chi^i = 0\) and \(\chi^i = 1\):

\[
M(Q^{k+1} | \zeta_k) = \sum_{l=1}^{m} q, M (p_l^{k+1} | \zeta_k) = 1 - \sum_{l \notin a_k} q, \exp \left[ -\Delta t \alpha^t \gamma_1 \right] + \sum_{l \notin a_k} q, \exp \left[ -\Delta t \alpha^t \gamma_2 \right] - \sum_{l \notin a_k} q, \exp \left[ -\Delta t + t^i \right] \alpha^t \gamma_1.
\] (28)
Considering (26) and (28) we find conditional population mean for function of quality of process of training

\[
M(Q^{k+1}|\zeta_k) = \frac{1}{l} \sum_{j=1}^{l} M(Q^{k+1}|\zeta_k) = 1 - \frac{1}{l} \sum_{i \in i_k} q_i \exp[-\Delta t \alpha_i | \gamma_1 ]
\]

\[
+ \sum_{i \in i_k} q_i p_i \left( \exp[-\Delta t \alpha_i | \gamma_1 ] - \exp[-\Delta t \alpha_i | \gamma_2 ] \right) - \sum_{i \in i_k} q_i \exp[-(\Delta t + t') \alpha_i | \gamma_1 ].
\]

(29)

For determination of necessary level of proficiency, we will use function which defines number of the sessions of training necessary for achievement of level \( Q \leq \sigma \), depending from: \( m \) – volume of all information; \( m_k \) – volumes of portions of information; \( \Delta t_k \) – durations of intervals between training sessions; \( s' \) – number of measurements of a state; \( Q \) – ignorance level; \( \sigma \) – ignorance borders.

This function has the appearance given in expression (30).

\[
n(\omega) = F(m, \{m_k\}_{k=1,2,...,N}, \{\Delta t_k\}_{k=1,2,...,N}, s', \sigma, (Q^k(\omega))_{k=1,2,...,N}).
\]

(30)

For definition of a type of function we will make the following assumptions:

1. On each session of training the identical quantity is given EDI \( m_k = \frac{m}{N} = m \).
2. Time between sessions of training we are constant \( \Delta t_k = \Delta t \).
3. The number of measurements of \( s \) for every portion of information is constant.
4. Initial speeds of a forgetting are identical to all EDI.

Taking into account above stated (20) we will transform in a look:

\[
\alpha_i^{k+1} = \gamma_i^k \alpha_i^k \chi_i^k + \alpha_i^k \left( 1 - \chi_i^k \right),
\]

(31)

where

\[
\gamma_i^k = \begin{cases}
\gamma_1, & \chi_i^k = 1 \text{ and } t_i^k = 0; \\
\gamma_2, & \chi_i^k = 1 \text{ and } t_i^k = 1.
\end{cases}
\]

(32)

Considering (32) and (22), we will receive expression for ignorance level:

\[
Q^{k+1} = \frac{1}{s} \sum_{j=1}^{s} \sum_{i=m}^{m-1} q_i \left( 1 - \exp\left[ -\left( \gamma_i' \alpha_i' \Delta t \chi_i' + \alpha_i' \left( \Delta t + t_i' \right) \left( 1 - \chi_i' \right) \right) \right].
\]

(33)

Considering the assumption, and the number of repetitions, considering certain, one session of training contains \( s \) of cycles of training.

Therefore, PTI are described by vectors:

\[
\chi^0 = \left( \begin{array}{c}
1, \ldots, 1, 0, \ldots, 0 \\
\end{array} \right), \quad \chi^1 = \left( \begin{array}{c}
1, \ldots, 1, 1, \ldots, 0, \ldots, 0 \\
\end{array} \right), \ldots,
\]

\[
\chi^{s-1} = \left( \begin{array}{c}
1, \ldots, 1, 0, \ldots, 0 \\
\end{array} \right), \ldots, \quad \chi^N = \left( \begin{array}{c}
1, \ldots, 1, 1, \ldots, 1 \\
\end{array} \right).
\]

(34)
Considering that on each session of $m$ EDI $s$ of times are given, and $0 < \gamma_1 \leq \gamma_i' \leq \gamma_2 < 1$, and $(\gamma_i', \alpha, \ldots, \gamma_i', \alpha) \leq \alpha' \leq (\gamma_2', \alpha, \ldots, \gamma_2', \alpha)$ through $N$ sessions all elements will be given $r < Ns$ time, therefore

$$\alpha'' \leq \left( (\gamma_2')', \alpha, \ldots, (\gamma_1')', \alpha \right); \quad \alpha'' \geq \left( (\gamma_1')', \alpha, \ldots, (\gamma_1')', \alpha \right).$$

(35)

Transforming (34) taking into account (33) and (35), we receive assessment $Q^{s'}$:

$$\frac{1}{s} \sum_{j=1}^{im} q_j \left( 1 - \exp \left[ - (\gamma_1')', \alpha N \Delta t \right] \right) \leq Q^{s'} \leq \frac{1}{s} \sum_{j=1}^{im} q_j \left( 1 - \exp \left[ - (\gamma_2')', \alpha N \Delta t \right] \right).$$

(36)

as $\frac{1}{s} \sum_{j=1}^{im} q_j = 1$, that

$$Q^{s'} \leq \left( 1 - \exp \left[ - (\gamma_2')', \alpha N \Delta t \right] \right) m, \; r = 1, 2, \ldots$$

(37)

Using expression $Q \leq \sigma$, we will receive the maximum number of issue of information to a portion necessary for achievement of level $\sigma$:

$$r_{max} \leq \frac{- \ln \left( \frac{m - \sigma}{m} \right)}{- \ln \left( \frac{\alpha N \Delta t}{\gamma_2} \right)}.$$  

(38)

Therefore, duration of training $n = Nr$ is estimated by expression:

$$n = \left[ \frac{- \ln \left( \frac{m - \sigma}{m} \right)}{- \ln \left( \frac{\alpha N \Delta t}{\gamma_2} \right)} \right] + 1.$$  

(39)

Above stated allows to define process of formation of the predicted training parameters.
1. Determination of probability of ignorance of $i$ EDI a session is defined on $k$ as follows:

$$p_i^k = 1 - \exp \left[ - \alpha_i^k t_i^k \right], \; i = 1, 2, \ldots, m, \; k = 1, 2, \ldots, N.$$  

(40)

2. Definitions of all $q_i$ by the teacher of material prior to training as importance of $i$ of a concept.
3. Calculate

$$Q_k = \sum_{i=1}^{m} p_i^k q_i.$$  

(41)

4. Definition of a threshold of quality of training:
4. Threshold task $\sigma$ and definition $S^*$. 
5. We set the sequence of experimental values: $T(t): T_j = T(t_j)$. 
6. We define also $Q_j$, $j > 0$ and calculate predictability interval size $L$.

Process of formation of the predicted parameters of training allows to evaluate on top training duration provided that portions of training and time slots identical among themselves. Results of experiments are given in table 1. As a result of experiments for each trainee personal characteristics i.e. fractal dimensionalities of assessment of quantity of the variables of function of quality necessary for execution of criterion of quality of training were defined and also the number of repeated passing of a portion of information was defined and comparing with predicted [5, 7, 15] was carried out. In table 1 are compared the duration of training received experimentally and predicted.

**Table 1.** The results of training received experimentally.

| $m_k$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ |
|-------|-------|-----|-----------|-------|-----|-----------|-------|-----|
| 5     | 1     | 2   | 0.18      | 1     | 2   | 0.23      | 2     | 3   | 0.31 |
| 10    | 1     | 2   | 0.2     | 2     | 3   | 0.31      | 3     | 4   | 0.38 |
| 15    | 1     | 2   | 0.23    | 2     | 3   | 0.34      | 3     | 4   | 0.39 |
| 20    | 2     | 3   | 0.28    | 3     | 4   | 0.38      | 3     | 4   | 0.4  |

**Table 2.** The predicted values of duration of training also are compared to the values received on the basis of expression (31) and (32).

| $m_k$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ |
|-------|-------|-----|-----------|-------|-----|-----------|-------|-----|
| 5     | 1     | 2   | 0.16      | 2     | 3   | 0.22      | 3     | 4   | 0.28 |
| 10    | 2     | 2   | 0.21     | 3     | 4   | 0.27      | 4     | 5   | 0.3  |
| 15    | 2     | 3   | 0.23    | 3     | 4   | 0.29      | 3     | 4   | 0.29 |
| 20    | 3     | 3   | 0.27    | 4     | 4   | 0.3       | 4     | 5   | 0.3  |

| $m_k$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ | $n_{rep}$ | $s^*$ | $Q$ |
|-------|-------|-----|-----------|-------|-----|-----------|-------|-----|
| 5     | 2     | 2   | 0.17      | 3     | 3   | 0.24      | 3     | 5   | 0.28 |
| 10    | 2     | 3   | 0.26     | 3     | 4   | 0.26      | 5     | 5   | 0.3  |
| 15    | 2     | 3   | 0.28    | 3     | 4   | 0.28      | 5     | 5   | 0.3  |
| 20    | 3     | 4   | 0.28    | 4     | 4   | 0.29      | 5     | 5   | 0.3  |

On the basis of values of table 1, values of table 2 are defined.

In table 2 the predicted values of duration of training also are compared to the values received on the basis of expression (31) and (32).

In table 2 the following designations are used: $n_{ex}$ – the average duration of training received experimentally; $n$ – the training duration received when using a formula (41).
\[ \frac{n}{n_{ex}} \] shows in how many times assessment of duration of training is worse than the average duration of training of the studied process.

Table 2. Results of comparison of average duration of training and her assessment for different values of parameters \( \gamma_1 \) and \( \gamma_2 \).

| \( N = 6, \sigma = 0.4, \Delta t = 1 \) | \( \gamma_1 = 0.19, \gamma_2 = 0.28 \) | \( \gamma_1 = 0.3, \gamma_2 = 0.49 \) | \( \gamma_1 = 0.51, \gamma_2 = 0.68 \) |
|---|---|---|---|
| \( m_k \) | \( n_{ex} \) | \( n \) | \( n \) | \( n \) | \( n_{ex} \) | \( n \) | \( n \) | \( n_{ex} \) |
| 5 | 14 | 20 | 1.43 | 14 | 34 | 2.43 | 14 | 66 | 4.71 |
| 10 | 14 | 22 | 1.57 | 14 | 40 | 2.86 | 14 | 77 | 5.5 |
| 15 | 14 | 23 | 1.64 | 14 | 42 | 3 | 14 | 80 | 5.71 |
| 20 | 20 | 25 | 1.25 | 20 | 44 | 2.2 | 20 | 84 | 4.2 |

| \( N = 10, \sigma = 0.3, \Delta t = 1 \) | \( \gamma_1 = 0.19, \gamma_2 = 0.28 \) | \( \gamma_1 = 0.3, \gamma_2 = 0.49 \) | \( \gamma_1 = 0.51, \gamma_2 = 0.68 \) |
|---|---|---|---|
| \( m_k \) | \( n_{ex} \) | \( n \) | \( n \) | \( n \) | \( n_{ex} \) | \( n \) | \( n \) | \( n_{ex} \) |
| 5 | 20 | 37 | 1.85 | 30 | 69 | 2.3 | 40 | 130 | 3.25 |
| 10 | 20 | 43 | 2.15 | 40 | 92 | 2.3 | 50 | 149 | 2.98 |
| 15 | 20 | 45 | 2.25 | 40 | 94 | 2.35 | 50 | 152 | 3.04 |
| 20 | 30 | 46 | 1.53 | 40 | 110 | 2.75 | 50 | 160 | 3.2 |

| \( N = 20, \sigma = 0.3, \Delta t = 1 \) | \( \gamma_1 = 0.19, \gamma_2 = 0.28 \) | \( \gamma_1 = 0.3, \gamma_2 = 0.49 \) | \( \gamma_1 = 0.51, \gamma_2 = 0.68 \) |
|---|---|---|---|
| \( m_k \) | \( n_{ex} \) | \( n \) | \( n \) | \( n \) | \( n_{ex} \) | \( n \) | \( n \) | \( n_{ex} \) |
| 5 | 40 | 88 | 2.2 | 60 | 160 | 2.67 | 60 | 298 | 4.97 |
| 10 | 60 | 99 | 1.65 | 60 | 179 | 2.99 | 100 | 326 | 3.26 |
| 15 | 60 | 103 | 1.72 | 60 | 186 | 3.1 | 100 | 338 | 3.38 |
| 20 | 60 | 106 | 1.78 | 80 | 191 | 2.39 | 100 | 356 | 3.56 |

We will consider in more detail dependence \[ \frac{n}{n_{ex}} \] which depends on EDI \( m \) number at various values \( \gamma_1 \) and \( \gamma_2 \). We will make approximation \[ \frac{n}{n_{ex}} = f(m) \] of expression function:

\[ \frac{n}{n_{ex}} = f(m) = a \ln m, \quad m > 1, \]  

(43)

where \( a \) – parameter.

At approximation we will use a method of the smallest squares. We will make assessment for various values \( \gamma_1 \) and \( \gamma_2 \). Therefore, considering expression (40) and (41), we will receive assessment of average duration of process of training in a look:
\[
N \left( \ln \left( \frac{m - \sigma}{m} \right) - \frac{m}{a \Delta t N} \right) + 1 \left( \frac{1}{a \ln m} \right) \]

(44)

In spite of the fact that the received assessment is approximate it is possible to use for forecasting of number of sessions of training for which the trainee with his individual parameters \( \gamma_1, \gamma_2, \) and \( \alpha \) at set \( N, \Delta t, m \) will reach proficiency level \( \sigma \). It is necessary to emphasize the fact that it is possible to solve also the return problem i.e. at the set number of sessions of training \( N_{\text{max}} \) it is possible to define quantities of EDI from \( m \) necessary trained at each session of training to reach level \( \sigma \) not later \( N_{\text{max}} \).

4. Conclusion

Development process of program and information components not only defines all necessary components when forming a program complex, but also sets the necessary sequence of actions (fig. 1-3).

The sequence of creation has the following appearance:
- a choice of work benches as by development of both components work benches superimpose the requirements of process of their creation;
- creation of the DB physical model;
- creation of software modules.

The control of social systems described above meets certain difficulties on the translation of these difficult systems from start state in finite, a status according to a main goal of control because of impossibility of the formalized determination of initial conditions of such system [2, 13].

To monitor computation process and dynamics of change of figures of merit of assimilation of discipline, information systems allow, it is information – computer systems and databases which save information on each trainee throughout the entire period of training [1, 16-19].

The developed program complex on the basis of the values of personal parameters received as a result of experiments on each trainee allows to calculate personal characteristics, to create rating and to monitor process of change of parameters.
Figure 3. An example of the text file with total values.

In the developed information complex, perhaps to store, process results of researches, to look through total parameters and to form the rating of students [3, 18].

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