Information Technologies and Neural Network Means for Building the Complex Goal Program "Improving the Management of Intellectual Capital"

Anzhelika Azarova(✉)

Vinnytsia National Technical University, Vinnytsia, Ukraine

Abstract. The article proposes a conceptual approach for finding partial coefficients of influence of alternatives in a complex goal program represented by a linear hierarchy of goals which is considered as a neural network. This becomes possible thanks to the fact that both in the decision tree and in this neural network there are no feedback and single-level connections, as well as threshold sub-goals. As an illustration of this approach, a simplified complex goal program of "Improving the management of intellectual capital of an enterprise" is proposed. To obtain the potential efficiencies of projects in such a CGP the author initially used the DSS "Solon-2". At the same time, in order to fully automate the proposed process of developing the CGP and its optimization, the author has developed an individual software. The conceptual approach proposed by the author has significant advantages over existing alternative methods. It allows automatically obtaining of the optimal weights of PCI, easily aggregating dynamic changing expert data. The proposed CGP has a great practical interest, since it helps you to optimize the process of managing the intellectual capital of an enterprise, firm or organization. It allows significantly increasing of the profitability of enterprise by obtaining multiple effects such as increasing the productivity of personnel etc.

Keywords: Decision support system - DSS · Alternative · Project · Goal · Sub-goal · Over-goal · Main goal · Complex goal program - CGP · Partial coefficients of influence · Potential efficiency of project

1 Introduction and Literature Review

Modern decision support systems are able to solve quite complex problems of human activity management in various fields in particular they are used to make complex management decisions in technique [5], economics [4,6,7], politics, sociology, medicine etc.

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One of the dominant problems of this level according to the author of the article is the assessment of intellectual capital of the enterprise, firm or organization.

The complexity and versatility of the tasks that need to be considered for effective management of intellectual capital, the need to take into account a large number of different impact parameters, a big set of expert information that needs to be processed, all these factors encourage to use the decision support system (DSS) which is a powerful computerized tool. DSS allows with using of a hierarchical approach and a method of goal evaluation of alternatives to solve such complex problem. It should belong to the DSS of the second class [23] which includes systems of individual use, the knowledge bases of which are formed directly by the user. They are intended for use by middle-ranking civil servants, as well as managers of small and medium-sized firms to support making decision in situations where a given set of variants need to select a subset of variants that are (according to expert evaluation) the best from them. Each expert evaluates only part of the variants for the full set of criteria. The ranking of criteria is done in DSS taking into account the total amount of funding and costs of each project.

Thus the most productive application of DSS of this class according to the author of the article is the automation of intellectual capital management processes of the firm, enterprise by building an appropriate complex goal program (CGP).

A complex goal program is a set of activities - projects that are united by a single global goal - the main goal and common limited resources for their implementation.

There are a lot of automation techniques of intellectual capital management processes in any branch of human activity [1–3, 8–11, 15, 17, 18]. Almost in each of them is affirmed that information technology contributes significantly to the management of intellectual capital. However, there are no clear mechanisms to manage the process of improving the use of intellectual capital through information technology. That's why the author proposes a new technique of improving the management of intellectual capital through the information technology by using a hierarchical approach for building the appropriate automated CGP.

The dominant **unsolved part of the problem** of making decision using a hierarchical approach is the search for all alternatives – sub-goals, projects (offered in the CGP) - partial coefficients of influence (PCI) on the main goal (or their over-goals or sub-goals). Totsenko V. G. performs a thorough analysis and description of existing approaches to the evaluation of alternatives, i.e. the determining of their PCI [23]. Among the most important of them are:

– statistical approach of determining the aggregate estimate of the alternative based on the presentation of estimates of the alternative given by various experts as the implementation of some random variable and on the application of methods of mathematical statistics [23]. The disadvantage of this approach is not proving validity of the application of the normal distribution law for the realization of a certain random variable. It's possible only in case of using

the same type of technical devices operating in the same conditions, rather than experts the difference in assessments of which is due to a number of psychophysiological factors such as level of knowledge, experience, intuition, health, mood etc. In addition the question arises as to what the threshold value of the degree of consistency of different expert assessments should be in order for the application of this method to be correct;
- the method of direct evaluation. By this method for each alternative have to be determined a number which is an expert assessment of the degree of presence in the alternative of a certain property which is determined by the relevant criterion. It is clear that this approach is quite subjective, inaccurate and cumbersome in case of large hierarchical structures of the CGP which contain hundreds of alternatives;
- group of methods of pairwise comparisons of alternatives [20,21] is widely used to determine the relative indicators of the alternatives significance under the condition of insignificant differences of the compared alternatives in relation to the chosen qualitative comparison criterion;
- method of goal evaluation of alternatives [19,22]. It presupposes the use of different methods for the assessment of PCI of each individual alternative - sub-goal. However the links between the projects and over-goals, their sub-goals and partial coefficients of influence corresponding to them may be too many in case of the complexity of the problem or in case of the large number of levels of hierarchy. These factors significantly complicate the search process.

Thus, to obtain estimates of the influence of projects on goals, their over-goals (or main goal), the author proposes to consider them in complex as a neural network [12–14,16] which is analogous to the decision tree due to the lack of feedback and one-level relationships, as well as threshold sub-goals (only the full implementation of such sub-goal affects the achievement of the main goal). Such a network is a linear hierarchy of the corresponding complex goal program. This allows you to automatically evaluate the optimal PCI of each alternative by neural network.

Thus, the **aim of this article** is to develop a method for finding optimal PCI in CGP represented by linear hierarchies of goals through the using of modern information technologies including DSS "Solon-2" and neural network tools [23] that enable the process of optimizing such PCI according to the approach proposed by the author of the article below.

2 Materials and Methods

Formal Problem Statement. Let there is a complex problem which have to be solved, in particular, it can be the problem of improving the management of intellectual capital of the enterprise, firm or organization. Since it is complex and poorly structured the author thinks that it is natural to solve it using a decomposition approach, in particular, a complex task - main goal (g_0) - divide into a sequence of more simple tasks - sub-goals and finally into projects (lowest-level sub-goals) - simplest tasks.

The author proposes to apply a hierarchical goal approach which is described in detail by V. G. Totsenko [23] to build the hierarchy of goals in such a CGP. It necessitates the application of expert knowledge which allows to achieve the main goal of g_0, in particular, to improve the management of intellectual capital of the enterprise, firm.

Thus:

1. Define a simplified linear hierarchy which represents a complex goal program "Improving of intellectual capital management" which has at the first level 3 sub-goals: g_{21} - "Improving human capital management", g_{22} - "Improving consumer capital management" and g_{23} - "Improving organizational capital management". At the lower level such a linear hierarchy is described by S projects x_s, $s = \overline{1, S}$, $S = 4$. CGP has an unknown required vector $\mathbf{W}^0$ of partial coefficients of influence of sub-goals and projects on their over-goals which are always non-negative ($PCI \geq 0$) as shown in Fig. 1.

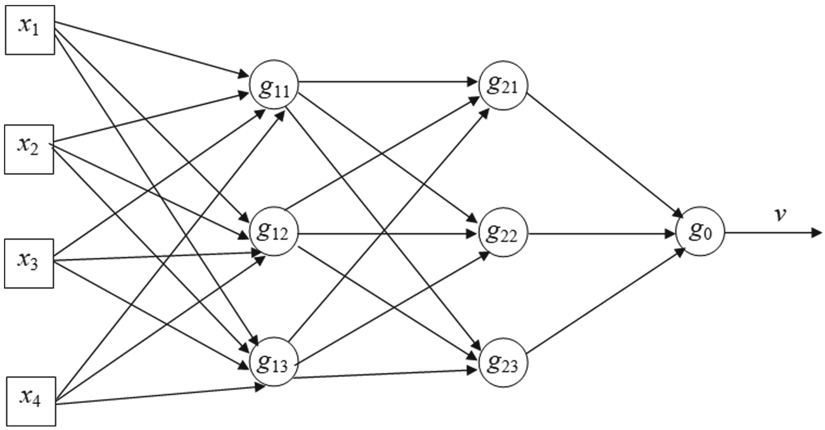

Fig. 1. The example of simplified hierarchy of CGP "Improving of intellectual capital management" with S, ($S = 4$) projects x_s, and unknown CPI vector $\mathbf{W}^0$

2. To search for the unknown vector $\mathbf{W}^0$ we first set the vector $\mathbf{V}^0$ of the indicators of potential efficiency of projects and check the concordance of the obtained estimates using the variance concordance coefficient. After checking the expert assessments for concordance we will use them expected values. As a result we obtain the potential effectiveness of the projects is

$$v_1^0 = 0,253; v_2^0 = 0,26; v_3^0 = 0,387; v_4^0 = 0,047. \tag{1}$$

3. For the hierarchy shown in Fig. 1 we generate an arbitrary (randomly obtained) PCI vector $\mathbf{W}^1$ as shown in Fig. 2 which satisfies the limitation (2)

$$\sum_{C=1}^{f} w_{l_C}^1 = 1, \tag{2}$$

where f - the number of sub-goals of the l-th goal.

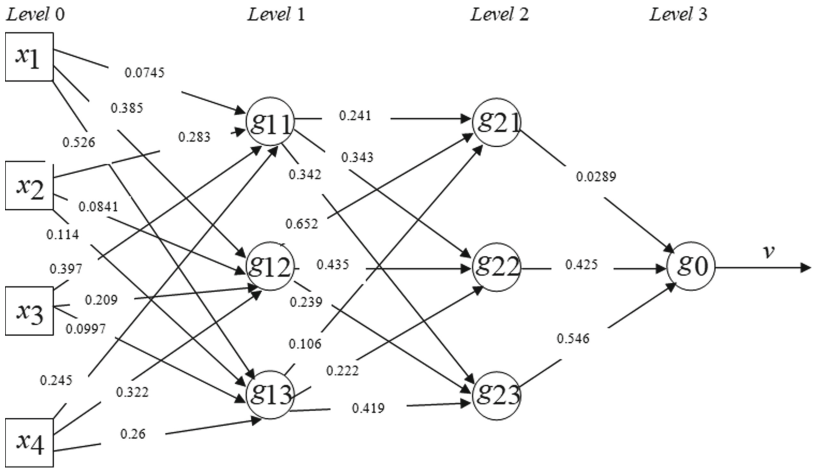

Fig. 2. Example of a linear hierarchy with S, $(S = 4)$ projects x_s, and arbitrary vector PCI $\mathbf{W}^1$

4. Calculate the vector $\mathbf{V}^1$ of indicators of projects potential effectiveness of the hierarchy with an arbitrary vector PCI $\mathbf{W}^1$ using the software DSS "Solon-2":

$$\begin{aligned} v_1^1 &= d^1_{(1,1,1,1)} - d^1_{(0,1,1,1)} = 1 - 0,674 = 0,326, \\ v_2^1 &= d^1_{(1,1,1,1)} - d^1_{(1,0,1,1)} = 1 - 0,838 = 0,162, \\ v_3^1 &= d^1_{(1,1,1,1)} - d^1_{(1,1,0,1)} = 1 - 0,762 = 0,238, \\ v_4^1 &= d^1_{(1,1,1,1)} - d^1_{(1,1,1,0)} = 1 - 0,807 = 0,193. \end{aligned} \quad (3)$$

5. Empirically the author of the article proved that the search for unknown values of PCI $\mathbf{W}^0$ only under given limitation (1) and limitation (2) leads to a set of optimal solutions. This caused to the adding of another criterion in this case which allows you to choose the best among those obtained with using of limitation (1) and limitation (2). As such an additional criterion the author of the article proposes a number of additional limitations.

As additional limitation we choose only those equations that describe the sum of the PCI links that connect the s-th project with the main goal g_0 in such directions which overlap all the links between the layers at least once. In this case we will choose the limiting equations based on two criteria - completeness and minimality: on the one hand, they should be taken so that they overlap all the links presented in the hierarchy at least once, on the other hand, the number of reselections of the same links should be minimal. Otherwise their excessive volume will increase the number of calculations and significantly complicate the work of expert evaluation.

In generally, there is an interest only in problems which solved with the help of hierarchies contained no more than 7 ± 2 layers, because in case of larger number of layers the complexity of the problem is extremely high for expert evaluation. It is confirmed by the theory set out in 1944 by G. Miller [16]. In the case of the number of layers greater than 9 it is advisable to aggregate the sub-goals and thus transform the hierarchy to this dimension.

For our case we select the following layers which is shown in Fig. 2: projects x_1, x_2, x_3, x_4 are located in the 0-th layer; sub-goals g_{11}, g_{12}, g_{13} will form a layer 1, etc.

Layer numbering allows you to enter a single notation for each PCI in the entire PCI hierarchy – w_{ij}^n where n - the number of the previous layer, i - the number of the sub-goal (project) in the previous layer, j - the number of the sub-goal in the current layer which is shown in Fig. 3.

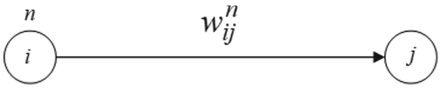

Fig. 3. Notation for each PCI links which unite sub-goal of i-th and j-th layers of goal hierarchy

Thus, on the basis of expert assessments for the hierarchy shown in Fig. 2 it is possible to formulate such a system (4) of additional limitations on the search for the optimal PCI vector $\mathbf{W}^0$:

$$\begin{cases} w_{11}^0 + w_{11}^1 + w_{11}^2 = 1.3; \\ w_{12}^0 + w_{22}^1 + w_{21}^2 = 0.8; \\ w_{13}^0 + w_{33}^1 + w_{31}^2 = 0.7; \\ w_{21}^0 + w_{12}^1 + w_{21}^2 = 1.0; \\ w_{22}^0 + w_{21}^1 + w_{11}^2 = 1.4; \\ w_{23}^0 + w_{31}^1 + w_{11}^2 = 0.9; \\ w_{31}^0 + w_{13}^1 + w_{31}^2 = 1.2; \\ w_{32}^0 + w_{22}^1 + w_{21}^2 = 0.8; \\ w_{33}^0 + w_{31}^1 + w_{11}^2 = 1.0; \\ w_{41}^0 + w_{13}^1 + w_{31}^2 = 0.8; \\ w_{42}^0 + w_{23}^1 + w_{31}^2 = 0.5; \\ w_{43}^0 + w_{32}^1 + w_{21}^2 = 0.5. \end{cases} \quad (4)$$

So, let's make the final statement of the problem in such form.
Given:

1. Linear hierarchy with S projects (see Fig. 1) represented by a neural network.
2. The vector $\mathbf{V}^0$ of potential efficiency indicators (1) given by experts which are considered as a training sample for the neural network which represents a hierarchy of goals. The training sample is a set of pairs of input indicators (mask $[1, \ldots, x_s = 0, \ldots 1]$ the presence of the influence of the s-th project on the achievement of the main goal g_0) and the corresponding output indicators v_s^0 of potential project effectiveness.

3. The system of additional limitations on PCI defined by an expert is presented in form of relations (4).
4. An arbitrary PCI vector $\mathbf{W}^1$ which satisfy limitation (2) is generated (see Fig. 2).

It is necessary: to find the optimal vector of PCI $\mathbf{W}^0$ which provides the optimization function:

$$\sum_{s=1}^{m} \left(v_s^0 - v_s^1\right)^2 \to min \tag{5}$$

at the points of the training sample (1) and satisfies the limitations (2) and (4).

Thus, to find the optimal vector of PCI $\mathbf{W}^0$ which provided the optimization function (5) author of the article proposes the further **Algorithm 1** and additional to them **Algorithm 2**.

3 Experiment

3.1 Development of Algorithm 1 to Determine the Optimal PCI in the Linear Hierarchy of Goals Represented by Neural Network for Building of the CGP "Improving the Management of Intellectual Capital"

To build the CGP "Improving the management of intellectual capital" the basic task is to determine the partial coefficients of influence of sub-goals and projects for their sub-goals (or main goal). For this, the author of the article proposes the following **Algorithm 1**.

Step 1.1. Let us represent a linear hierarchy by a neural network which is described by S projects x_s, $s = \overline{1, S}$ and an unknown vector $\mathbf{W}^0$ of the PCI (which have to be fined) satisfying the condition $w_{i_C}^0 \geq 0$ for the each i-th goal and project.

Step 1.2. Introduce the vector $\mathbf{V}^0$ obtained with the help of the expert knowledge verified for consistency (this procedure is described in the problem statement) of the relative indicators of potential efficiency v_s^0 for S projects, $s = \overline{1, S}$.

Step 1.3. For the created linear hierarchy with S projects we will generate a vector $\mathbf{W}^{(1)}$ of arbitrary weights of the PCI $w_{i_C}^1$ for the i-th goal with f sub-goals (where f is the cardinality of the set of sub-goals - their number) (for projects also). In this case, the total weight of the partial influence coefficients $w_{i_C}^1$ (for the i-th goal) is equal to 1: $\sum_{C=1}^{f} w_{i_C}^1 = 1$.

Step 1.4. For the vector $\mathbf{W}^{(1)}$ of arbitrary weights of the PCI $w_{i_C}^1$ to calculate the vector $\mathbf{V}^{(1)}$ of relative indicators of potential efficiency consisting of S relative indicators of potential efficiency v_s^1 for S projects, $s = \overline{1, S}$:

$$v_s^1 = d_{(1 \ldots 1)}^1 - d_{(1,1 \ldots s=0, \ldots, 1,1)}^1, \tag{6}$$

were $d^1_{(1\ldots1)}$ – the degree of achievement of the main goal, provided that all S projects are completed; $d^1_{(1,1,\ldots,s=0,\ldots1,1)}$ – degree of achievement of the main goal, provided that all S projects are completed, except for this project s.

Step 1.5. To calculate the deviation (error) of the relative indicators of potential efficiency as

$$\Delta = \frac{1}{S}\sum_{s=1}^{S}\left|v_s^1 - v_s^0\right|. \tag{7}$$

Step 1.6. Set the permissible deviation equal to 0,05.

<u>**1.6.1.**</u> If $\Delta > 0,05$, it is necessary to recalculate the PCI $w^1_{i_C}$ for each i-th goal that has f sub-goals $\left(\sum_{C=1}^{f} w^1_{i_C} = 1\right)$ (also for projects), i.e. to train the neural network according to rule (8) using the optimal training parameter $\eta^{(opt)}$ obtained in Algorithm 2:

$$\begin{aligned} w^1_{i_C}(n+1) &= w^1_{i_C}(n) + \Delta w^1_{i_C}(n) \\ &= w^1_{i_C}(n) + \eta^{(opt)} w^1_{i_C}(n) = w^1_{i_C}(n)\left(1+\eta^{(opt)}\right), \end{aligned} \tag{8}$$

were $w^1_{i_C}(n+1)$ – PCI value $w^1_{i_C}$ at the next $(n+1)$-th iteration; $w^1_{i_C}(n)$ – PCI value $w^1_{i_C}$ at the current (n)-th iteration; $\eta^{(opt)}$ – optimal training parameter obtained in **Algorithm 2**.

After changing the weights in accordance with (8), we return to **step 1.4** to recalculate (based on the vector of weights obtained at this step) the relative indicators of potential efficiency for S projects, $s = \overline{1,S}$.

This procedure is repeated until the condition $\Delta \leq 0,05$ becomes true.

<u>**1.6.2.**</u> If

$$\Delta \leq 0,05 \tag{9}$$

then we fix the vector of weights (obtained with such Δ) as the vector $\mathbf{W}^{(opt)}$ of ideal weights (PCI $w^{(opt)}_{i_C}$) of sub-goals and projects.

3.2 Development of Algorithm 2 to Determination of the Optimal Training Parameter $\boldsymbol{\eta^{(opt)}}$

Let consider Algorithm 2 to determination of the optimal training parameter $\eta^{(opt)}$ which used in (8).

Step 2.1. We take the vector $\mathbf{W}^n$ of the PCI with the values $w^{(n)}_{i_C}$ obtained at the (n)-th iteration of **Algorithm 1**.

Step 2.2. Generate the value of the training parameter η as $\eta^{(p+1)} = \eta^{(p)} \cdot 0,5$, $p = \overline{1,P}$, that is P - is the cardinality of the training parameters η set, $P = 20$. Let $\eta^{(1)} = 1$, then $\eta^{(2)} = 0,5$, $\eta^{(3)} = 0,25$, $\eta^{(4)} = 0,125$, $\eta^{(4)} = 0,0625$ … etc.

Step 2.3. For each generated training parameter $\eta^{(p)}$ to calculate the PCI $w_{i_C}^{(p)}$ for each i-th goal that has f sub-goals $\left(\sum_{C=1}^{f} w_{i_C}^{1} = 1\right)$ (also for projects), i.e. to train the neural network according to rule:

$$\begin{aligned} w_{i_C}^{(p)}(n+1) &= w_{i_C}^{(p)}(n) + \Delta w_{i_C}^{(p)}(n) \\ &= w_{i_C}^{(p)}(n) + \eta^{(p)} w_{i_C}^{(p)}(n) = w_{i_C}^{(p)}(n)\left(1+\eta^{(p)}\right), \end{aligned} \tag{10}$$

were $w_{i_C}^{(p)}(n+1)$ – PCI value obtained with $\eta^{(p)}$ at the next $(n+1)$-th iteration; $w_{i_C}^{(p)}(n)$ – PCI value at the current (n)-th iteration;

Step 2.4. The vector $\mathbf{W}^{n(p)}$ of the values of the PCI $w_{i_C}^{(p)}$ obtained with (10) must be checked for the fulfillment of the condition $\sum_{C=1}^{f} w_{i_C}^{(p)}(n+1) = 1$.

2.4.1. If this condition is fulfilled, then we go to the **step 2.5.**

2.4.2. If this condition is not fulfilled, then it is necessary to normalize the weights in this way

$$w_{i_C}^{(p)norm}(n+1) = \frac{w_{i_C}^{(p)}(n+1)}{\sum_{C=1}^{f} w_{i_C}^{(p)}(n+1)}$$

and go to **step 2.5.**

Step 2.5. For the vector $\mathbf{W}^{n(p)}$ obtained for a given $\eta^{(p)}$ with the weights of PCI $w_{i_C}^{(p)}$ calculate the vector $\mathbf{V}^{n(p)}$ of relative indicators of potential efficiency consisting of S relative indicators of potential efficiency of projects $v_s^{n(p)}$, $s \in S$:

$$v_s^{n(p)} = d_{(1\ldots1)}^{n(p)} - d_{(1,1\ldots s=0,\ldots 1,1)}^{n(p)}, \tag{11}$$

where $d_{(1\ldots1)}^{0}$ – the degree of achievement of the main goal, provided that all S projects are completed; $d_{(1,1\ldots s=0,\ldots 1,1)}^{n(p)}$ - the degree of achievement of the main goal, provided that all S projects are completed, except for this project s.

Step 2.6. To calculate the deviation (error) of the relative indicators of potential efficiency with current $\eta^{(p)}$ as

$$\Delta^{(p)} = \frac{1}{S}\sum_{s=1}^{S}\left|v_s^{n(p)} - v_s^{0}\right|, \tag{12}$$

were $v_s^{n(p)}$ - relative indicators of potential efficiency for S projects, $s = \overline{1,S}$, obtained for a vector $\mathbf{W}^{(n)p}$ with the weights of PCI $w_{i_C}^{(p)}$ defined with training parameter $\eta^{(p)}$; v_s^{0} - relative indicators of potential efficiency for S projects, $s = \overline{1,S}$ obtained with the help of the expert knowledge verified for consistency.

Step 2.7. From $P = 20$ generated $\eta^{(p)}$ is chosen as the optimal training parameter $\eta^{(opt)}$ such for which deviation (error) $\Delta^{(p)}$ is minimal: $\Delta^{(opt)} = min\{\Delta^{(p)}\}$.

The End of Algorithm 1
Thus, the author of the article proposes to use the optimal value $\eta^{(opt)}$ obtained with Algorithm 2 in Algorithm 1 which, in turn, determine the optimal PCI in a simplified linear hierarchy of goals representing the CGP "Improving intellectual capital management".

3.3 Automatization of Experimental Process

To automate the experimental process author has developed the software for realization of CGP "Improving the management of intellectual capital of an enterprise" an excerpt from the listing of which is illustrated below.

```
>Gradient( 1, 0 );
mysystem.NormalizeWeights();
ga->Gradient( 1, 0 );
mysystem.NormalizeWeights();
//ga->Gradient( 0 );
cond_vert += (calculated_rez-pvle)*(calculated_rez-pvle);
}
CLink **plinks;
int con_num;
double con_vle;
double con_sum;
for( gi=0; gi<pcond->GetConditionsNum(); gi++)
{
if( pcond->Get_Data( gi, &plinks, &con_num, &con_vle ) )
{
*rez=-3;
return 0.0;
}
con_sum=0.0;
for( kol=0; kol<con_num; kol++ )
{
con_sum += plinks[kol]->GetWeight() ;
}
if( fabs(con_sum-con_vle) > (*radug_max) )
{
*radug_max = fabs(con_sum-con_vle);
}
*radug_avg= *radug_avg + fabs(con_sum-con_vle);
radug_num+=1.0;
cond_horiz+=(con_sum-con_vle)*(con_sum-con_vle);
}
double nevyazka= nevyaz_koef * main->NevyazkaNormalizacii();
switch( frezh )
{
```

```
case 0:
cond_vert = cond_vert+cond_horiz + nevyazka;
break;
case 1: cond_vert = cond_vert ;
break;
case 2:
default:
cond_vert = cond_horiz ;
break;
}
*radug_max = *radug_max;
*radug_avg= (*radug_avg)/radug_num ;
return cond_vert.
```

4 Results and Discussion

According to the above approach implemented using the software developed by the author, the following PCI for linear hierarchy of CGP "Improving the management of intellectual capital of an enterprise" were obtained such results:

- for the goals with edges coming out of the 2nd layer:
  $\omega^2_{11}(\tau+1) = 0,031361;$
  $\omega^2_{21}(\tau+1) = 0,427519;$
  $\omega^2_{31}(\tau+1) = 0,548416;$
- for the goals with edges coming out of the 1st layer:
  $\omega^1_{11}(\tau+1) = 0,241097;$
  $\omega^1_{12}(\tau+1) = 0,344435;$
  $\omega^1_{13}(\tau+1) = 0,343842;$
  $\omega^1_{21}(\tau+1) = 0,652065;$
  $\omega^1_{22}(\tau+1) = 0,435953;$
  $\omega^1_{23}(\tau+1) = 0,240224;$
  $\omega^1_{31}(\tau+1) = 0,10605;$
  $\omega^1_{32}(\tau+1) = 0,222735;$
  $\omega^1_{33}(\tau+1) = 0,419943;$
- for the projects (with edges coming out of the 0th layer):
  $\omega^0_{11}(\tau+1) = 0,0745;$
  $\omega_1 2^0(\tau+1) = 0,385;$
  $\omega^0_{13}(\tau+1) = 0,526;$
  $\omega^0_{21}(\tau+1) = 0,284;$
  $\omega^0_{22}(\tau+1) = 0,0853;$
  $\omega^0_{23}(\tau+1) = 0,115;$
  $\omega^0_{31}(\tau+1) = 0,399;$
  $\omega^0_{32}(\tau+1) = 0,21;$
  $\omega^0_{33}(\tau+1) = 0,101;$
  $\omega^0_{41}(\tau+1) = 0,246;$
  $\omega^0_{42}(\tau+1) = 0,323;$
  $\omega^0_{43}(\tau+1) = 0,261.$

Thus, as a result of application of the approach offered by the author it was received the optimum (by criterion (9)) vector $\mathbf{W}^{(opt)}$ of ideal weights (PCI $w_{i_C}^{opt}$) of sub-goals and projects in linear hierarchy of CGP "Improving the management of intellectual capital of an enterprise".

5 Conclusions

The article proposes a conceptual approach for finding PCI of alternatives in a complex goal program represented by a linear hierarchy of goals which is considered as neural network. This becomes possible thanks to the fact that both in the decision tree and in this neural network there are no feedback and single-level connections, as well as threshold sub-goals. As an illustration of this approach, a simplified complex goal program of "Improving the management of intellectual capital of an enterprise" is proposed.

To obtain the potential efficiencies of projects in such a CGP the author initially used the DSS "Solon-2". At the same time, in order to fully automate the proposed process of developing the CGP and its optimization, the author has developed an individual software, an excerpt from the listing of the program code of which was illustrated above.

The conceptual approach proposed by the author has significant advantages over existing alternative methods. It allows automatically obtaining of the optimal weights of PCI, easily aggregating dynamic changing expert data. The proposed CGP (under the condition of its more complete presentation) has a great practical interest, since it allows you to optimize the process of managing the intellectual capital of an enterprise, firm or organization. She allows significantly increasing of the profitability of enterprise by obtaining multiple effects such as increasing the productivity of personnel etc.

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