DEVELOPING A MODEL FOR COMPREHENSIVE AND SIMILARITY ANALYSIS OF SYSTEMS

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Abstract - This article presents a graphical model that allows you to determine the similarity of complex structural systems and place fragments of complexity. The system of stratification of graph models is considered, which makes it possible to form and study a wide range of new relations of structural similarity. The proposed models make it possible to develop a substructural approach to the analysis of the similarity of systems and the identification of new types of similarity of relations in graph models of systems.

Keywords: Complex structural systems, Model, Graph, Fragment, Matrix, multigraphs, Semantic networks.

1. Introduction

The concept of similarity of systems is inextricably linked with the concept of complexity of systems and occupies a special place in general systems theory and especially in artificial intelligence systems.

The structural similarity of systems is one of the key concepts in the intellectual analysis of data, realization of realistic reasoning, image identification, word processing in natural languages, and other areas of artificial intelligence. This highlights the need and relevance of the need to develop a methodology and software tools to determine the similarity of structural non-digital objects.

The following is an approach to constructing structural and numerical invariants that describe the location of fragments in graphs. The construction stratification of explicit invariants is achieved by applying the expanding bases of structural descriptors (SD) and leads to the construction of a system of stratification of the equivalence and tolerance relations of graph models in systems.

If $F^{i}(G)=\{F^{l1},F^{l2},...,F^{lt},...,F^{lT}\}$ is a set of defined fragments of the graph $G=(V,E)$, here $F^{lt}=\{f_1^{lt},f_2^{l2},\ldots,f_j^{\ lt},\ldots,f_{rt}^{\ lt}\}$ - a set of fragments of the t type, j - fragment number, rt - the number of fragments of the t type. In that case $SK=(G,F^{l},sr)$ like a trinity of sorts, $f_j^{l}\in F^{l}(G)$ the medium representing the location of the fragments is determined, here sr - relationships in the set $F^{l}\times F^{l}$, that is $<f_i^{lm},f_j^{\ln}>$, and $f_i^{lm},f_j^{\ln}\in F^{l}$ in double elements $f_i^{lm}(sr)f_j^{\ln}$ of binary relations. If sr - "$\cap$ a relationship that reflects the isomorphic intersections defined by the ends " in that case $G=(V,E)$ the resulting graph model of the graph (RGM) is understood as the tip and edge of a two-sided graph in the following view:

$$GM\cap(G)=w_e^{l}F^{l}w^{l}L\cap F^{l}w^{l}R(G)=(VL\cup VR,sr,E,WVL,w_L,WVR,w_R,WE,w_e) \quad (1)$$

here VL - left share and a set of tips $|VL| = |F^l| = k$; VR - right share and set of tips of $|VR| = |F^l| = k$; $sr = \cap$ - defined attitude to $WVL \times WVR$; $E \subseteq (VL \times VR)$ - a set of edges; $v \in VL$ and $u \in VR$ tips $w_L(v)(sr)w_R(u)$, where the relationship is bounded by the edge when it is true $w_L(v) \in WVL$, $w_R(u) \in WVR$; WVL - VL a set of dimensions of the ends (F^l the structural dimensions of the graph, which is a fragment of, are considered); w_L - dimension function for the left fraction of vertex, w_L : $VL \rightarrow WVL$; WVR - VR a set of vertex sizes (F^l the structural dimensions of the graph, which is a fragment of, are considered); w_R - a measurement function for the left portion of the vertex, w_R : $WR \rightarrow WVR$; WE – E a set of edge dimensions (maximum isomorphic intersecting structural dimensions of the identified fragments are considered); w_e - E, w_e : $E \rightarrow WE$,

The weight function for peaks consisting of s, where each $\{v,u\} \in E$ for peaks $w_L(v) \cap w_R(u)$ all types of interagency integration platform (IIP) packages are compared in appearance. If $\max(f_i^{lm} \cap f_j^{\ln})$ then, f_i^{lm} $f_j^{\ln}$ isomorphic intersections of fragments represent the maximum number of peaks. $w_e^l F^l w_L^l \cap F^l w_R^l(G)$ as the matrix of the dependence of the peaks of the graph model as matrix is understood $M\_GM(G) = \|mcf_{ij}\|$; $i = 1,2,\ldots,k$; $j = 1,2,\ldots,k$; here vcf_{ij}^l - if $f_i^{lm} \cap f_j^{\ln} \neq \varnothing$ and 0, or $f_i^{lm} \cap f_j^{\ln} = \varnothing$ when $f_i^{lm} \cap f_j^{\ln}$ is the maximum isomorphic intersection in terms of the number of ends.

We introduce a generalized system of description of RGM:

$$\left[w_e^{[l]}\right]L\left[w_L^{[l]}\right](sr)R\left[w^{[l]}\right] = \left[w^{[l]}\right]L\left[w^{[l]}\right](sr)R\left[w^{[l]}\right] \quad (2)$$

here L - WVL represents an array; R - WVR, array; sr - attitudes related to $WVL \times WVR$; w_e - Presence of RGM graph-weight peaks; w_L - the graph-weight peak of the left fraction of RGM; w_R - Graph-weight peak of the right portion of RGM; l - the presence of marked peaks in the graph-weight. In parentheses in the absence of some parameters [ ] defined, different classes of graph models formed from RGM appear.

We will now consider RGM classes in which the operation of isomorphic placement of fragments is used instead of the intersection operations of fragments. A refers to fragments that are the same type $F^l w_L^l \subseteq F^l w_R^l(G)$ If the RGM correlation matrix is a column, and a single column is replaced by a variable column equal to the sum of the element values and the sum of the element values, the result is $(F^l w_L^l \subseteq F(G)) = (F^l w^l \subseteq F(G))$ the base graph-model correlation matrix is formed. Here $F(G)$ - СД represents a set of graph fragments that emerge as a base. The elements in the SD database are sorted by the complexity index value.

A distinctive feature of basic graph models is the need to use an expandable structural descriptor base to express the location of fragments in the graph. Such an approach is considered to be practical in developing effective (explicit and approximate) algorithms for solving complexity and similarity analysis tasks of graphs adapted to the family of graph models of the systems under analysis. If G for the graph B if its complete structural spectrum (CSS) is built based on:

$$WF(G/B) = (w_1 b_1, w_2 b_2, \ldots, w_i b_i, \ldots, w_{k1} b_{k1}) \quad (3)$$

here b_i - base fragments; w_i - G in a graph b_i the number of canonical isomorphic applications of the fragment; k - representing the complexity of the graph B number of base fragments. Of course, $w(K_1) = p$, $w(K_2) = q$. $ISC(K_1) = 1$, $ISC(K_2) = 3$ accepted. All f_i its CSS for the fragment, G Since it is possible to determine the CSS for all fragments of the fragment, recursively B SD-based G the CSS of the graph can be calculated.

$$ISC(G/B) = w_1 \times ISC(b_1) + w_2 \times ISC(b_2) + \ldots + w_i \times ISC(b_i) + \ldots + w_k \times ISC(b_k) \quad (4)$$

For graphs (Figure 1) the following expression is formed:

$$ISC(G_1/B) = ISC(G_2/B) = 281,$$

here $B =< P_o, P_1, P_2, C_3 >$.

It should be noted that different $B \subseteq F$ by selecting the base (here F - G a set of relevant fragments of a graph) can build different complexity indices depending on the importance of these bases in different applications and calculate the effect of fragments on the overall complexity of the graph.

If SD base $B = <b_1, b_2, ..b_j..b_{k1}>$ then, w_{ij} through G into isomorphic fragment $f_i \in F$ fragments can be expressed as the number of reconstructions. G in the graph b_j without counting the peaks to f_i^l isomorphic applications (reconstruction) $EM(F^l\_B(G)) = \|w_{ij}\|$ $i = 1,2,\ldots,k$; $j = 1,2,\ldots,k1$ to the visible matrix.

$P_0^l \subseteq P_{0-1} \cup C(G)$ of the base graph models in view, $EM(P_0^l\_P_{0-1} \cup C(G))$ an example of the reconstruction matrices (Figure 1) is given in Table 1.

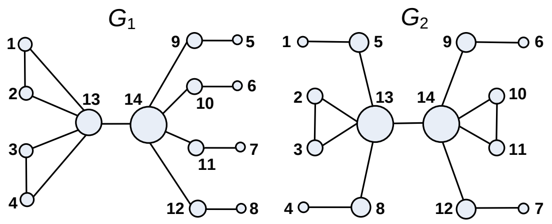

Figure 1: Diagram of system complexity analysis by separating graph peak applications

$P^l{}_{0-1} \subseteq P(G)$ graph-model of the matrix w_{ij} element value $B = < P_0, P_1, P_2, C_3 >$ of a graph whose base element is isomorphic P_0^l is equal to the number of reconstructions from the peak to the bottom of the graph.

2. An Extended Matrix of Fragment Reconstruction

The following is an extended matrix of fragment reconstruction, based on which a method of hierarchical analysis of the similarity of graphs is proposed, taking into account the complexity of the graphs and the state of attachment of fragments to the overall complexity of the graphs.

If, $Aut(G)$ - *G* automorphism group for graph peak, $Aut(f^t)$ then – *G located on the graph* f^t representing the symmetry of the fragment f^t if the fragment has an automorphism group, then $|Aut(f^t)|$ through $|Aut(f^t)|$ the serial number of the group is determined. As an example, f^t we can consider the 3 (C_3) long cycles of the fragment, where G_2 for the graph (Fig. 1 $Aut(f^t)$ the group consists of two automorphisms:

$$g_1 = \begin{pmatrix} (1,2,13),(3,4,14) \\ (1,2,13),(3,4,14) \end{pmatrix} = \begin{pmatrix} 1,2 \\ 1,2 \end{pmatrix} \quad (5)$$

$$g_2 = \begin{pmatrix} (1,2,13),(3,4,14) \\ (3,4,14),(1,2,13) \end{pmatrix} = \begin{pmatrix} 1,2 \\ 2,1 \end{pmatrix} \quad (6)$$

For the example under consideration $|Aut(f^t)| = |Aut(f^{C_3})| = 2$. $EM(F^l\_B(G))$ we add four new rows to the matrix:

Table 1. An extended matrix of fragment reconstruction

V	*P*0	*P*1	*P*2	*C*3	*V*	*P*0	*P*1	*P*2	*C*3
5,6,7,8	1	1	1	0	5,6,7,8	1	1	1	0
9,10,11,12	1	2	5	0	9,10,11,12	1	2	5	0
14	1	5	18	0	1,2,3,4	1	2	3	1
1,2,3,4	1	2	3	1	13,14	1	5	15	1
13	1	5	12	2					

1. $Slw(F^l / B) = < Slw(F^l / b_1), Slw(F^l / b_2), \ldots, Slw(F^l / b_i), \ldots, Slw(F^l / b_{k1}) >$

   here $Slw(F^l / b_j) = \sum_{f^{lt} \in F^l} \sum_{i=1}^{rt} w_{ij}$

2. $Sw(F^l / B) = < Sw(F^l / b_1), Sw(F^l / b_2), \ldots, Sw(F^l / b_j), \ldots, Sw(F^l / b_{k1}) >$, here

   $$Sw(F^l / b_j) = \sum_{t=1}^{T} \frac{f^t(b_j)}{|Aut(f^t)|} = \sum_{t=1}^{T} w(f^t / b_j).$$

3. $Fw(G / B) = < w_1(b_1), w_2(b_2), \ldots, w_j(b_j), \ldots, w_{kj}(b_{kj}) >$.

4. $V\_ISC(G / B) = < w_1(b_1) \times ISC(b_1), \ldots, w_j(b_j) \times ISC(b_j), \ldots, w_{k1}(b_{k1}) \times ISC(b_{k1}) >$.

Lemma in G graph $b_j \in B$ canonical isomorphic applications $w(b_j)$ considering the number $EM(F^l\_B(G))$ has a regenerative quality and is determined by the following formula.

$$w(b_j) = \frac{Slw(F^l / b_j)}{Sw(F^l / b_j)} = \frac{\sum_{f^{lt} \in F^l} \sum_{i=1}^{rt} w_{ij}}{\sum_{i=1}^{T} w(f^t / b_j)}$$

If $|E(b_j)| \le |E(G)|$ then, $EM^*(F^l\_B(G))$ it will be possible to construct an extended reconstruction matrix of fragments.

Matrix for adding complex graph fragments $EM^*(F^l\_B(G))$ based on $MIR(F^l\_B(G) = \|irc(f_i^t / b_j)\| \quad i = 1,2,\ldots,k+4)$ we construct a matrix representing the contribution of the fragments relative to the complexity of graph V representing the location of the fragments in the graph relative to the SD base. This matrix allows a hierarchical analysis of the complexity of graphs, and on its basis allows you to analyze the similarity of the graphs, taking into account the similarity of the location of fragments in the graph and the similarity of the location of fragments.

The value of the matrix elements is calculated using the following formula

$$irc(f_i^t / b_j) = \frac{w_{ij}}{Sw(F^l / b_j)} \times \frac{ISC(b_j)}{ISC(G/B)}.$$

In that case $irc(f_i^t / B)$ when calculated by the following formula

$$irc(f_i^t / B) = \frac{1}{ISC(G/B)} \times \sum_{j=1}^{k1} w_{ij} \frac{ISC(b_j)}{Sw(F^l / b_j)},$$

B the relative contribution to the overall complexity when using an SD base determines f_l^t.

It has the same valuable contributions t kind of f_l^t fragments, t equivalent to the fragments located in the species $f^t(c)$ classes, while the base is sufficiently complete $irc(f^t(c)/B)$ has a common contribution $Aut(f^t)$ group orbit. *The sum of the relative contributions on t all fragments of the same type is the contribution* $irc(f^t / B)$. At the same time with three columns $irc(f^t(c,n)/B)$ with value $(k1+1)$; (2) $irc(f^t(c)/B)$ and with value $(k1+2)$; $irc(f^t / B)$ with value (3) $(k1+3)$ reconstruction of filled fragments extended matrix taking into account the location of fragments, equivalent placement classes of fragments and complexity G represents takes the location of each fragment in and the following view $MIRC(F^l\_B(G))$.

$MIRC(F^l\_B(G))$ based on G we construct a matrix of the absolute contribution of fragments to complexity, that is $ISC(G/B)$ using the complexity index $MIRC(F^l\_B(G))$ we construct the matrix.

For graphs (Figure 1) $MIRC(P_0^l\_P_0 \cup C_3(G))$ the matrix is given in Table 2 as an example. In the graphs diagrams, it can be seen that the size of the ends corresponds to the contribution of the peaks in the overall complexity of the graph.

The analysis of the matrices shows that the graphs being analyzed are given $B = < P_0, P_1, P_2, P_3 >$ both the index and the vector-index in the database have the same value and the difference between them $irc(f^t(c))$ vector-indices of contributions are reflected only in comparison.

Table 2. Relative contribution matrix of complex graph peak

G_1	P_0	P_1	P_2	C_3	$irc(f^t(c,n)/B)$	$irc(f^t(c))$	G_2	P_0	P_1	P_2	C_3	$irc(f^t(c,n)/B)$	$irc(f^t(c))$
5	0,004	0,005	0,011	0	0,020	0,078	5	0,004	0,005	0,011	0	0,020	0,078
6	0,004	0,005	0,011	0	0,020		6	0,004	0,005	0,011	0	0,020	
7	0,004	0,005	0,011	0	0,020		7	0,004	0,005	0,011	0	0,020	
8	0,004	0,005	0,011	0	0,020		8	0,004	0,005	0,011	0	0,020	
9	0,004	0,011	0,053	0	0,068	0,270	9	0,004	0,011	0,053	0	0,068	0,270
10	0,004	0,011	0,053	0	0,068		10	0,004	0,011	0,053	0	0,068	
11	0,004	0,011	0,053	0	0,068		11	0,004	0,011	0,053	0	0,068	

12	0,004	0,011	0,053	0	0,068		12	0,004	0,011	0,053	0	0,068	
14	0,004	0,027	0,192	0	0,222	0,222	1	0,004	0,011	0,032	0,014	0,060	0,242
4	0,004	0,011	0,032	0,014	0,060	0,242	2	0,004	0,011	0,032	0,014	0,060	
1	0,004	0,011	0,032	0,014	0,060		3	0,004	0,011	0,032	0,014	0,060	
2	0,004	0,011	0,032	0,014	0,060		4	0,004	0,011	0,032	0,014	0,060	
3	0,004	0,011	0,032	0,014	0,060		13	0,004	0,027	0,160	0,014	0,205	0,409
13	0,004	0,027	0,128	0,028	0,187	0,187	14	0,004	0,027	0,160	0,014	0,205	
Slw	14	30	66	6	116	1	***Slw***	14	30	66	6	116	1
Sw	1	2	3	3	9		***Sw***	1	2	3	3	9	
Fw	14	15	22	2	53		***Fw***	14	15	22	2	53	
V_ISC	14	45	198	24	***ISC=281***		***V_ISC***	14	45	198	24	***ISC=281***	

3. Research Methods

A method of analyzing similarity in the location of fragments, taking into account the contribution of the graph in complexity. The matrix or graph of the pair distances of the fragment or classes being analyzed as a result of calculating the similarity of the location of the fragments in G, the equivalently located fragments, i.e.

$MIRC(F^{l}\_B(G))$ the same value fragments of the matrix string are understood.

1. A hierarchical analysis of the similarity of the location of classes of fragments includes:

2. $(irc(f^{t}(c)))$ relative or $iac(f^{t}(c))$ determine the double distance between fragments based on the calculation of the difference of the index of absolute contributions;

3. The number of elements based on Euclidean metrics $MIRC(F^{l}\_B(G))$ determines the distance between the values of the rows of the matrix and the contributions of the expanding vectors (relative and absolute).

G_1, G_2 (Figure 1) the absolute contributions of the classes of peaks to the overall complexity of the graphs are given in Table 3. Figure 2 the similarity graph of the peak classes is given.

Table 3. A matrix of absolute contributions of the three classes to the complexity

Classes for G_1	*Number of peaks*	P_0	P_1	P_2	C_3	$iac(f^{t}(c))$	Classes for G_2	*Number of peaks*	P_0	P_1	P_2	C_3	$iac(f^{t}(c))$
1	5,6,7,8	4	6	12	0	22	1	5,6,7,8	4	6	12	0	22
2	13	1	7.5	36	8	52.5	2	9,10,11,12	4	12	36	16	68
3	14	1	7.5	54	0	62.5	3	1,2,3,4	4	12	60	0	76
4	1,2,3,4	4	12	36	16	68	4	13,14	2	15	90	8	115
5	9,10,11,12	4	12	60	0	76							

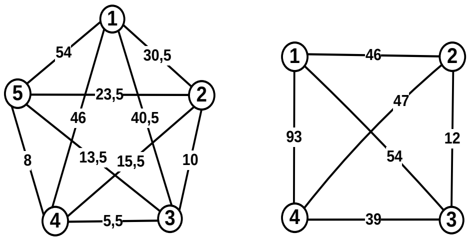

Figure 2: A pair of distance graphs between peak classes for G_1 and G_2

For the first time, this method allows the analysis of trends in the similarity of the location of fragments (class of fragments, orbits of fragments) based on the construction and analysis of distance-varying graphs in SD expansion bases. This is especially necessary when the graphs being analyzed are not isomorphic but have the same number when the equivalently located fragments and the fraction class fraction match values.

When analyzing the similarity of graphs, using a subsystem approach based on calculating the maximum value of the total fragment for each pair of graphs, it is possible to analyze the similarity of graphs, taking into account the similarity of the

A method of hierarchical analysis of the similarity of graphs based on a matrix of conditional contributions of fragments.

$MIRC(F^l\_B(G))$ hierarchical analysis of the similarity of graphs by determining the successive results in the following two directions using matrices:

1. (*ISC*) index, (*V_ISC*) vector index, $MIRC(F^l\_B(G))$ matrix;
2. $irc(f^t)$, $irc(f^t(c))$, $irc(f_i^t)$ vector index of contributions, matrix-matrix.

The double similarity value of the graphs in line 1 is determined by:

- for indices based on the calculation of the modulus of proportionality of their value;
- based on the calculation of the distance between graphs using Euclidean metrics for vector indices;

$F^l \subseteq B(G)$ for graph-type models based on their UMF and based on the calculation of the distance value based on the determination of the D total maximum fragment (mcf) of graph models, ie.

$$D(G_1,G_2)=\left|V(F^l\subseteq B(G_1))\right|+\left|E(F^l\subseteq B(G_1))\right|+\left|V(F^l\subseteq B(G_2))\right|+\left|E(F^l\subseteq B(G_2))\right|-$$
$$-2\left|V(mcf(F^l\subseteq B(G_1),F^l\subseteq B(G_2)))\right|,(7)$$

$$MSI(G_1,G_2)=(\left|V(mcf(F^l\subseteq B(G_1),F^l\subseteq B(G_2)))\right|+\left|E(mcf(F^l\subseteq B(G_1),F^l\subseteq B(G_2)))\right|^2)/$$
$$/(\left|V(F^l\subseteq B(G_1))\right|+\left|E(F^l\subseteq B(G_1))\right|)\times(\left|V(F^l\subseteq B(G_2))\right|+\left|E(F^l\subseteq B(G_2))\right|).(8)$$

As a result of calculating the similarity of graph sets, it is possible to understand the matrix of double distances between graphs or the study of variable similarity trends in the graph of relative similarity indices of expanding graphs based on SD for the analyzed graphs.

If P^{Sc} represents all the connected sub-graph chains of the graph, the graph-models are calculated for each *mcf* pair in its stratification system, e.g.

$$P^I w\subseteq Pw\rightarrow P^{IS}w\subseteq Pw\rightarrow P^{IS}w\subseteq P^S w\rightarrow$$

$$\rightarrow P^{ISc}w\subseteq P^S w\rightarrow P^{ISc}w\subseteq P^{Sc}w\rightarrow P^{ISc}w\subseteq P^{Sc}w$$

That leads to the possibility of studying the trend of similarity changes of graphs in the direction of stratification of three more basic models: (1) monotonous expansion of SD bases; (2) monotonous expansion of fragment types by complexity index value; (3) Expansion of the graph by both bases and fragment types.

1. The following procedure is used to study the effect of indices of complexity on increasing the base B on the relative similarity of the graph to the monotonous value:
2. Being analyzed B at the base, i.e. the last elements $(k-1),(k-2),\ldots 0$ at the base formed by dropping $1,2,\ldots,k$ component, for bases $SM_i(i=1,\ldots,k)$ The graphs are a pair of similarity (distance) matrices.
3. For each graph, each SMi has an average value of avij similarity to the other graphs, where, j – graph sequence number. This is the average conversion G_j similarity indices in the graph $\{G\setminus G_j\}$ the value obtained by adding the graphs in the set $\left|\{G\setminus G_j\}\right|$ is done by dropping down.
4. αv_{ij} a coefficient of coordination equal to the mean value nk_i is (conversion to average value j index).

5. $i\ rs_{ij} = \alpha v_{ij} / nk_{i}$ i. length G_j is the relative similarity of the graph.

6. For each graph under study, graphs are constructed based on the value of similarity relative to the length of the base.

Relative similarity indices classify the similarity of one graph for all other graphs, which allows an integrated assessment of the motion of the values of pairs of similarity indices relative to the base length.

For the graphs in Figure 4 (Figure 3) $P^{IS} w \subseteq Pw$ the graph of the similarity value calculated based on the application of the graph models in the view is given as the average value. They allow the analysis of changes in the growth of the sub-chain base.

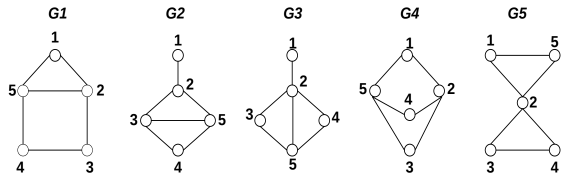

Figure 3: Diagram of graphs with 5 triangles and 6 edges

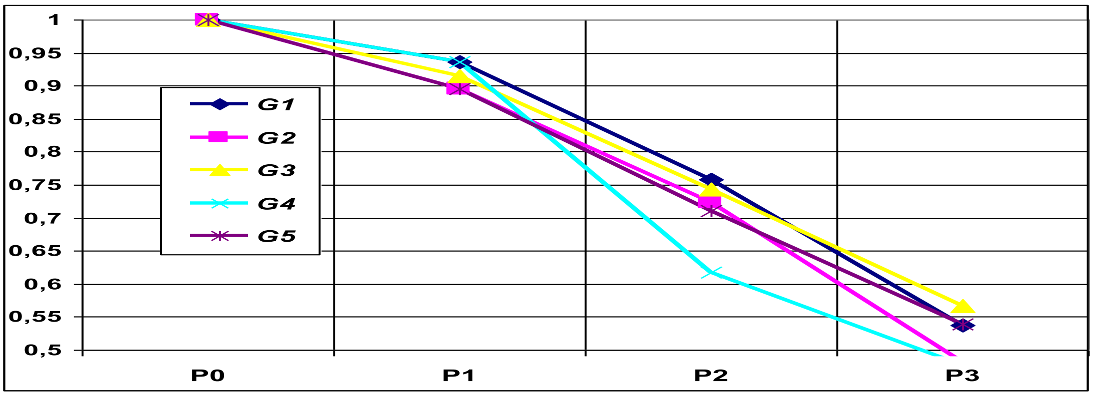

Figure 4: Graph of changes in the average value of the similarity of graphs

Depending on the type of SD base, 2 different class functions can be distinguished: (1) if $< b_1, b_2, ..., b_k > = < \Re(G_1) \cup \Re(G_2) \cup ... \cup \Re(G_n) >$ if so, the global similarity of the graphs is here $\Re(G_i)$ – the whole set of fragments is under the set G_i kits;

(2) If $< b_1, b_2, ..., b_k > \subset < \Re(G_1) \cup \Re(G_2) \cup ... \cup \Re(G_n) >$ if so, the local similarity of the graphs.

A methodology and its computer support will be developed to solve the problem of analyzing the accuracy of solving the global similarity detection problem based on SD expanding bases. In contrast to the substructural approach to analyzing the similarity of graphs, the proposed approach is based on two basic mcf and efficient computation (from a range of computational complexity) algorithms is used to determine the model.

4. Conclusions

In conclusion, basic graph models make it possible to analyze the similarity of system structures and form classes of problems to determine a stratified system of equivalence relations in nature based on the similarity of tolerance relations in the structures of the system. The aforementioned models and methods of similarity analysis are implemented in the GMN ASIS and MEI (TU) educational process.

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