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RESEARCH ARTICLE

Percolation and connectivity formation in the dynamics of data citation networks in high energy physics

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Abstract
Objectives. The object of the research is to study citation information networks structured on the basis of a sample from the arXiv database related to theoretical high energy physics (high energy physics, HEP). Since 1974, this database has indexed more than 500000 articles, including their complete citation trees. The paper proposes a method for detecting percolation transitions in the dynamics of cluster formation of articles with similar content. Improving the accuracy of information cycles in knowledge networks can help resolve applied problems related to the quality of scientometrics and its indicators.
Methods. An optimized algorithm for dynamic network separation in the *Pajek* software environment was applied, in order to detect the emergence of a largest component equivalent to a percolation transition. This approach enables a detailed study of dynamic and general parameters to be carried out in each reduced network with a given time step. The clustering algorithm combines citation structure and temporal information about data.
Results. It was found that a percolation transition occurs in the HEP network. The indicator of this transition is the formation of a largest component near the critical point which occurs at the 10th month of the time sample interval. At the same time, a generalized conclusion about the behavior of network parameters shows a positive trend in the growth of connectivity for the entire time period (from 1991 to 2003). Furthermore, a generalized analysis of citation distribution reveals eleven laureates of highly cited articles who set the basic vector for development in the field of HEP. It is worth noting that the prominent scientists from the top three in terms of citations are linked by a shared field of research: string theory. Verification of this fact confirms that our citation evaluation method is effective. Determining the characteristics of the HEP (high-energy physics) network enables an important indicator of the researcher's activity and behavior to be identified.
Conclusions. In the column of authors linked by co-authorship, of the 9200 authors in the HEP physics community, 7304 belong to a single connected component. The temporal nature of citations indicates a rapid uptake and understanding of relevant new work. Percolation transitions, which are indicators of sudden conceptual shifts in citation networks, allow us to identify and link articles into research schemes which form clusters of new ideas and theories.

Keywords: information network, citation network, high energy physics, HEP, percolation, percolation transition, connectivity, largest component, cluster, dynamics

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НАУЧНАЯ СТАТЬЯ

Перколяция и формирование связности в динамике сетей цитирования данных по физике высоких энергий

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Резюме

Цели. Объектом исследования выступают информационные сети цитирования, структурированные на основе выборки в arXiv базы данных, связанной с теоретической физикой высоких энергий (high energy physics, HEP), индексирующей с 1974 г. более 500000 статей, включая их полное дерево цитирования. Предлагается методика обнаружения перколяционного перехода в динамике образования кластеров статей, имеющих схожее содержание и тесно связанных друг с другом. Повышение точности количественной оценки информационных циклов в сетях знаний может быть использовано в решении прикладных задач качества наукометрии и ее индикаторов.

Методы. Применен оптимизированный алгоритм по динамическому разделению сети в программной среде *Pajek* с целью обнаружения появления в ней гигантского компонента, эквивалентного перколяционному переходу. Данный подход позволяет с заданным временным шагом реализовать детальное исследование динамических и общих параметров для каждой новой сокращенной сети. Используемый алгоритм кластеризации объединяет структуру цитирования и темпоральную информацию о данных.

Результаты. Обнаружено, что в сети HEP происходит перколяционный переход, индикатором которого является образование вблизи локальной критической точки (10-го месяца интервала временной выборки) гигантского компонента. В то же время обобщенный вывод поведения параметров сетей свидетельствует о положительной динамике в росте связности исследуемой сети для всей временной выборки (с 1991 г. по 2003 г.). Обобщенный анализ распределения цитируемости обнаруживает 11 лауреатов высокоцитируемых статей, которые задавали базовый вектор развития в разделе HEP. Примечательно, что выдающиеся ученые из главной «тройки» цитирования связаны единой динамичной областью исследования – теорией струн. Верификация

вышеуказанного факта подтверждает то, что предложенный метод оценки цитируемости – рабочий. Определение характеристик сети HEP позволяет определить важный для исследователя показатель и его поведение.
Выводы. В графе авторов, связанных отношениями соавторства, 7304 из 9200 авторов научного сообщества физиков HEP относятся к одному связному компоненту. Временной характер цитирования указывает на быстрое понимание и использование соответствующих новых работ. Перколяционный переход, являясь индикатором внезапных концептуальных изменений в сетях цитирования, позволяет выявлять и связывать статьи в исследовательскую схему, составляющую кластер новых идей или теорий.

Ключевые слова: информационная сеть, сеть цитирования, физика высоких энергий, HEP, перколяция, перколяционный переход, связность, гигантский компонент, кластер, динамика

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INTRODUCTION

A distinct category of complex networks, together with social, biological, and technological networks, is represented by information networks, also referred to as *knowledge networks*.

Newman defines an information network as "consisting of data elements linked together in some way" [1]. Two of the most studied information networks are citation networks of scientific publications and text page networks of the World Wide Web [2–5]. In them, the vertices are articles or web pages, and the directed edges are citations of one article in another article or hyperlinks.

Certain other information networks have been studied to a lesser extent. For example, the network of citations between patents which in some respects are similar to citations between academic research articles.

Keyword index networks are closely related to networks of web pages and academic documents. They are different from direct link networks between documents. An index is a bipartite network of links between a record of keywords and the document which they indicate. They are used, for example, as the basis for search engine algorithms which try to find documents or pages that are similar to each other.

The network of relations between classes of words in a thesaurus, which has been studied in a number of works [4, 6, 7], can also be regarded as informational. Thesaurus users move through the network from one word to another in search of a specific term which perfectly reflects the idea they have in mind.

Semantic links between terms and mental constructs used for semantic representation of a special scientific language represent conceptual or terminological networks. In [8], the parameters of the dynamics of link formation dynamics in networks structured on the basis of dictionaries of model predictive terms thematically related to promising information technologies were studied.

The network of citation references between scientific publications, the structure of which quite accurately reflects the structure of information stored in its vertices—articles, corresponds well to the concept of *information network*.

Citation analysis can identify articles and link them into a research pattern which forms a cluster defined by the research specialty. An indicator of sudden conceptual changes resulting from new theories or ideas is sudden changes in the citation network.

There are two basic areas of network analysis of citation references, reflecting the gradual development of knowledge in dynamics.

A widespread method is main path analysis method [9, 10], which represents citation networks as a system of channels carrying scientific knowledge or information. Main path analysis calculates the extent to which a particular citation or article is used as a reference. This is called a traversal count. Paths or components from the source vertex to the destination vertex with the highest traversal weight, assumed to define the main information flow, are extracted. Analysis of their dynamics over time reflects the integration or specialization of the scientific community.

Analyses of this kind related to data fragmentation also include approaches based on the identification of key routes, islands, and probabilistic flows [11].

These methods focus on localization, highlighting highly cited articles and leaving out a large stratum of the entire data set expressed in weak long-range network correlations [12, 13].

Another trend of simulation and analysis of information processes occurring in networks with irregular structure is related to the application of methods of percolation theory known in solid-state physics [14–19], capable of answering important applied questions. Percolation theory is successfully applicable in applications which provide protection of technological networks from virus attacks [20], nanotechnology for the design of virus-like particles [17], and algorithms for monitoring and predicting the evolution of information in sociotechnical systems [21].

Percolation in social networks by the analysis of knowledge networks or information percolation is a relevant, popular and developing trend at the intersection of scientific concepts. A coherent theory of this area, including the conceptual range, is just being formed. Its elements are being collated within the framework of a number of works by domestic and foreign authors [21–24], in order to reflect different sides of a complex multidimensional phenomenon. A more universal view of the analysis of the critical behavior of percolation transitions shows the need to take into account global information about network connectivity, resolved by artificial intelligence and machine learning algorithms [24].

Percolation theory from statistical physics focuses on patterns of network connectivity, namely the clusters of nodes which can be reached from each other. The main interest is the relative size of the largest cluster, i.e. the fraction of nodes in the largest (giant) component P_∞, which acts as a measure of functionality.

With regard to more complete coverage of network processes, it is important that long-range correlations control the percolation transition, as in the case of thermal phase transitions. Another significant factor is that the corresponding quantities near the critical point p_c are described by the formulas of power laws and critical indices.

The structure of clusters formed by elements of citation networks from the same section of theoretical high-energy physics is a significant factor in the detection of percolation phase transitions [25, 26].

This is important in the development of network science and its applications [18]:

- in terms of heterogeneous interaction models of the components which make up complex networked systems;
- as a paradigm of random and semi-random connectivity of components of networked systems;
- as a confirmation of the principle of universality of phase transitions in a large variety of physical and socio-technical systems.

Understanding percolation theory facilitates the understanding of network systems and can be used to quantify and resolve some basic problems in applied informatics and scientometrics. It can in particular help with the detection of clusters of articles with similar content and which are closely related to each other. This approach to analyzing the links between scientific publications improves the accuracy of information cycle assessment in scientometrics and the quality of indicators.

Thus, identifying and understanding the topological properties of the clusters formed, as well as the distribution of cluster sizes and the average distance between network elements belonging to the same cluster is of interest.

Simulation of clusters formed by elements of citation networks, which reflect both nonlinear processes occurring in a certain scientific field and a wide variety of its complex systems, enables their dynamics, reveal hidden connections, correlations, and cycles to be predicted.

The object of the study is the international information networks structured on the basis of the Stanford Linear Accelerator Center SPIRES-HEP database. Since 1974, the literature on theoretical high-energy physics (HEP) has been comprehensively cataloged online and more than 500000 articles, including their full citation tree, have been indexed.

TOOLS AND METHODS

The basic research methodology proceeds from mapping the dynamics of formation of a complex associated structure of the studied citation network with nodes, links taking into account the weight of various elements according to three basic criteria: degree of nodes, distance, and strength of links between nodes.

In the most general form, regardless of the physical nature and model of the system, percolation theory answers the following question: what is the probability that there exists an open path from zero to infinity (or whether there exists an infinite cluster of interconnected pores or nodes)? Thus, the problem boils down to whether such paths exist for a given probability p. Basically, the theory is concerned with the existence of such a cluster and its structure with respect to the probability of filling p.

Unlike thermal or magnetic phase transitions, the percolation transition is a geometric phase transition and is characterized by the structural properties of clusters near the critical probability p_c.

The measure of functionality is the probability that a node (or link) belongs to an infinite cluster. At $p < p_c$ there are only finite clusters and $P_\infty = 0$. At $p > p_c$ P_∞ behaves similarly to the density below the critical temperature T_c and increases with increasing p according to the power law:

$$P_\infty \sim (p - p_c)^\beta. \quad (1)$$

The linear size of the finite clusters below and above p_c is characterized by the correlation length ξ. The correlation length is defined as the average distance between two nodes in the same finite cluster. When p approaches p_c, ξ increases with the same degree v below and above the threshold:

$$\xi \sim (p - p_c)^{-v}. \quad (2)$$

The average number of nodes (mass) of a finite cluster S also diverges from the index γ above and below p_c:

$$S \sim (p - p_c)^{-\gamma}. \quad (3)$$

The indices β, v and γ describe the critical behavior of typical quantities associated with the percolation transition and are called critical indices.

These degree indices are universal and depend neither on the structural details of the lattice (e.g., square or triangular), nor on the type of percolation (node, link, or continuum). They depend only on the dimensionality of the space (see the table). Dimensionless quantities are used in network science.

Table. Estimates of critical percolation indicators

	Space dimensionality				
	$d = 2$	$d = 3$	$d = 4$	$d = 5$	$d \geq 6$
β	5/36	0.417 ± 0.003	0.5	0.7	1.0
v	48/36	0.875 ± 0.008	0.7	0.6	0.5
γ	86/36	1.795 ± 0.005	1.8	1.6	1.0

From the point of view of forming a coherent information network, structural parameters such as distance between nodes, network diameter, clustering and intermediacy indices are of great importance.

Since the structure of percolation clusters is well described by the fractal concept [27], let us pay attention to the fractal dimensions d_f, d_{min} and d_l which describe the distance between vertices.

The fractal dimension d_f describes $M(r)$, i.e., the way in which, on average, the mass M of a cluster inside a sphere of radius r scales with r. Dimension d_{min} describes the self-similarity and structure on the shortest path between two arbitrary nodes A and B, while d_l describes $M(l)$, i.e., how M at the shortest distance l from a given node scales with l. They are related to each other:

$$d_l = \frac{d_f}{d_{min}}. \quad (4)$$

The concept of shortest distance (or optimal distance) also plays an important role in describing dynamical phenomena in disordered systems, such as the spread of wildfires or epidemics spreading along the shortest path from the source. In [27], it is shown that the rate of propagation of a fire front or epidemic is related to the measure of degree v. In a knowledge network, the shortest or optimal paths are important because they tell us how information will propagate with the highest probability.

Based on the well-known and tested [9, 28] *Pajek*[1] software environment, we can propose an optimized algorithm for dynamic network partitioning to detect the appearance of a largest component in the network, equivalent to a percolation transition.

The following factors are emphasized therein:

1. We select the source network, either complete or containing some subnet, with which we are going to work further. In our case, the network parameter (.net) represents the citation graph of the part of the arXiv[2], database corresponding to HEP. The vertices of the graph are arXiv article identifiers in the form of nodes. Relationships between these entities, such as article citations, are represented by links between the entities, i.e., *X* cites *Y*. The vector parameter (vec) represents a temporal data series (dates of article data release) with different time step (day, month, year);
2. In order to extract a part of the network, i.e., to create a localized representation, the sets (or classes) of vertices to be extracted need to be determined. We divide the vertices of the original network into a certain number of mutually exclusive subsets (clusters) with a given time threshold (initial state) and step;
3. Computation and a detailed study of dynamic and general parameters for each new reduced network [29]. Particular attention is paid to the dynamics of the largest component, measured as percentage. The splits (steps) end when this parameter in the new network is no longer significant, i.e. from the minimum value to the maximum value;
4. Processing and visualization of the obtained data of time dependencies of link parameters in citation networks.

There is currently considerable interest in the problem of how the largest component in networks is formed and whether it is possible to predict this process. A methodology involving detailed analysis in citation networks can be applied to a much wider range of disciplines: from chemistry, physics and biology to the social sciences. The approach proposed uses a clustering algorithm which combines citation structure and data information. The proposed methodology is expected to identify clusters relevant to promising scientific trends.

[1] http://mrvar.fdv.uni-lj.si/pajek/. Accessed April 20, 2024.
[2] https://arxiv.org/archive/hep-th. Accessed April 20, 2024.

RESULTS AND DISCUSSION

For the purpose of this analysis, the high energy physics citation network from August 1, 1991 to May 12, 2003 in the arXiv[2] database, which contains 27770 publications of articles in High Energy Physics—Theory (HEP or hep-th) at the time of data collection, is considered.[3]

Transformed into *Pajek*[1] format, the files allow us to conduct a study using this citation network. The first file hep-th-new.net is a network file with 27770 vertices and 352807 graphs. A vector file called date-new.vec contains the dates of the articles converted to the number of days since August 1, 1991. The number of days is broken down into months, in order to visualize the results of the study.

The description of the graphs of time dependencies and citation distribution begins with a detailed analysis of the dependence of the largest component on the time interval. The abscissa axis shows time t in months, where 0 is March 1993, month 28 is July 1995.

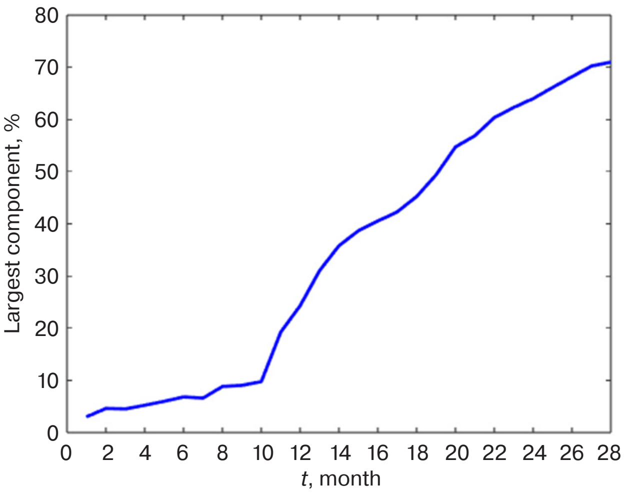


Fig. 1. Time dependence of the largest component

In Fig. 1, a sharp increase in the largest component is observed in the interval between 1993–1994, indicating the presence of a largest component. At a certain critical value, the dependence graph shows a sharp increase from a very small value to a finite fraction of the whole system, characteristic of a percolation phase transition. The graph ceases to be linear, signaling the formation of the largest component at a certain point in time equal to 10 months. The key moment for the percolation transition, found by the study, is a speech at a string theory conference in 1994 made by Edward Witten who proposed M-theory. In the months following Witten's statement, hundreds of new papers appeared on the Internet confirming that the new theory plays an important role in HEP. Today, this flurry of papers is known as the second superstring revolution. After a while, five superstring theories (type I, type IIA, type IIB, HO, and HE) became considered as different limits of the unified M-theory.

Observing the sharp increase in the size of the largest component in month 10, is can be assumed that the formation of the largest component is caused by the large publication activity in HEP during this period. However, when conducting a detailed study, it was found out that the peak of publications falls in the period between 1997–1998. The dependence graph confirming this fact is shown at the end of the article.

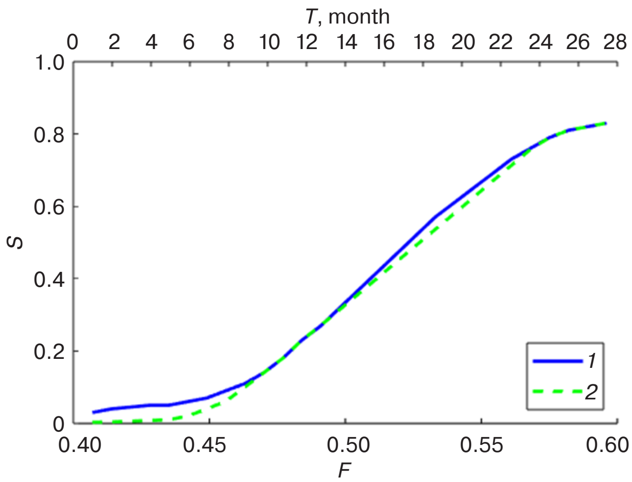


Fig. 2. Largest component size as a function of probability in network growth dynamics: (*1*) normalized daily dependence of the presented algorithm; (*2*) normalized stepwise dependence based on simulation data [30]

In Fig. 2, the size of the largest component S is de-dimensionalized and expressed in fractions. The normalized daily dependence (curve *1*) of the algorithm presented herein bears a strong positive correlation with the normalized stepwise dependence on the percolation probability F (curve *2*) in the dynamic opinion model (non-consensus opinion, NCO) obtained in [30]. The phase transition in the NCO model was found to belong to the same universality class as the invasion penetration with capture.

It was also found that in [30], the formation of a largest component can be observed in the interval of 0.4–0.6 simulation steps. The simulation step is understood as a fraction of the probability F of the network reaching a stable state. This interval coincides with the data at time interval T of 28 months obtained in this study. Due to the identity of the input datasets for HEP, the relationship of these dependencies is expected.

In order to understand why percolation occurs at this moment, let us study the general and dynamic parameters of the investigated network in the time

[3] http://vlado.fmf.uni-lj.si/pub/networks/data/. Accessed April 15, 2024.

interval. Figures 3–6 show the series of dependencies of the main network characteristics for HEP.

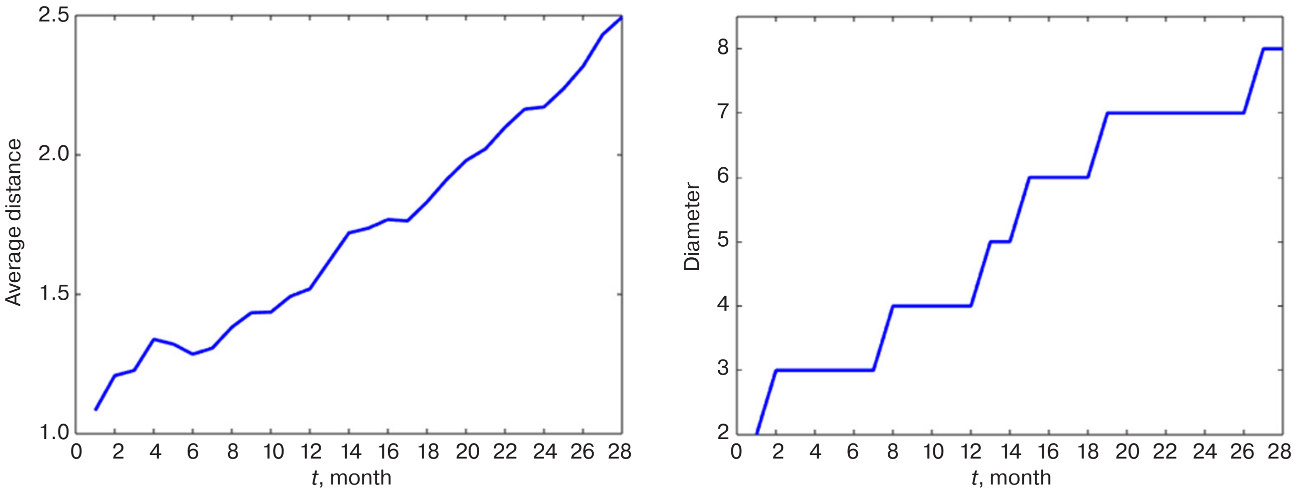
The average distance parameter is responsible for the average path length among all reachable pairs of nodes in the network [29]. From Fig. 3a, it can be seen that the average distance in the network increases with time, which contributes to the next parameter in Fig. 3b, the diameter of the network. The network diameter is the maximum eccentricity among all vertices of the network.

Figure 4 shows the dependence of clustering coefficients on time in months. The transitivity coefficient is responsible for the average probability that two vertices which are network neighbors of the same other vertex will themselves be neighbors. A sharp increase in the parameter indicates an increase in the probability of two different vertices being neighbors in the period from months 1 to 7, then the situation stabilizes and the coefficient varies around 0.1.

An unweighted average known as the Watts–Strogatz clustering coefficient is also used, although it does not give the exact proportion of closed dual parts. In Fig. 4b, the coefficient increases to 0.18 at month 10 and stabilizes at a value of 0.13 after month 18.

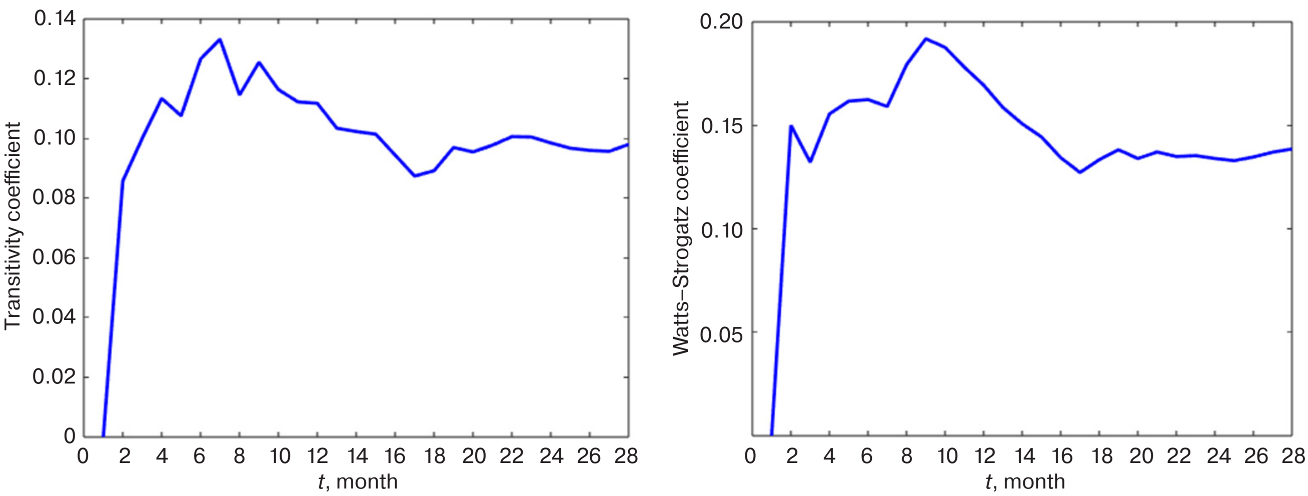
Figure 5a shows a positive linear increase in the total link strength parameter, confirmed by the growth of citations in articles throughout the entire study interval. The average degree parameter is responsible for the structural cohesion of the network. Its increase indicates that the number of links per node is increasing.

The last dynamic parameter in the study is the betweenness centralization. It determines the frequency of interval values between vertices in the network divided by the maximum possible value in a network of the same



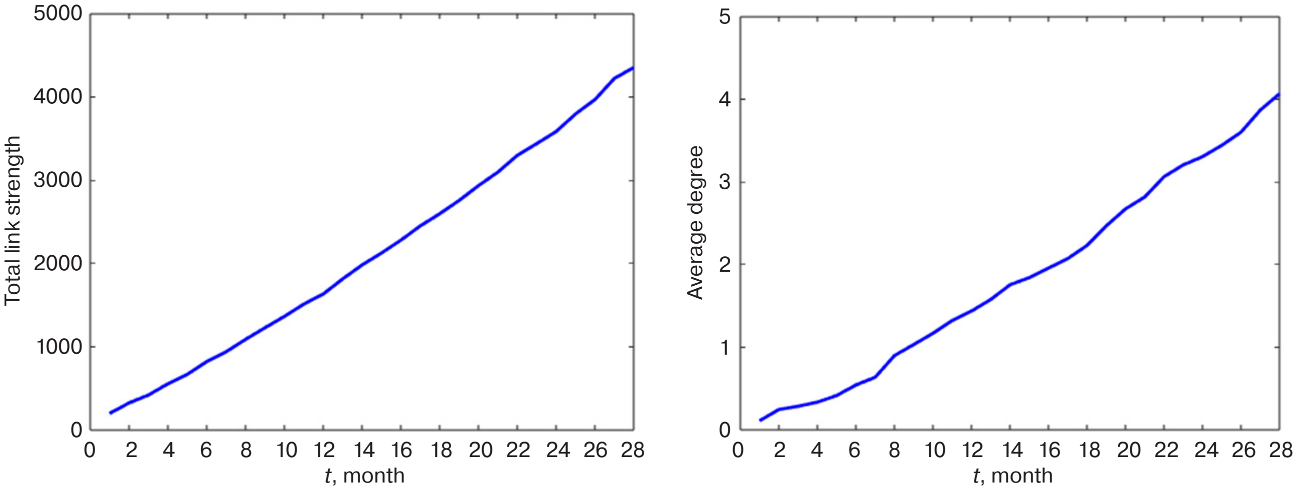
(a) (b)

Fig. 3. Dependence of average distance to the top (a) and network diameter (b) on time



(a) (b)

Fig. 4. Time dependence of clustering coefficients:
(a) transitivity coefficient; (b) Watts–Strogatz coefficient



(a) (b)

Fig. 5. Dependence of the total link strength in the network (a) and average degree of all vertices (b) on time

size. In other words, it is a measure of how central some vertices in the network are when compared to others. In Fig. 6, an increase in this parameter indicates that elements with an increased number of intermediate links are formed in the network, further indicating an increase in its connectivity. The significance of the betweenness centralization and average distance which determine the degree of information transmission without loss and distortion, is obvious [29].

Analysis of the behavior of dynamic and general network parameters for each time sample over the entire study interval enabled us to find that the HEP network contains a largest component. Each of the analyses performed contributes to the general understanding of the processes of dynamics of conceptual changes in the field of theoretical high-energy physics. This could not be achieved without a detailed study of individual network properties.

The final step of this study is to analyze the citation distribution from 1991 to 2003.The overall structure of the subgraph is examined to identify influential authors. Finally, potential laureates of the prize for theoretical high-energy physics can be predicted.

Authors who submitted articles to arXiv from 1991 to 2003 were ranked according to the number of citations. Next, a dependence of the share of citations of authors on the number of articles was built (Fig. 7). Based on the results of the study, 11 laureates of highly cited articles were found, establishing the vector of development in the HER section. For clarity, the graph lists the articles from the main "top three". The list is headed by Juan Martin Maldacena, Edward Witten, and Steven Scott Gubser [31–33]. It is worth noting that the validity of the results in this dependence is confirmed by the fact that these outstanding scientists are related by a single field of research: string theory. In addition,

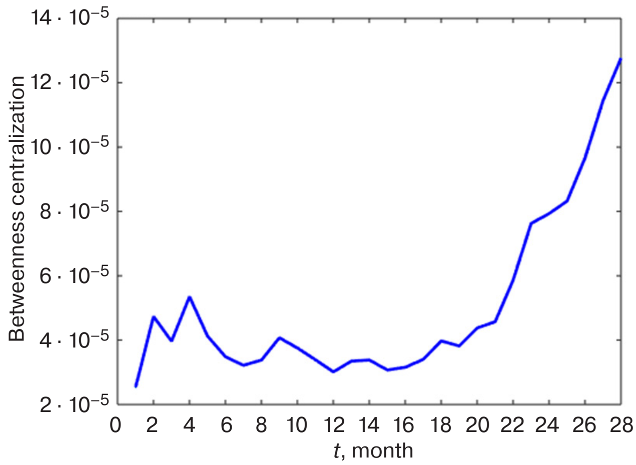


Fig. 6. Time dependence of the betweenness centralization between vertices of the network

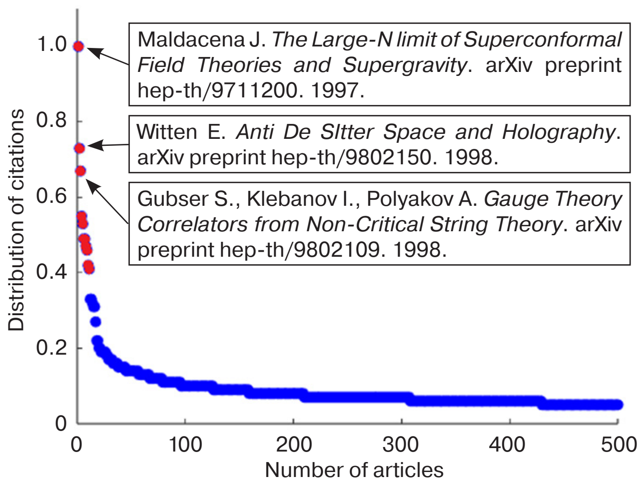


Fig. 7. Distribution of citations of HEP research articles between 1992 and 2003

verification of the above fact confirms that the proposed method works.

Thus, the characterization of the HER network enables a new method for citation evaluation to be introduced. In this study, the first step is to create a user-friendly database from the uploaded network. The second step is to determine the parameters of the source file. Then, in practice, the construction of a series of dependencies of parameters will allow us to determine the importance for the researcher indicator of the network and its behavior.

The practical application of this method allows us to discover non-trivial dependencies of different networks, the study of which leads to the discovery of new results. For specialists in a narrowly focused field, there is a need to find valuable information from a large amount of data of a certain network. The methodology proposed will allow us to identify not only the moment of time when this information appeared, but also the very area in which it is located.

CONCLUSIONS

The study finds that percolation results partially reflect the connective properties of networks and thus can be used as an algorithm to identify special subsets of networks, identifying communities of agents holding the same conceptual opinion.

In the steady state, nodes adhering to the same state exhibit a phase transition from small clusters to large linking clusters when citation concentration increases. Percolation transition, as an indicator of sudden conceptual changes in citation networks, allows us to identify and link articles into a research scheme which constitutes a cluster of new ideas or theories.

In the column of authors linked by co-authorship relationships, of the 9200 authors, 7304 belong to one cohesive component. The citation and authorship networks reflect the structure of close communication through formal and informal scientific literature. The HEP physics community publishes a large number of papers, and the temporal nature of citations indicates rapid understanding and utilization of relevant new work.

Percolation is a common model of disordered systems, and its close connection with the fractal concept, from self-similarity to multifractality, is emphasized. The behavior of the dynamic and general parameters of the real information network for each time sample over the entire study interval, shows that the HEP network contains a largest component. However, analysis of the degree of self-similarity of random processes, their stationarity or non-stationarity is an area for further study. In this regard, the logical continuation of the work is the fractal analysis of time series of information flows in HEP.

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