IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier xx.xxxx/ACCESS.2021.DOI

Evolution of Publications, Subjects, and Co-authorships in Network-on-chip Research from A Complex Network Perspective

WEILONG CHEN[1], XIAOHANG WANG[2], YE SUN[3], QIAO HU[4], LETIAN HUANG[5], YINGTAO JIANG[6], AMIT KUMAR SINGH[7], TERRENCE MAK[8], MEI YANG[9]

[1]South China University of Technology, Guangzhou, China (201836390079@mail.scut.edu.cn)
[2]South China University of Technology, Guangzhou, China (xiaohangwang@scut.edu.cn)
[3]Queen Mary University of London, London E1 4NS, UK (ye.sun@qmul.ac.uk)
[4]Swarma Campus (Beijing) Technology Co. Ltd. , Beijing, China (huqiao@swarma.org)
[5]University of Electronic Science and Technology of China, Chengdu, China (huanglt@uestc.edu.cn)
[6]University of Nevada Las Vegas, Las Vegas, USA (yingtao.jiang@unlv.edu)
[7]University of Essex, Colchester, UK (a.k.singh@essex.ac.uk)
[8]University of Southampton, SO17 1BJ Southampton, UK (tmak@ecs.soton.ac.uk)
[9]University of Nevada Las Vegas, Las Vegas, USA (mei.yang@unlv.edu)

Corresponding author: Xiaohang Wang (e-mail: xiaohangwang@scut.edu.cn).

This research program is supported by the National Natural Science Foundation of China No. 61971200, the Natural Science Foundation of Guangdong Province No. 2018A030313166, Zhejiang Lab No. 2021LE0AB01, Pearl River S&T Nova Program of Guangzhou No. 201806010038, Open Research Grant of State Key Laboratory of Computer Architecture Institute of Computing Technology Chinese Academy of Sciences No. CARCH201916, and the Fundamental Research Funds for the Central Universities No. 2019MS087, The National Key Research and Development Program of China No. 2019QY0705, and the Key Laboratory of Big Data and Intelligent Robot (South China University of Technology), Ministry of Education. We also thank Dr. Jianlin Zhou for his invaluable comments.

ABSTRACT The academia and industry have been pursuing network-on-chip (NoC) related research since two decades ago when there was an urgency to respond to the scaling and technological challenges imposed on intra-chip communication in SoC designs. Like any other research topic, NoC inevitably goes through its life cycle: A. it started up (2000-2007) and quickly gained traction in its own right; B. it then entered the phase of growth and shakeout (2008-2013) with the research outcomes peaked in 2010 and remained high for another four/five years; C. NoC research was considered mature and stable (2014-2020), with signs showing a steady slowdown. Although from time to time, excellent survey articles on different subjects/aspects of NoC appeared in the open literature, yet there is no general consensus on where we are in this NoC roadmap and where we are heading, largely due to lack of an overarching methodology and tool to assess and quantify the research outcomes and evolution. In this paper, we address this issue from the perspective of three specific complex networks, namely the citation network, the subject citation network, and the co-authorship network. The network structure parameters (*e.g.*, modularity, diameter, *etc.*) and graph dynamics of the three networks are extracted and analyzed, which helps reveal and explain the reasons and the driving forces behind all the changes observed in NoC research over 20 years. Additional analyses are performed in this study to link interesting phenomena surrounding the NoC area. They include: (1) relationships between communities in citation networks and NoC subjects, (2) measure and visualization of a subject's influence score and its evolution, (3) knowledge flow among the six most popular NoC subjects and their relationships, (4) evolution of various subjects in terms of number of publications, (5) collaboration patterns and cross-community collaboration among the authors in NoC research, (6) interesting observation of career lifetime and productivity among NoC researchers, and finally (7) investigation of whether or not new authors are chasing hot subjects in NoC. All these analyses have led to a prediction of publications, subjects, and co-authorship in NoC research in the near future, which is also presented in the paper.

INDEX TERMS Networks-on-chip, science of science, complex network

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

I. INTRODUCTION

At the turn of the 21^{st} century, it became a pressing issue that shared bus interconnection could not keep up with the scalability and bandwidth requirements essential for then system-on-chip (SoC) designs featuring tens or even hundreds of cores. In response, a few new interconnection architectures and technologies were considered and emerged. Noticeably, on-chip packet-switched micro-network of interconnects, later coined by the academic and industry communities as network-on-chip (NoC) architecture, stood out and has been accepted as a viable solution to on-chip interconnection after 20 years of active research and development. More than ever, NoC plays an even more important role in today's CPU- and GPU-based many-core chips (*e.g.*, Epiphany-V has 1024 64-bit RISC cores), and particularly so, in emerging neural network accelerators with tens or even hundreds or thousands of cores (*e.g.*, $400,000$ AI cores exist in Celebras) that need to communicate with each other.

Set to provide scalable, high bandwidth, and low latency interconnection for various SoC systems, NoC actually encompasses a wide array of research topics and paradigms, ranging from those inherited from traditional computer networking (*e.g., topology, routing, etc.*) to the latest ones that are aligned with machine learning applications and emerging technologies. Over its twenty years of timespan, the entire area of NoC has gone through three phases and stages, as shown in Figure 1: the start-up (2000-2007), the growth and shakeout (2008-2013), and the mature and stable (2014-2020), broadly measured by the numbers of publications and new authors per year.

Over the past twenty years, a number of good survey papers covering one or a few specific aspects of NoC, including *application mapping* [1]–[3], to *topology design* and *routing algorithms* [4], to *fault tolerant NoC* [5], to *optical NoC* [6], [7], to *low power design* [8], [9], *NoC for QoS* [10], [11], *testing* [12], *simulators* [13], and *reconfigurable network* [14], and many others, have been published. Since these survey papers only focus on specific research subjects/topics, by human experts and based on the authors' own knowledge of the subjects, these surveys did not provide an overarching and objective view of the NoC, and the surveys did not quite follow a data-driven analysis method to quantify the dynamics of NoC research and make a sound prediction of what is lying ahead.

Based on a methodology that marks a significant departure from that was adopted by the existing NoC survey papers, this paper instead conducts a data-driven analysis of the evolution of publications, subjects, and co-authorships of the NoC area from the perspective of complex network [15]. To this end, we construct three networks, the citation network, subject citation network, and co-authorship network, that can represent three key elements of NoC research, namely publications, subjects, and authors. Furthermore, we examine the network structures (*e.g.*, network diameter, cluster coefficient, average degree, *etc.*) and the dynamics of these networks. This exercise shall not only help us quantify the progress made in NoC, the shift of research topics over the time, and career development of both new and established NoC researchers, but also create an opportunity to dig out the reasons behind these accomplishments and changes that have happened in the past 20 years. One specific goal of this study is to track the knowledge flow among different subjects and how NoC research was shaped by other factors, which include the relationship between subjects, and the collaboration patterns among authors, and the authors' preferences in choosing specific NoC subjects.

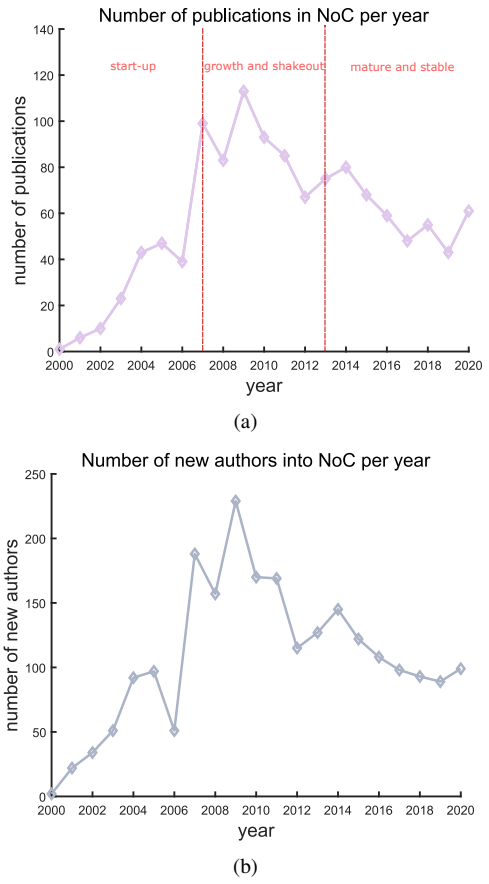


FIGURE 1. Numbers of publications in NoC area from Y2000 to Y2020. (b) Numbers of new authors entering the NoC area from Y2000 to Y2020. An author is recognized as a new author in the year when his/her first publication got published or made publicly accessible. Name ambiguity is handled by checking the names and the affiliations altogether.

The rest of the paper is organized as follows. Section 2 takes a glimpse of the 20 years of research on NoC. Section 3 goes on to survey the related work. In Section 4, the analysis methodology followed in this paper is presented, followed by the network structure and evolution of NoC publications, NoC subjects, and co-authorship as detailed in Sections 5, 6, and 7, respectively. In these sections, we also provide the analysis regarding the reasons that drive the formation and evolution of the networks/data. Actually, the data and the analyses in Sections 5 through 7 lay down the ground for the prediction for the evolution of publications, subjects, and co-authorship, as presented in Section 8. Finally, Section 9

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

summarizes the paper.

The contributions of the paper as follows.

1) A data-driven complex network analysis is performed to study the evolution of NoC research over its entire 20 years of existence. A longitudinal study by nature, this study is based on the build of three complex networks, namely citation network, subject citation network, and co-authorship network.
2) Network structures and dynamics of the three networks are analyzed to reveal the evolution of publications, subjects, and author behaviors. A few interesting results about NoC area have been thus unveiled. (i) Six subjects, *i.e., topology, routing, flow control, router design, mapping,* and *emerging technology* have been identified as the most influential subjects in NoC research, and they are found highly related to each other. The knowledge flow among them can be clearly measured with the metrics defined in this study. (ii) A few subjects, noticeably *reliability*, are becoming increasingly influential as time goes by, while some others, such as *physical design*, is gradually losing its momentum. (iii) The collaboration among the authors shows interesting motifs (sub-graphs that frequently appear in a network), indicating different collaboration patterns.
3) Researchers, not limited to those working in the NoC area, can adopt this methodology, along with use of the analysis tools developed in this study, to understand and gauge the scientific research areas of their interest and have the ability to make the predictions about the future directions.

II. TWENTY YEARS OF RESEARCH ON NOC: A REVIEW

The start-up of the NoC area was marked by a few highly influential early works (*e.g.,* [16], [17]), rightfully recognizing the fact that interconnection infrastructure based on conventional bus, crossbar, or point-to-point connections could no longer keep up with the scalability, bandwidth, and efficiency requirements as more processing cores (elements) were integrated into the same silicon. As a viable alternative, NoC enables efficient communication among the processors, memory units, and IO units with data packetization and transmission in a manner as similar to that in computer networks, which was poised to provide high bandwidth, low latency, and scalability. But since there are physical limits imposed by material and layout, there are unique requirements for NoC in term of size, system performance, and power consumption.

A generic NoC architecture, shown in Figure 2, is made of blocks like tiles and links that are set to allow packetized data to flow through. Each tile is composed by a core, a memory unit, a network interface (NI), and a router. The routers are connected to form a network topology. This generic NoC architecture often in a real setting needs to include additional features and/or be tailored to handle diversified traffic patterns and meet the traffic demands. The NoC research has been driven by three main factors, including 1) demands of emerging applications, 2) emergency of various architectures, and 3) emerging technologies.

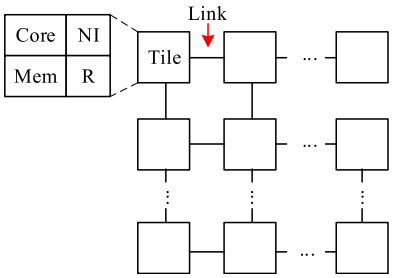


FIGURE 2. Illustration of a generic NoC system that has multiple routers and links. Each processing element interfaces with its attached router through a network interface (NI). A router typically has a number of components like input/output buffers, routing computation unit, and switching fabric. Core is the processor core. Mem is the local memory or L1 cache or L2 cache bank. R refers to router.

(1) In the past 20 years, a myriad of new applications have emerged, ranging from embedded systems to cloud computing. These emerging applications can also be broadly classified into multimedia processing, machine learning and AI, graph-based computing, telecommunications, *etc.*, and they exhibit vastly different needs in terms of bandwidth and/or latency.

(2) Different NoC architectures have different levels of support for different traffic patterns and demands. For example, in a cache coherent many-core system, its data traffic relies on some coherent protocols, including read request, write invalidate, *etc.*, and such traffic is one-to-many in nature. GPU, on the other hand, sees a great deal of many-to-few-to-many (*i.e.*, from tiles to memory controllers and back to tiles) type of traffic. In addition, the rise in FPGA-based AI accelerators calls for more efficient and scalable NoC to support broadcasting, multicasting, and many-to-one types of traffic.

(3) The last a couple of decades have witnessed great improvements in semiconductor material and frontier technologies, including silicon photonics, wireless technologies, transmission line, interposer, and 3D integration, which have opened up new opportunities to build non-electrical, or wireless, or true 3D NoCs. There has been a hype and hope that, 3D integration that uses through silicon vias (TSV) or monolithic inter-layer vias (MIV) for vertical interconnection can significantly reduce the lengths of the global wire. As a more radical approach, wireless NoC can provide a multicast-based interconnection without the need of wire links, which is poised to connect large systems with extremely low latency. Silicon photonics, either on chip or in package, provide low power and high bandwidth communications for cores or dies. Interposer-level networks have become one of the most popular research topics in recent a few years, as chiplet design paradigm has dominated the design landscapes. The new chiplet-based processors that rolled out from Intel and AMD use SERDES (serializer/deserializer) or transmission line sitting on an interposer for data communications.

Above three research drivers actually impacted NoC re-

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

search quite differently over the time. From 2000-2007, research and development of NoC were in their start-up stage, and the focus was mostly on the *network structure design* (*topology, routing, flow control, etc.*), *application mapping, design space exploration* and *tools*. All the major early works were capped by a survey paper that was published in 2006 [18]. From 2008-2013, as NoC research hit its peak, the dominant subjects shifted to *emerging technologies, new applications, simulators, new NoC architectures, power management*, *etc.* Various important NoC architectures, including dimension decomposed router [19], virtual channel (VC) design and express VC design [20], 3D NoC [21], WiNoC [22], [23], optical NoC [6], all came to light during this time. Once the NoC research enters its next phase (2014-2020), *NoC for AI accelerators*, and many new subjects like *approximate NoC, security, network on interposer in chiplet based systems* have dominated the publication and development landscape. The timeline (history) of the NoC research and the changing research topics will be qualitatively analyzed in later sections.

III. RELATED WORK

A. SURVEY PAPERS IN THE NOC AREA

Several survey papers were published, covering many aspects of NoC research, ranging from *application mapping* [1]–[3], *topology design* and *routing algorithms* [4], [18], [24], [25], *fault tolerant NoC* [5], *optical NoC* [6], [7], *low power design* [8], [9], *NoC for QoS* [10], [11], *testing* [12], *simulators* [13], to *reconfigurable network* [14], *etc.* However, all these survey papers are based on the domain knowledge of the human experts (authors). They do not follow a qualitative approach to classify and merit the exiting research merely based on the survey contributors' own understanding of the subjects at hand. This paper differs from those survey papers as we aim to provide a comprehensive view of the NoC publications from a complex network perspective, and thus, in a more objective manner, to reveal how the NoC evolves, what relationships among different NoC subjects hold, and what collaboration features we can perceive within the NoC community by analysing the network structure and dynamics quantitatively.

B. SCIENCE OF SCIENCE, IN THE EYES OF COMPLEX NETWORK

Science of science studies what science is really about or what constitutes a specific discipline. Specifically, it identifies the features or dynamics of a specific discipline of science or the whole science, focusing on how knowledge, publications, and scientist behaviors would evolve [15]. In the literature, complex networks or complex systems, as a powerful mathematical tool, have been applied to empower data-driven analysis of science of science [26]–[30]. Of the many complex networks that can be built, citation network and co-authorship network are the two most commonly used [31]–[34], while other kinds of networks, such as network of subjects and network of keyword occurrence, can also provide a useful perspective in studying the flow of knowledge and evolution of a scientific area. For instance, the authors in [35], used the conference publications in bio-informatics to study the evolution of that area. [36] built a network of academic conferences to track the changes of research topics and the dissemination of scientific ideas. [37] modeled the co-authorship network evolution, while [38] modeled the population of the computer science community using the DBLP dataset.

IV. ANALYSIS METHODOLOGY

Following the methods established in science of science, we investigate how the overall properties of publications, research subjects, and author behaviors in the NoC area have changed over time. Figure 3 shows the analysis methodology adopted in this paper.

- First, preparing the dataset. All the NoC related publications presented in the five top conferences (DAC, DATE, HPCA, ISCA, and NoCS) as well as high-impact NoC papers (being cited at least 100 times from Microsoft Academic Search, including both journal and conference papers), are collected from the IEEE Xplore and ACM digital libraries. We adopted 100 as the threshold for citation count to determine if a paper is considered as a high impact paper. The highest citation count of an NoC paper is found around 5000, and most of the papers understandably receive much fewer citations. We picked up the threshold to be 100 such that the high impact papers account for around 20% of the total dataset, which follows the Pareto Principle or the 20/80 rule, with the assumption that the top 20% most cited papers are the most influential ones. Microsoft has a team working on science of science with many publications. They also released an open source dataset for academic relationship, see https://www.microsoft.com/en-us/research/project/microsoft-academic-graph/. We thus use Microsoft Academic Search for convenience. This does not exclude people from using Google Scholar or any other similar service for the same analysis and prediction purposes. DAC, DATE, HPCA, ISCA, and NoCS are generally agreed as the most important conferences by NoC researchers, and all the major contributions in NoC research over the past 20 years appeared in these conferences. We can certainly include more papers from other conferences and journals in the future. There are a total of 997 articles that fall into these categories, and the bibliometric information of all these publications, such as titles, author lists, author affiliations, abstracts, keywords, references, and full texts, are downloaded from the ACM and IEEE Xplore digital libraries. As conference proceedings are a timely medium to publish new ideas than journals, and most influential conference papers later on are converted/extended to appear in journal formats, the proceedings of the flagship conferences are justifiably

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

determined to allow us to grabble with the evolution of NoC research thoroughly and timely.

- Second, building an NoC subject tree. We build a subject tree that presents the NoC subjects in a hierarchical manner. The tree takes NoC as the root node, and each topic in NoC can be divided into several smaller subtopics at the next levels, until there is no point to divide a subtopic further. Figure 4 shows a snapshot of the NoC subject tree, where the level 1 branches are *wireline NoC* and *emerging technology* (including *optical, wireless*, *etc.*). Under *wireline NoC* there are *application, system, networking, micro-architecture,* and *circuit and physical* layers. Note that usually we use the tags at the bottom of the subject tree (leaf nodes) to annotate articles, but *emerging technology* alone becomes a tag instead of its subtopics. The full subject tree is available at https://github.com/FCAS-SCUT/Science_of_Science_NoC. Since this subject tree has been checked by multiple NoC researchers, there is a high degree of confidence of its accuracy and completeness. Terms in this subject tree are the subjects in NoC, which serves as a dictionary for subject labeling. That is, the text processing algorithm in Appendix uses this dictionary to automatically label each paper for its subject(s). Note that a paper may be affiliated with multiple labels as it may fall into multiple subject areas.
- Third, building three complex networks and analysing them.
    1) The citation network is built based on the citation relations between the NoC publications. Both the network structure and dynamics are studied.
    2) To get the evolution and interrelationship of subjects in NoC, it is inadequate to just examine the citations between publications. Rather, by aggregating the citation relations to the subjects at different levels, the subject citation network needs to be built. Again, its network structure and dynamics are analyzed.
    3) The co-authorship network is further built, to understand the behaviors of the NoC researchers, which also contributes to our knowledge about the evolution in NoC research.

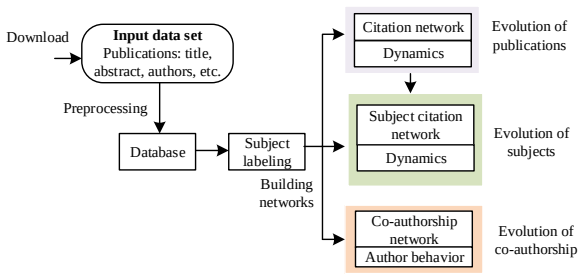


FIGURE 3. The analysis methodology that is followed in this paper.

We have developed corresponding software tools including data processing program and analysis algorithms for the whole process shown in Figure 3. These tools can be easily extended to analyze the evolution of other research areas, and the source code can be found in https://github.com/FCAS-SCUT/Science_of_Science_NoC.

V. EVOLUTION OF PUBLICATIONS BASED ON THE NOC TEMPORAL CITATION NETWORK

The NoC citation network is represented as a directed graph, where each node is an NoC paper and a directed link is inserted from node A to node B when paper A cites paper B. The size of a node corresponds to the number of being cited after publication, *i.e.*, the in-degree of a node. The links are unweighted (*i.e.*, the weight is always set to 1) due to the nature of a citation relationship.

A. NETWORK STRUCTURE AND DYNAMICS OF THE NOC CITATION NETWORK

Evolution of the network structures can be visualized from the four citation networks drawn at four milestone years, namely Y2005, Y2010, Y2015, and Y2020 (Figure 5). A community detection algorithm [39] is performed to examine the relationship among the NoC publications. To reflect the structural strength of these communities, they are color-coded. The vertices painted with the same color belong to the same community. Notice that there are still a few papers that are neither cited nor citing other papers in our dataset, such papers are hereinafter referred as isolated papers.

Table 1 summarizes the number of nodes, clustering coefficient, network diameter, average degree, modularity (with resolution =1.0), and percentage of the giant connected branch for NoC citation networks in four milestone years. One can see that the number of nodes in NoC citation network increases rapidly (rising from 107 to 997), especially from 2005 to 2015, indicating that the NoC field is evolving and knowledge is accumulating at a fast speed. Since the number of papers in the dataset is much smaller than the total number of citations they have, the average degree of the network is low (smaller than 3), and the network diameter grows over the years (rising from 3 to 9). On the other hand, the increase of average degree indicates that the knowledge base in the NoC field is maturing, and more publications in NoC area are citing articles within the NoC itself. The modularity and clustering coefficient of the network are always low, indicating that the citation is a weak relationship with no clear preference. In another word, it is difficult to form an obvious and stable community in NoC. Another interesting phenomenon is that the giant connected branch of the NoC citation network grows larger each year, suggesting that there are increasingly fewer isolated nodes in the citation network. Table 18 in Appendix further shows that, as time goes by, small communities tend to merge into large ones, corresponding to the growth of the NoC knowledge base.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

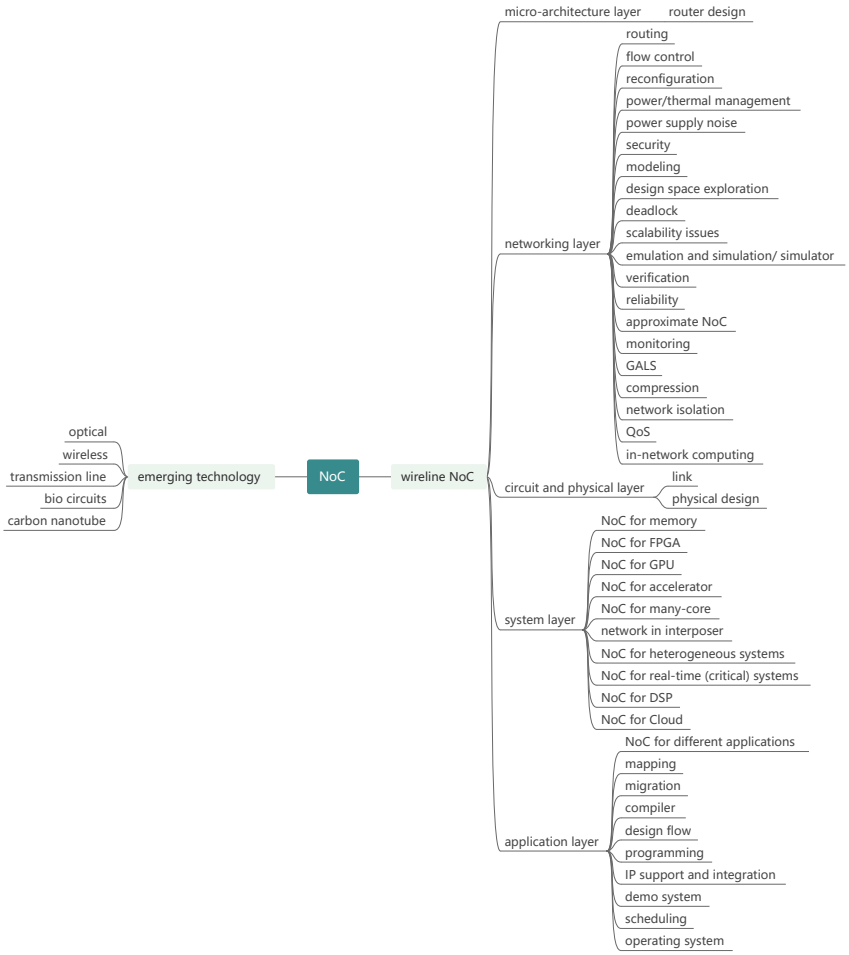


FIGURE 4. A snapshot of the NoC research area subject tree. Each node in this tree can be further expanded.

TABLE 1. Network parameters of the NoC citation network up to 2005, 2010, 2015, and 2020*

Year	Nodes	Clustering coefficient	Network diameter	Average degree	Modularity (resolution 1.0)	Percentage of the giant connected branch
2005	107	0.047	3	0.841	0.421	72.12%
2010	462	0.042	5	1.976	0.508	74.22%
2015	801	0.049	8	2.539	0.514	77.73%
2020	997	0.053	9	2.748	0.528	80.74%

* (1) The degree (the sum of in-degree and out-degree) of a node is the number of links it has to other nodes. (2) The clustering coefficient of a node is the ratio of the number of connections within the node's neighborhood and the number of connections for a fully connected network. (3) The diameter of a network is the maximum distance between any two nodes in the network. (4) The modularity of a network measures the strength of division of the network into communities (modules). Networks with high modularity have dense connections between the nodes within communities but sparse connections between nodes in different communities. (5) In a directed graph G, if any two different vertices are mutually accessible, the graph is said to be strongly connected. The largest strongly connected sub-graph of a directed graph G is called the giant connected branch of G.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

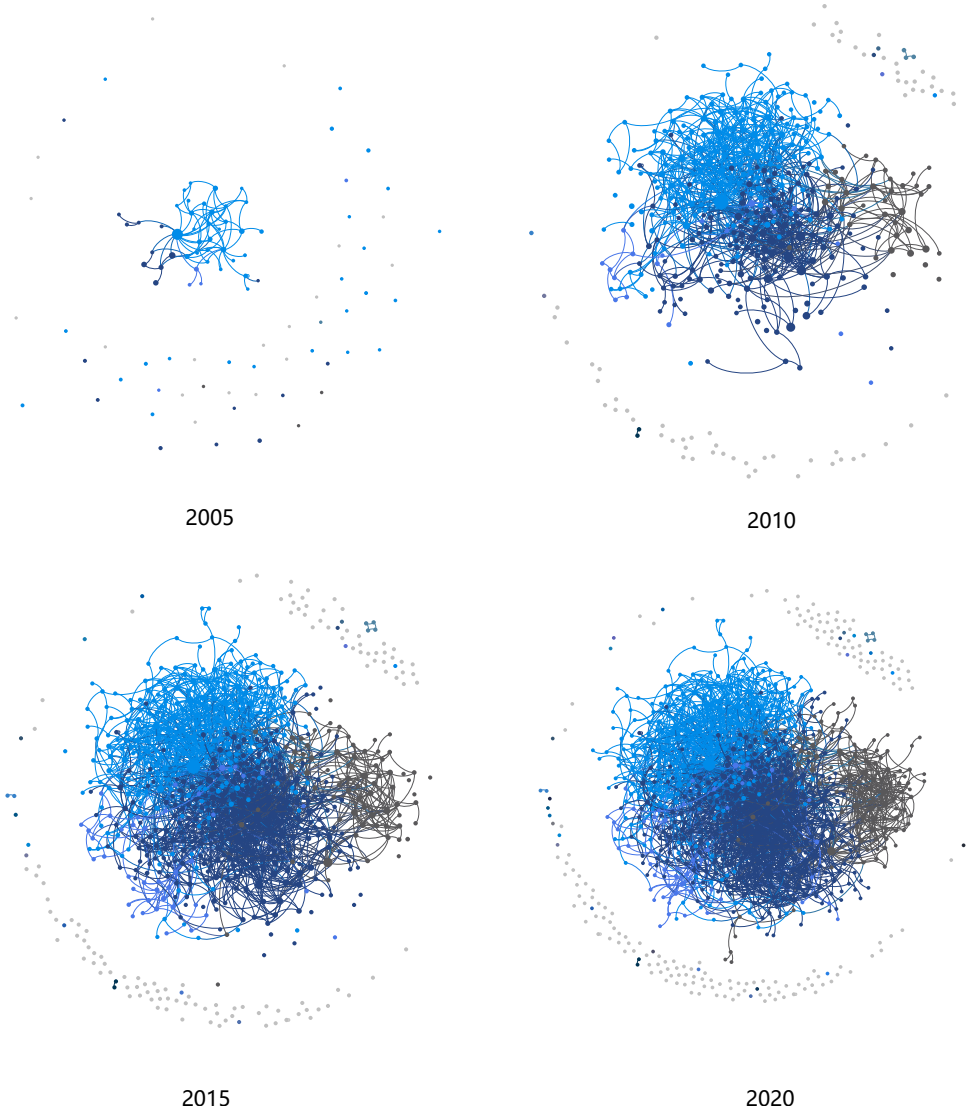


FIGURE 5. The NoC citation networks up to 2005, 2010, 2015, and 2020.

A close look at the early papers reveals that they mostly cited works outside the NoC area, which means before 2010, the NoC research benefited from the inward knowledge flow from other areas to the NoC. For instance, the references of [17] (the largest node in the citation network in 2005, centering in the graph), a paper published as early as in 2002, were drawn from the traditional areas like *computer network, digital system design, IC design, and power optimizations*. In a sharp contrast, the papers published in 2015 or later had a lot of internal citations itself (*i.e.*, the cited papers were from the NoC area). Such increase of internal citations is a clear indicator that the NoC area became more matured and a significant amount of knowledge was created and spread within the NoC circle. Correspondingly, the NoC citation network became more densely connected.

Table 16 and Table 17 in the Appendix further tabulate the top 5 most cited publications in each calendar year. One can see that, in the early years, [17] as one of the earliest papers in the NoC area, ranked top one in terms of the number of being cited. Later on, the two papers describing NoC simulators [40] and [41] got more citations, as these simulators were adopted by the mainstream of the researchers in the NoC community. In a similar token, another two papers, [42] and [43], were recognized as the milestones in NoC designs, featuring high speed and low delay router/network designs.

B. RELATIONSHIP BETWEEN COMMUNITIES IN THE CITATION NETWORK AND NOC SUBJECTS

A paper is more likely to be cited by those that fall into the same subject areas, and such citation relationships thus are generated and grabbed in the citation network. Correspondingly, a paper and all the papers that cite it appear to be "close" to each other in the citation network and they together are likely to form a community. Based on these observations,

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

we test whether all NoC publications in a community belong to a single subject or not. In another word, we try to figure out if there is a one-to-one mapping from a community to a particular subject. Table 15 shows the subject distribution in selected large communities in the NoC citation network. Each of these communities has an ID generated by the community detection algorithm. From Table 15, we have the following observations.

1) The communities do not show a strong correspondence with single subjects. That is, publications in a community often do not belong to only one subject, but several main subjects can broadly cover the community.
2) In the communities, subjects like *flow control, routing, router design, topology, emerging technology*, and *mapping* are closely correlated. These subjects appear together frequently and always show similar (high) distributions, and the reason is provided in the next section.

VI. EVOLUTION OF SUBJECTS BASED ON THE NOC SUBJECT CITATION NETWORK

The NoC subject citation network is defined as a directed graph, where each node represents an NoC subject, and a directed link from node A to node B is established if a paper that falls into subject A cites a paper in subject B. The links of the NoC subject citation network are weighted, and the weight of the link between nodes A and B corresponds to the number of citations by the papers in subject A citing those in subject B. Note that the NoC subject citation network includes self-loops to account for self-citations. The node size is proportional to the in-degree of each node, which corresponds to the total number of papers being cited in that subject.

A. NETWORK STRUCTURE AND DYNAMICS OF THE NOC SUBJECT CITATION NETWORK

Figure 6 shows the subject citation networks created at Y2005, Y2010, Y2015, and Y2020. Table 2 summarizes the number of nodes, network diameter, average degree (weighted and unweighted), and clustering coefficient for NoC subject citation networks in four milestone years. One can see that the number of nodes grows at a fast pace over time (starting with 26 and rising to 81), indicating that many new subjects emerge in the NoC field, particularly during the early days of the NoC era. The subject networks had a shorter network diameter (from 7 to 4), while the average degree (rising from 3.308 to 13.272) and the clustering coefficient (from 0.174 to 0.645) rapidly grew. All these observations point to the fact that the NoC subjects tend to increasingly cluster together and the knowledge flows among them are becoming more frequent over the years.

1) Dynamics of three representative subjects

The evolution of the influence of specific subjects in the NoC area over time is also studied, expecting to identify the trends and measure them quantitatively. We plot the changes of the influence for three typical subjects, namely *physical design, reliability*, and *topology* in Figures 7–9. The networks are presented in "Fruchterman Reingold" style layout that nodes/subjects with higher weighted in-degrees (*i.e.,* nodes/subjects with their publications being cited more frequently) are placed close to the center.

The influence of a subject is quantified by the percentile rank scores of its weighted in-degrees. For example, the weighted in-degree of *physical design* ranked top 10% among all the NoC subjects up to 2005, so its influence score is 90% (meaning it is more popular than 90% of the NoC subjects). The greater the weighted in-degree of an NoC subjects, the greater its influence score and the closer it is to the center of the network. Figure 10 shows the change of influence scores of three NoC subjects over time. One can see that: (1) the influence score of *physical design* drops from 90% in 2005 to only 50% in 2020; (2) the influence score of *reliability* jumps from lower than 30% to higher than 80%; and (3) the influence score of *topology* is kept relatively flat, at around 80% or slightly higher.

The reasons behind these trends can be explained as follows. (1) *Physical design* was recognized as a critical issue in the early phase of NoC development, and as such, it was at the center of NoC research before 2005. Once it became more matured, the research interest faded away. As so, this subject moved towards the periphery of the NoC subject citation network. We believe in the future this topic will draw some attention again as the physical design may require early floorplaning for chiplets sitting on an interposer or substrate. (2) Moving in a direction quite opposite to *physical design*, *reliability* in NoC has gained more attention and traction in the research community. Performance, rather than reliability, was the primary optimization objective in the early years of NoC. But due to relentless increase of chip power density and continued device minimization and wire shrinkage, which together contribute to higher failure rates, more soft errors, or faster aging, there has been growing concerns on NoC reliability, which mandates more research to address these problems. Reliability and DFT (Design for Test) will become more important for the interconnect, circuits, and logic in the interposer or substrate. (3) *Topology* holds almost the same location (near the center) in the NoC subject citation network, indicating that it stands the test of time of its popularity as a main research subject. This phenomenon may be explained by the fact that, with the emergence of new technologies and new architecture designs, there is more space to explore when it comes to topological design. Correspondingly, the research community still maintains a high level of enthusiasm for this subject. With the aforementioned analysis tools and method, a quick and objective data-driven survey on any NoC subject can be established. For instance, a brief survey of NoC *reliability* is done by solely reviewing the papers from our dataset.

According to the topic tree, the subject *reliability* can be further divided into 3 subjects that appear as the children of the *reliability* node:

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

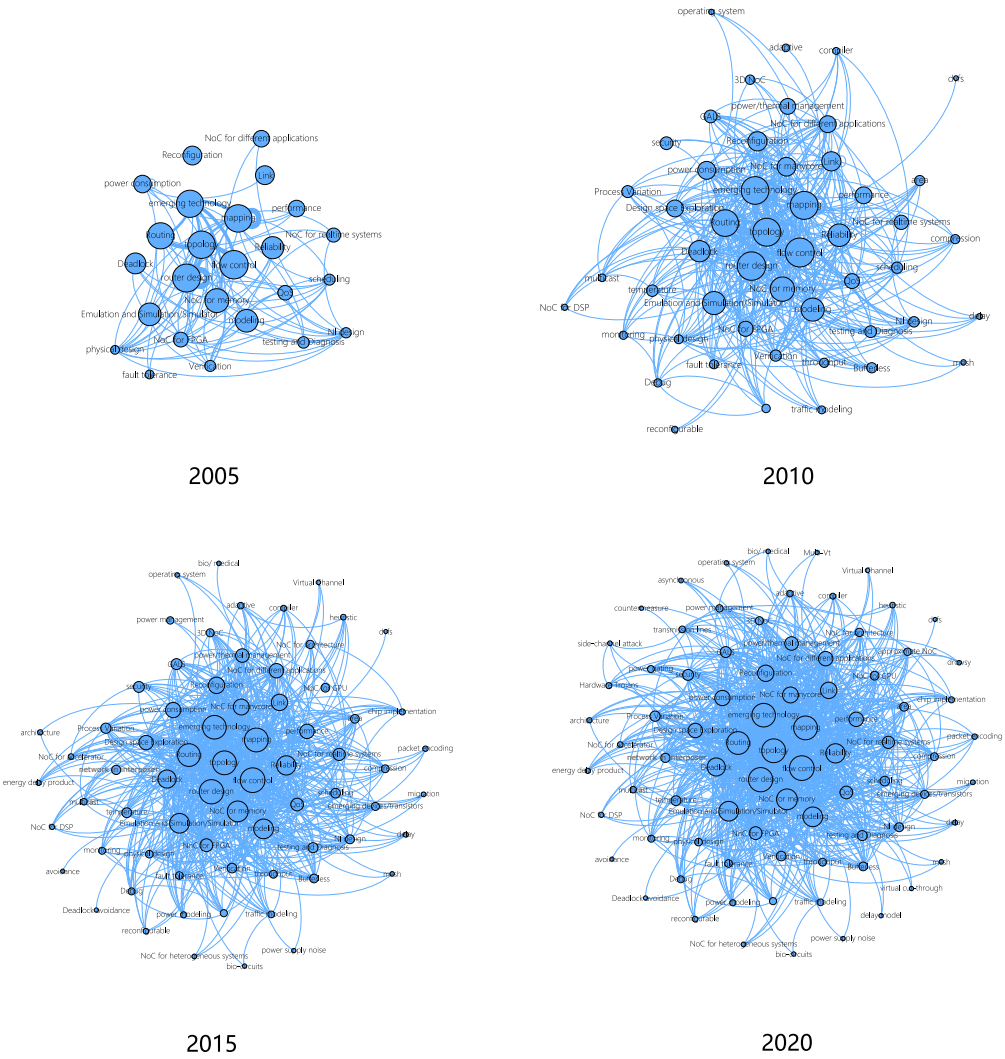


FIGURE 6. The NoC subject citation networks up to 2005, 2010, 2015, and 2020.

TABLE 2. Network parameters of the NoC subject citation networks up to 2005, 2010, 2015, and 2020

Time	nodes	Clustering coefficient	Network diameter	Average degree	Average degree (weighted)
2005	26	0.174	7	3.308	37.308
2010	50	0.399	5	8.12	92.14
2015	70	0.518	4	11.029	91.914
2020	81	0.645	4	13.272	104.296

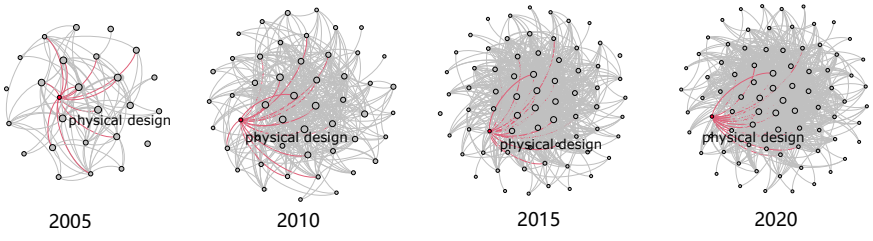


FIGURE 7. Temporal evolution of the subject *physical design* through the years of 2005, 2010, 2015, and 2020. One can see that the subject *physical design* gradually moves away from the center of network as time goes by.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

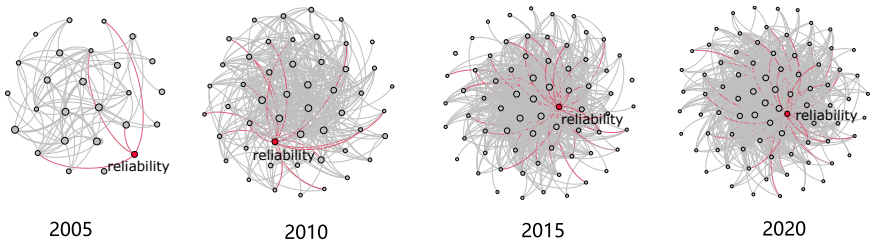


FIGURE 8. Temporal evolution of the subject *reliability* through the years of 2005, 2010, 2015, and 2020. One can see that the subject *reliability* continues its move to the central location of the network as time goes by.

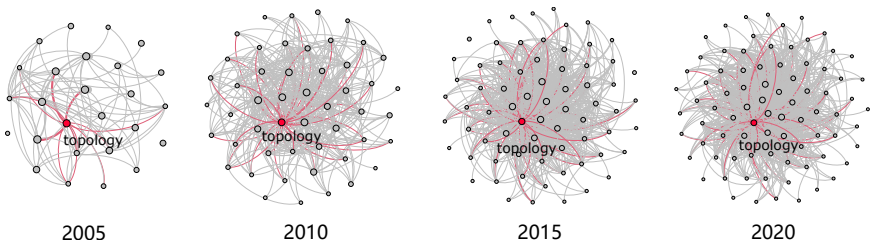


FIGURE 9. Temporal evolution of the subject *topology* through the years of 2005, 2010, 2015, and 2020. One can see that the subject *topology* holds its central location of the network throughout all the years.

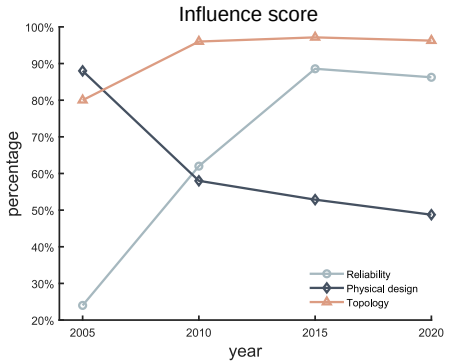


FIGURE 10. The change of influence scores of the three NoC subjects over time

- First sub-subject: Fault-tolerant approaches using fault tolerant routing or reconfigurable typologies to bypass faulty components, or using remapping or migration to move tasks to fault-free cores [5], [44]–[56]. Collectively, the total citation number received by these papers is 45 in our database.
- Second sub-subject: Modeling of soft errors in routers/links or approaches to handle soft errors using error correction link/router designs [57]–[65]. The total citation number received by these articles is 11.
- Third sub-subject: Modeling or mitigating aging through adaptive routing or remapping/mapping [66]–[71]. The total citation number received by these articles is 7.

From the number of citations, it can be seen that the research concerning fault-tolerance in NoC remains the most popular one under *reliability*, as permanent faults are becoming a serious concern these days.

B. DYNAMICS OF SIX MOST INFLUENTIAL AND HIGHLY CORRELATED SUBJECTS IN NOC

From Figure 6, one can see that *topology, routing, flow control, router design, mapping,* and *emerging technology* are the most influential and strongly connected subjects in NoC. Since these six subjects also happen to have the highest eigenvector centrality values (>0.95), as reported in Table 3, their importance in NoC design is further confirmed. For instance, *topology* has always been the most fundamental element of the network infrastructure, and *routers* are the primitive building blocks of an NoC network. *Flow control* and *routing* are the two key elements to improve network performance. *Application mapping* has a key implication on the system performance in NoC. In recent years, *emerging technology* has been a driver for NoC research. In the following, we will examine the relationships of these six subjects through the lens of subject citation network.

When paper a cites paper b, we claim knowledge flows from b to a. Note that the direction of knowledge flow is opposite to that of the citation direction (as shown in Figure 11 (a)). Because the number of papers falling in one subject can vary significantly from that of papers in another subject, it can be misleading to simply use the number of citations between subjects to represent the knowledge flows. For example, suppose there are 100 articles in subject A and 10 in subject B, and articles in A reference 9 papers in B, while articles in B reference 10 papers in A 10. In this case, it could be wrong to conclude that the knowledge flow from A to B is greater than that from B to A. In order to eliminate factors that might lead to inaccurate knowledge flow assessments (for example, each subject has different number of papers), the statistical significance of each citation relationship has to be verified with respect to a null model.

In Figure 11 (b), we illustrate the calculation method of

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 3. The eigenvector centrality values of a few NoC subjects

Subject	Eigenvector centrality*
mapping	1
topology	0.992
flow control	0.984
emerging technology	0.970
routing	0.957
router design	0.950
modeling	0.947
deadlock	0.920
NoC for manycore	0.882
emulation and simulation/simulator	0.876
NoC for memory	0.865
...	...

*Eigenvector centrality is a measure of the influence of a node in a network. If a node is pointed to by many other nodes, this node has a high eigenvector centrality value. Eigenvector centrality can be computed by following the method reported in [72]. The NoC subjects that have an eigenvector centrality value lower than 0.86 are not included into the table.

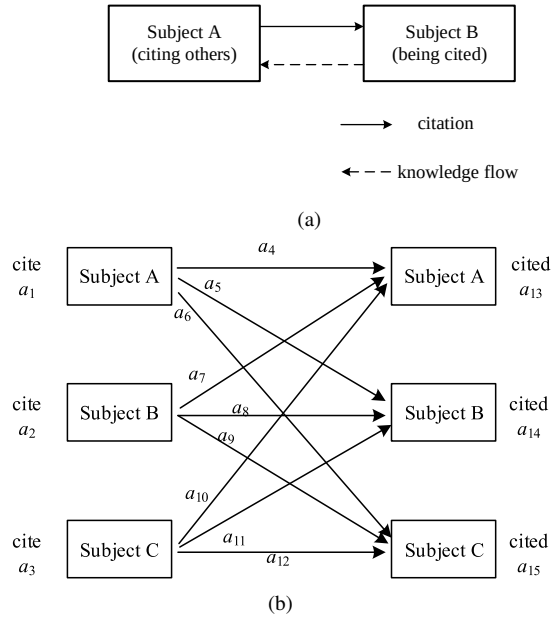


FIGURE 11. (a) Knowledge flow and citation flow have opposite direction. (b) An example of measuring the knowledge flow between subjects

knowledge flow in a simple subject network with three subjects A, B, and C to illustrate the null model and statistically significant network. Assume the papers in subjects A, B, and C reference a_1, a_2, and a_3 papers, respectively. a_{13} through a_{15} respectively represent the numbers of citations received by papers in subjects A, B, and C. a_4 through a_{12} are the numbers of citations between each pair of subjects A, B, and C respectively, for example, a_5 is the number of citations that papers in subject A cite those in subject B. The total citation count T_c is the total number of references, given as $a_1 + a_2 + a_3$, which is also equal to the total number of citations received by papers in these three subjects, counted as $a_{13} + a_{14} + a_{15}$. We thus have,

$$\begin{aligned} T_c &= a_1 + a_2 + a_3 \\ &= a_4 + a_5 + a_6 + a_7 + a_8 + a_9 + a_{10} + a_{11} + a_{12} \\ &= a_{13} + a_{14} + a_{15} \end{aligned} \quad (1)$$

$P(A \rightarrow B)$ is defined as the possibility of a paper from subject A cites that from B. So, in the statistically significant network, we have:

$$P(A \rightarrow B) = \frac{a_5}{T_c} \quad (2)$$

We then consider a null model in which the papers published in subject X randomly select papers as their references, regardless of which subject they belong to. Let X_{citing} be the subject whose papers cite those in other subject(s) and Y_{cited} be the subject whose papers are cited by other subject(s). Hence the probability in the null model can be written as follows:

$$\begin{aligned} P^{null}(A \rightarrow B) &= \Pr(X_{citing=A}) \times \Pr(Y_{cited=B}) \\ &= \frac{a_1}{a_1 + a_2 + a_3} \times \frac{a_{14}}{a_{13} + a_{14} + a_{15}} \\ &= \frac{a_1}{T_c} \times \frac{a_{14}}{T_c} \end{aligned} \quad (3)$$

The knowledge flow metric F [73] is defined as follows.

$$F(B \dashrightarrow A) = \frac{P(A \rightarrow B)}{P^{null}(A \rightarrow B)} \quad (4)$$

$B \dashrightarrow A$ indicates that the knowledge flows from B to A. $F = 1$ is adopted as the critical threshold to distinguish whether the knowledge flow from subject B to subject A is statistically significant or not. When $F > 1$, it means that subject A is more likely to have extracted knowledge from subject B than would be expected at random. The F values of the subjects in 2020 are computed in Table 4.

Figure 12 shows a sub-graph of the subject citation network, and this sub-graph contains the six most influential subjects, namely, *topology, emerging technology, mapping, flow control, router design*, and *routing*. In the figure, each node represents a subject and a directed link between node A and node B is established if node A flows knowledge to B. The size of a node is not distinguished, and the weight of an edge corresponds to the value of F. One can see that:

1) For each subject, the number of self-citations is much more than that of citations across different subjects. For example, *emerging technology* shows a very strong self-citation ($F = 2.4$), indicating that this subject tends to rely on the knowledge contributed by the publications from the same subject.
2) The knowledge flows between a pair of subjects are symmetric, with a maximum difference of only 0.2. The contribution of subjects A to B and that of B to A are almost equal.
3) By removing the edges whose F values are below 1, the six subjects can be further divided into two communities as in Figure 12 (b). That is, *emerging technology, mapping*, and *topology* form a community, and so do *routing, router design*, and *flow control*.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 4. The knowledge flow metric values (F) among the six NoC subjects

Knowledge flow metric	*Emerging technology*	*Flow control*	*Mapping*	*Router design*	*Routing*	*Topology*
Emerging technology	2.423	0.531	0.760	0.374	0.689	1.134
Flow control	0.527	1.556	0.645	1.317	0.988	0.703
Mapping	0.816	0.704	2.162	0.718	0.985	1.082
Router design	0.568	1.131	0.775	1.828	0.891	0.897
Routing	0.523	1.145	0.901	0.896	1.616	0.818
Topology	1.221	0.759	1.053	0.824	0.821	1.386

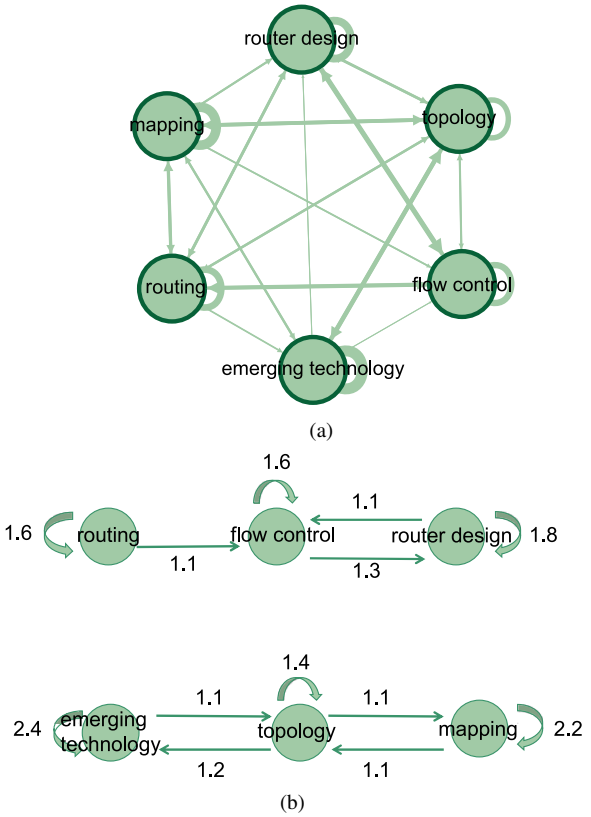


FIGURE 12. (a) The study of subject citation network with the six most influential subjects using a "magnifier". (b) The six subjects can be further decomposed into two communities, showing only edges with $F > 1$.

C. NUMBER OF NOC PUBLICATIONS OF THE SUBJECTS EACH YEAR

All the NoC publications are clustered into three time periods, *i.e.*, 2000-2007 (period 1), 2008-2013 (period 2), and 2014-2020 (period 3). The subjects may evolve, following these three trends:

- Rising, the number of publications in one NoC subject increases from period i to period $i + 1$.
- Declining, the number of publications of one subject decreases from period i to period $i + 1$.
- Stable, the number of publications of one subject remains flat in two consecutive periods.

Figure 13 (a) shows the number of publications falling into

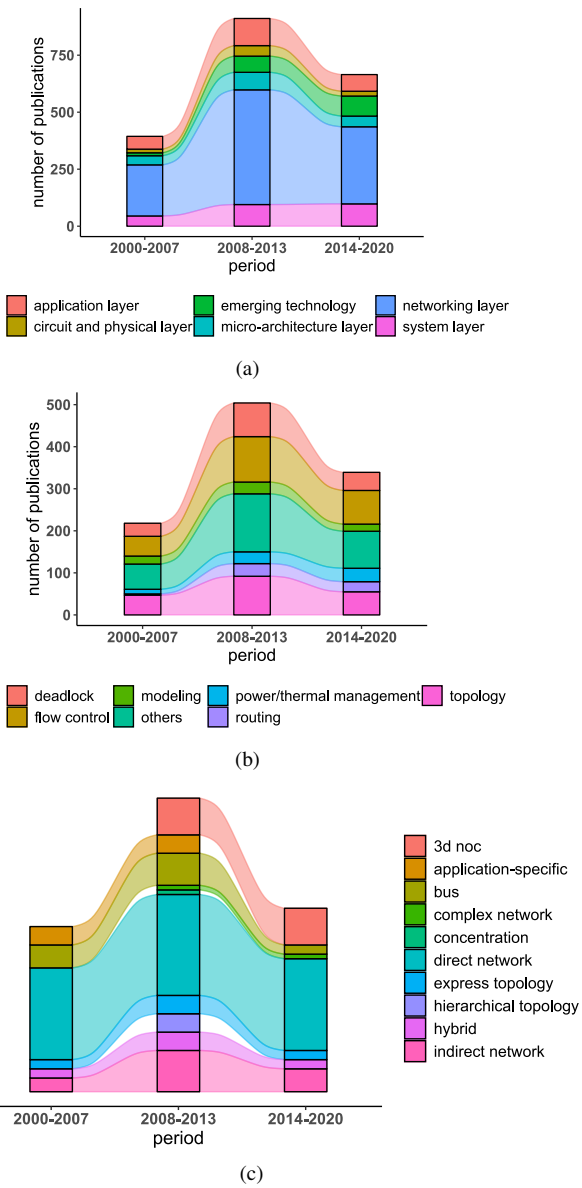


FIGURE 13. (a) Evolution of subjects at the top level. (b) Evolution of the subjects under the *networking* layer and its child nodes. (c) Evolution of the subjects under the *topology* branch. All layer hierarchies can be found in the subject tree, see Figure 4. Each color bar represents a subject or a layer, and the height of the bar is the number of publications belonging to it.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

the subjects at the top level (level 1) of the NoC subject tree (see Figure 4). The trend change of a subject at any level, in terms of number of publications, actually follows a similar pathway. Starting from a low number, the publication number climbs up to reach its peak, and afterwards, it goes down. As the *networking* layer has always been the center of NoC architecture, the publications in this subject have consistently outnumbered those in other NoC subjects in each period. It is worth noting that *emerging technology* soars and remains strong in recent years, setting it as an important driving force to push the envelope of the NoC research.

Figure 13 (b) shows the numbers of publications of the subjects under the parent node of *networking layer* (level 2) in the NoC subject tree. In the *networking* layer, *deadlock, modeling, flow control*, and *topology* are the main research subjects, while most of these subjects were seeing an upward tick from period 1 to period 2 and their numbers declined from period 2 to period 3 with their percentages literally unchanged.

Figure 13 (c) shows the number of publications of the subjects under the subject *topology* (level 3) in the NoC subject tree. *Direct network* is the subject with most publications under the *topology* layer, and its publication number is stable across all three periods, while subjects *application-specific* and *bus* declined rapidly from period 2 to period 3. 3D NoC appeared in period 2 and kept stable up to 2020.

A closer look at the history of the conference NoCS will enable us to better understand why NoC research reached its peak in 2008-2013 and started to decline from 2014. The inaugural NoCS conference was held in 2007 which was right before the NoC research hit its peak. Between 2008 and 2013, NoCS benefited from the uptick of NoC research and was considered one of the main vehicle to publish/present NoC research with a good number of publications. However, in line with the decline of NoC research after its peak in 2013, NoCS received smaller number of submissions, and eventually, this anemia forced NoCS to become part of ESWEEK conference in 2017. Except for a small bounce back in terms of the number of publications in 2020 (Figure 1), the overall trend is that the conventional NoC subjects continue to decline in their significance and popularity among researchers, and there is continued and sustained interest on *emerging technology* and new subjects like *chiplet* and *security*.

D. CONTRIBUTIONS OF THE EMERGING TECHNOLOGY

NoCs built upon emerging technologies, *e.g.*, silicon photonics, wireless, carbon-nano-tube-based antenna, inductive coupling between vertical layers in 3D IC, and transmission line, are being investigated with noticeable progress. These new technologies are largely driven by a pressing demand for much greater bandwidth efficiently, extremely low power consumption, and superb scalability that current interconnect technologies are hard to deliver. For instance, a chiplet/2.5D/wafer scale system is found possible to integrate a sea of cores or memory vaults (up to 850,000 AI cores in Celebras wafer scale system) into one single package. Many AI applications exhibit heavy one-to-many traffic, meanwhile, photonics and wireless NoCs are able to genuinely support multicast or broadcast traffic. By having an optical NoC along with components to perform optical computing, it is even possible to see the emergence of all-optical chip systems with extremely low power consumption. Many of these new technologies can benefit more than just intra-chip, networked communications. There is a growing trend is to build up hierarchical networks to link on-chip, inter-chiplet, to inter-node levels together for HPC systems. Actually, quite a few HPC systems are already using optical connections to connect compute nodes. Silicon photonics can pave the path to enable an all-optical interconnection network that goes from on-chip to inter-node levels. In addition, wireless NoC enables short distance communication among HPC compute cards which can reduce the wiring complexity and/or cost in HPC networks.

VII. EVOLUTION OF THE NOC CO-AUTHORSHIP NETWORKS AND AUTHOR BEHAVIORS

In this section, we study both the NoC co-authorship network and the author behaviors. The co-authorship network is an undirected network, where each node represents an author, and an edge is established between two authors if they have collaborated on at least one publication. The weight of a node reflects the contribution of an author to the NoC field and is defined as the total weighted number of articles published by this author. Note that the contributions of authors in a paper are inversely proportional to the order of the author list, *i.e.*, the i^{th} author has a contribution weight of $1/i$. The weight of an edge corresponds to the number of joint publications between the two authors.

A. NETWORK STRUCTURE AND DYNAMICS OF THE NOC CO-AUTHORSHIP NETWORK

Figure 14 shows the NoC co-authorship networks created for Y2005, Y2010, Y2015, and Y2020. The different communities in each of these networks are color-coded.

Table 5 shows the clustering coefficient, network diameter, average (weighted) degree, modularity, and the percentage of the giant connected branch of the co-authorship network. The modularity of the network is always very high (close to 0.9), indicating the NoC co-authorship network has a very significant community structure. That is, the NoC authors have tendency to collaborate with peers from the same research community. Different from the weak citation relationship seen in the citation network, the NoC co-authorship networks come with much higher clustering coefficients (the value is almost ten times that of the former), which means that NoC researchers have relatively dense connections with each other. Note that many of the authors in our dataset were students at the time when they published their papers. Majority of them left academia after graduation, and they stopped collaborating with other authors, leading to a high network diameter (mostly greater than 10) and low average (weighted) degree (smaller than 5) in the NoC co-authorship

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

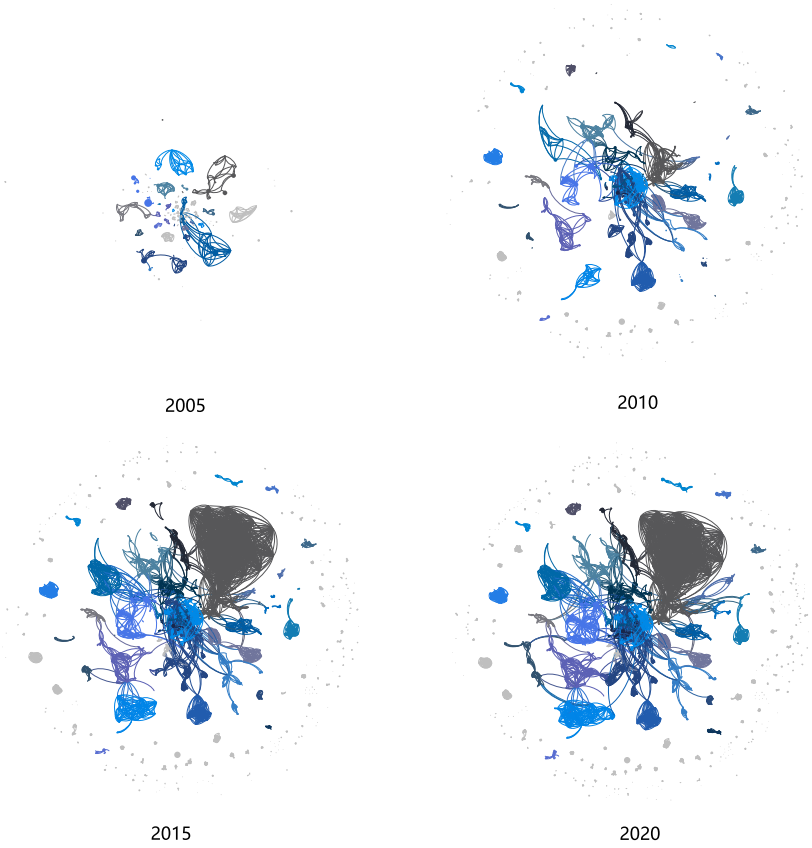


FIGURE 14. The NoC co-authorship networks up to 2005, 2010, 2015, and 2020.

network. Either from the perspective of the increased average degree and clustering coefficient, or from the phenomenon of small communities merging into larger ones over the four milestone years (further detailed in Table 18 in Appendix), it suggests that there is frequent collaboration among the authors.

Furthermore, we apply the method in [74] to check whether the NoC co-authorship network is a small world network. Let $N, \overline{k}$, and $\overline{d}$ be the number of nodes, average degree, and average network diameter respectively. If a network satisfies $\overline{d} \approx \ln N/\overline{k}$, it can be regarded as a small world network [74]. In our case, $N, \overline{k}$, and $\overline{d}$ are 2184, 3.106, and 5.85 respectively in 2020, and $\ln(N)/\ln(\overline{k})$ is 6.81. Therefore, formula $\overline{d} \approx \ln(N)/\ln(\overline{k})$ holds. We hence conclude that the NoC co-authorship network is indeed a small world network, in agreement with most research findings. In a small world network, most nodes are not adjacent to each other, but the neighbors of any given node are likely to be neighbors of each other, and most nodes can be accessed from any other nodes with very little steps or jumps. This indicates that, the distance between two randomly selected nodes (authors) in this co-authorship network is very short.

B. COLLABORATION PATTERNS AND CROSS-COMMUNITY COLLABORATION PHENOMENON

In this section, the collaborative patterns and interesting cross-community collaborations in the co-authorship network are investigated, shown in Figure 15 and Tables 6–8.

The NoC co-authorship network shows salient collaborative patterns as in Figure 15. A node is referred as a small, medium, or big node if its weight is less than 5, between 5 and 10, or greater than 10 respectively. Three collaborative patterns are found 1) collaboration pattern A: a big node (a person with a large number of publications), a medium node (a person with a moderate number of publications), and several small nodes (persons with few publications), 2) collaboration pattern B: that consists of a medium node and small nodes, and 3) collaboration pattern C: that involves a mixture of several medium nodes and small nodes. Collaboration pattern A corresponds to an academic group with one prolific leader, one rising young scholar, and several students or postdoc fellows. Collaboration pattern B is drawn from a smaller group with one faculty member and some students, while pattern C indicates the collaboration between research groups of similar composition of faculty and students. Table 6 reports the numbers of the three collaborative patterns. Note that there are 9 big nodes and 38 medium nodes in our dataset, representing the most experienced and influential authors in the NoC field.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 5. Network parameters of the NoC co-authorship networks up to 2005, 2010, 2015, and 2020

Year	Nodes (authors)	Clustering coefficient	Network diameter	Average degree	Modularity (resolution = 1.0)	Average degree (weighted)	Percentage of the giant connected branch
2005	291	0.323	5	1.621	0.896	2.029	52.55%
2010	1078	0.404	15	2.49	0.895	3.479	54.29%
2015	1753	0.410	18	3.116	0.869	4.046	51.55%
2020	2184	0.412	14	3.103	0.865	3.948	60.55%

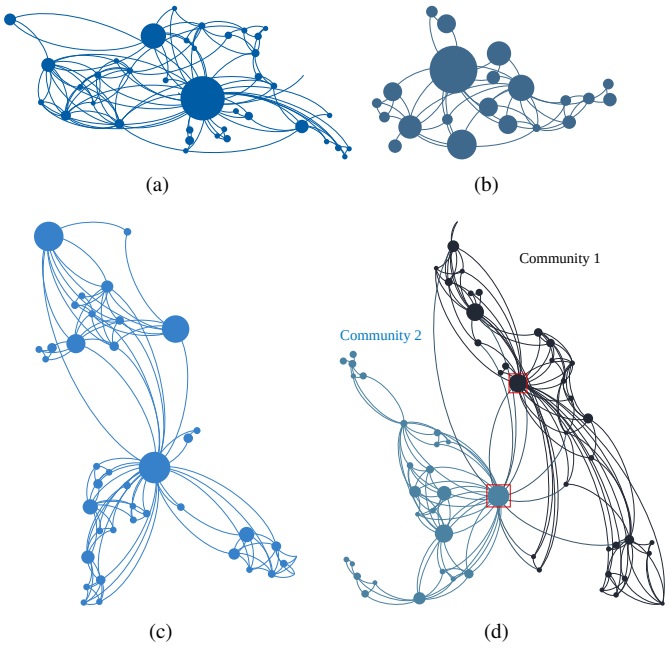


FIGURE 15. (a) Collaboration pattern A: a big node (a person with a large number of publications), a medium node (a person with a moderate number of publications), and several small nodes (persons with few publications). (b) Collaboration pattern B: a medium node with several small nodes. (c) Collaboration pattern C: several medium nodes with several small nodes. (d) An example on cross-community collaborations: collaboration between two medium nodes in two respective communities. The data are collected up to 2020.

The cross-community collaboration frequencies of different types of nodes and edges are also measured. The cross-community collaboration frequency of an edge is defined as the ratio of the number of collaborations of the two end nodes to the total number of edges of the same type in cross-community collaborations, whereas the six edge types are listed in Table 7. The cross-community collaboration frequency of a node is defined as the ratio of number of its participation in cross-community collaborations to the total number of nodes of the same type, whereas the node types are big, medium, and small. In Table 7, the frequency of the cross-community collaboration between big and big nodes is 1.57, meaning that the average number of collaborations between two large nodes belonging to two different communities is 1.57. On the other hand, as seen from Table 8, the cross-community collaboration frequency of big node is 10.67, meaning that a big node collaborates 10.67 times

TABLE 6. Counts of the three collaborative patterns

Collaboration pattern	Number
A	4
B	9
C	6

on average with authors in other communities. One can see that: (1) The cross-community collaboration frequencies of the edges are greater (>1.5) if their node types are medium or big, indicating that if a big/medium node collaborates with another big/medium node, there is a high probability for them to cooperate multiple times. (2) The collaboration frequency is increasing rapidly when the size of nodes grows, indicating that a bigger node is easier to communicate with others and plays a more important role in cross-community collaboration than a small one.

C. AUTHOR BEHAVIORS

We study the career lifetime (the interval between the year an author published his/her very first NoC paper and the year he/she published his/her most recent paper). Figure 16 (a) shows the distribution of the career lifetime of all the authors, which follows a power law distribution (with R^2 of 0.9961). The maximum career lifetime of NoC authors is set to be20 years, which is the same as the life cycle of NoC. Note that only a handful of authors have that long career lifetime, and most of the authors actually have a career lifetime of only 1 or 2 years. The reason is that, these authors were students, and they did not remain in academia after publishing a few papers and graduated. Figure 16 (b) shows the average number of articles published by each author per career year. One can see that, for each author, the number of publications is 0.9 per year on average. These authors are most productive in their first career year, and least productive in their 19^{th} career year.

Figure 1 (b) shows the number of new authors per year. One can see that around 2008 to 2010, NoC reached its peak in attracting new authors. After that fewer authors entered this area, which can be mainly attributed to the fact that NoC was becoming mature and fewer authors would feel they could contribute to the study of NoC. Another possible reason is that new topics like *neural network architecture* or *security* were becoming more appealing, shifting away researchers' attention to pursue more rewarding research. Figure 17 and Table 9 further show the subjects chosen by the new authors for their first papers. In 2015-2016, new authors

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 7. Cross-community collaboration frequencies for different types of edges*

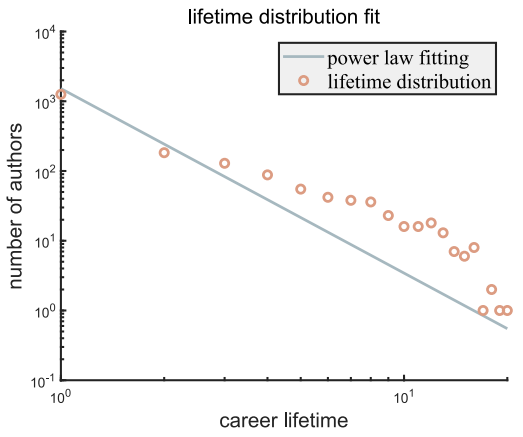
Edge type (node types of the two end nodes)		Number of collaborations (T_e)	Edge number** in cross-community collaborations (E)	Cross-community collaboration frequency (T_e/E)
small	small	141	127	1.11
small	medium	91	80	1.14
small	big	56	42	1.33
medium	medium	10	6	1.67
medium	big	18	12	1.50
big	big	11	7	1.57

*Two authors can collaborate multiple times, so $T_e \geq E$.
** Edge number is the total number of edges of the same type in our dataset.

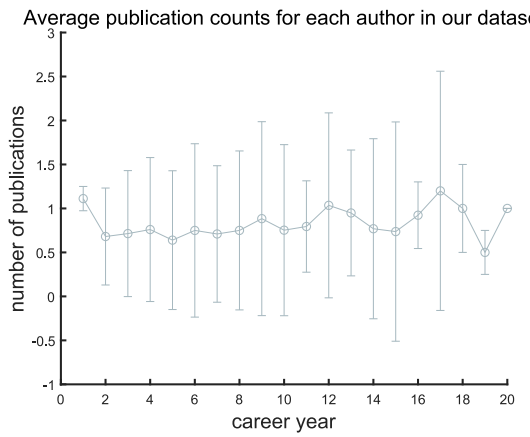
TABLE 8. Cross-community collaboration frequencies for different types of nodes

Node Type	Number of its participation in cross-community collaborations (T_n)	Node number*(N_n)	Cross-community collaboration frequency (T_n/N_n)
small	429	2148	0.20
medium	129	37	3.49
big	96	9	10.67

*Node number is the total number of nodes of the same type in our dataset.



(a)



(b)

FIGURE 16. (a) Career lifetime distribution, with log-log scale. (b) Average publication counts for each author per career year. The bars are variation.

were more likely to choose *emerging technology* and *flow control* as the starting points for their careers. However, more recently, fewer people are choosing these subjects. Instead, *network in interposer* (*a.k.a.*, chiplet systems), *topology* and *router design* are being chosen by more new authors, and these subjects are widely accepted as the frontiers of the NoC area.

TABLE 11. Kendall tau rank correlation coefficient to compare the hotness ranks of the subjects selected by the new authors and those of the previous years.

Ranking by publications	Ranking by new authors	Kendall tau rank correlation coefficient
Hot subject ranking of total publications in 2015	Hot subject ranking selected by new authors in 2016	0.66674
Hot subject ranking of total publications in 2016	Hot subject ranking selected by new authors in 2017	0.66697
Hot subject ranking of total publications in 2017	Hot subject ranking selected by new authors in 2018	0.41194
Hot subject ranking of total publications in 2018	Hot subject ranking selected by new authors in 2019	0.17655
Hot subject ranking of total publications in 2019	Hot subject ranking selected bynew authors in 2020	0.21664

To investigate whether the newly published authors are more likely to track the "hot" research subjects, we use the Kendall's tau rank correlation coefficient to estimate how the hotness rank of subjects selected by new authors in a given year is correlated to the rank by the hotness of subjects for all the papers published in the same year in Table 10. Here, the hotness (or popularity) of a subject is measured by the total number of publications published in that subject, or the number of new authors entering into that subject. One can see that, the correlation coefficients are very high. However, when choosing their research subjects, the new authors tend to be dragged into hot subjects in terms of the articles

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

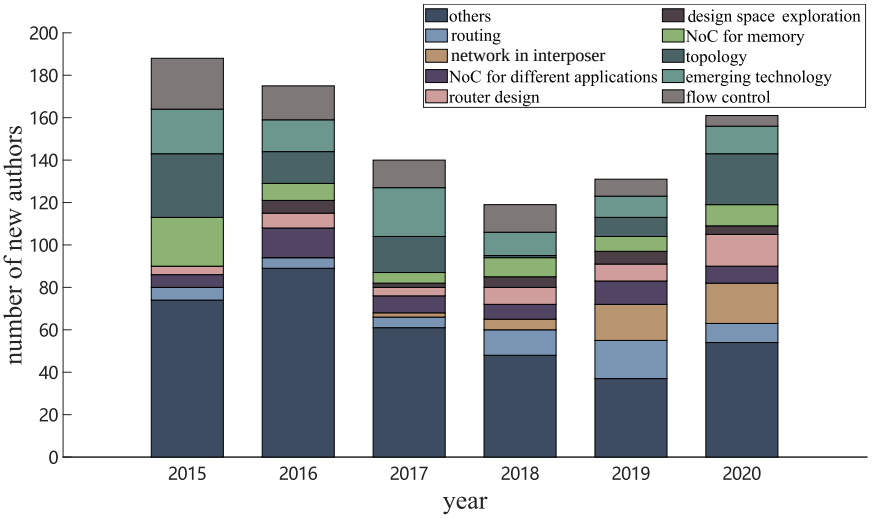


FIGURE 17. The subjects chosen by the new authors.

TABLE 9. The top 5 subjects in NoC research each year between 2015 and 2020.

2015	Top 5 hot subjects	*emerging technology*	*flow control*	*topology*	*router design*	*reliability*
	Number of papers	11	11	9	7	6
2016	Top 5 hot subjects	*emerging technology*	*flow control*	*topology*	*power/thermal management*	*NoC for memory*
	Number of papers	12	10	10	7	6
2017	Top 5 hot subjects	*emerging technology*	*topology*	*flow control*	*routing*	*reliability*
	Number of papers	12	9	6	5	5
2018	Top 5 hot subjects	*emerging technology*	*routing*	*NoC for memory*	*flow control*	*security*
	Number of papers	8	8	7	6	4
2019	Top 5 hot subjects	*routing*	*router design*	*network in interposer*	*NoC for different application*	*emerging technology*
	Number of papers	7	6	6	6	4
2020	Top 5 hot subjects	*network in interposer*	*topology*	*routing*	*router design*	*NoC for memory*
	Number of papers	9	6	5	5	4

TABLE 10. Kendall's tau rank correlation coefficient* to compare the hotness ranks of the subjects selected by the new authors and those of the same year.

Year	Kendall tau rank correlation coefficient
2015	0.61765
2016	0.62750
2017	0.86577
2018	0.70619
2019	0.75332

*Kendall's tau rank coefficient is a non-parametric measure of relationships between columns of ranked data. It returns a value of 0 to 1, where 0 indicates no relationship, 1 is a perfect relationship. A quirk of this test is that it can also produce negative values (*i.e.* from -1 to 0). Kendall's tau rank correlation = $(C - D/C + D)$, where C is the number of concordant pairs and D is the number of discordant pairs.

published in the previous year, for example, an author had a publication in 2010 could only track hot subjects in 2009, as he/she could not foresee the hot subjects in the same year 2010. Table 11 further shows the Kendall tau rank correlation coefficient by comparing the ranks of the subjects selected by the authors and hot subject ranking of total publications in the previous years. One can see that this correlation is very low especially in recent years. Therefore, we conclude that, new authors do not show obvious behaviors of tracking hot subjects, instead, they are contributing to the hot subjects each year.

VIII. ENVISIONED EVOLUTION OF PUBLICATIONS, SUBJECTS, AND CO-AUTHORSHIPS BEYOND 2020

From the analysis presented in previous sections, we are ready to make a prediction of the evolution of publications, subjects, and co-authorship in NoC research going forward.

1) *Evolution of publications*: As discussed earlier, NoC is considered as a matured research area after 2013 and the citation network gets more densely connected. Our analysis has indicated that communities do not show

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

a strong correspondence with a subject. These results can be extrapolated to make the following prediction of the NoC evolution: i) Citations among the publications will be more frequent due to maturity of the topic. ii) The communities will continue to belong to more than one subject and publications will likely touch upon more than one NoC subject. iii) The self-referencing in NoC will become more obvious, as the NoC area grows mature and diversified.

2) *Evolution of subjects*: Based on the observations presented in Section VI, we envision the following: i) The NoC area will be matured further, but new topics will continue to emerge and they tend to expand the breadth of the NoC area. ii) The "hot" NoC research subjects will have a much shorter lifespan, typically lasting only 2-3 years. The 6 most influential subjects (*topology*, *routing*, *flow control*, *router design*, *mapping*, and *emerging technology*), however, will continue to dominate the research map and keep their popularity. iii) New topics, such as *package level network (a.k.a., network on interposer)*, *security, NoC for neural network (NN) accelerators*, and *emerging technology empowered NoC (e.g., silicon photonics and wireless NoC)* will likely gain traction. Many of the future research works are expected to span multiple subject area. For instance, we are already witnessing looming photonic interconnection network tailored for connecting chiplets to build large scale neural network (NN) accelerators. iv) Going forward, evolution of the six most influential subjects and the emerging topics need to take many practical issues into consideration. For example, the *topology* and *router* of a network on an interposer should consider the pin count constraint of each chiplet; the network topology for applications like an NN accelerator should be tailored to customized its unique data flow patterns and requirements.
3) *Evolution of co-authorships*: Based on our analysis in Section 7, we envision the following: i) The willingness of authors to collaborate will increase, and authors who previously collaborated will be more likely to continue their collaboration in the near future. ii) As the collaboration network becomes denser, there will be fewer isolated nodes (*i.e.,* authors who have not collaborated with others). iii) New and more collaboration patterns will emerge due to the diversified interests of the researchers. iv) New authors will contribute more to NoC publications, especially in the hot topics.

IX. CONCLUSIONS

Between 2000 and 2020, the NoC area has gone from startup, to growth and shakeout, to maturity. In this paper, we used the complex network approach to visualize and quantify NoC evolution in these 20 years. Specially, we built the citation network, subject citation network, and co-authorship network, and for each of them, we analyzed their respective network structure and dynamics (evolution). The main findings of this paper are summarized as follows:

1) As time goes by, the citation network, subject citation network, and co-authorship network have more nodes and links, and their community structure is becoming more salient. Communities in the citation network and co-authorship network are merging into larger ones, indicating that the citations and author collaborations are becoming more frequent in NoC community.
2) Due to the strong connections among the subjects, the communities in the citation network do not show a strong correspondence with the subjects, *i.e.*, publications in a community in the citation network do not belong to only one single subject. Instead, several main subjects can broadly characterize a community.
3) The influence scores of different NoC subjects change over time. A few subjects, noticeably *reliability*, are becoming increasingly influential as time goes by, while some others, such as *physical design*, is gradually losing its momentum. However, with the rise of chiplet designs, we expect *physical design* might enjoy revived research enthusiasm in the near future.
4) Six subjects, *i.e., topology, routing, flow control, router design, mapping,* and *emerging technology* were identified as the most influential NoC subjects, and they are highly related to each other. Among them, the knowledge flows between pairs of subjects are symmetric.
5) The number of publications concerning most subjects reached maximum during 2008-2013, and declined after 2014. However, the number of publications of *emerging technologies* (*e.g., optical* or *wireless NoCs*) is stable.
6) Author collaborations exhibit three interesting patterns, as reflected in the co-authorship network. High profile and productive researchers, shown as the big nodes in the co-authorship network, have the highest frequency of cross-community collaborations.
7) The NoC authors' career lifetime follows a power law distribution. For each author, the average number of publications is 0.9 publications per career year. The first career year is most productive, and the 19^{th} year the least.
8) New authors do not show obvious behaviors of tracking hot subjects; instead, they are contributing to the hot subjects each year.

Will NoC ever come back strong in the near future and reach a second or even third peaks? This is an ongoing question and can only be answered with continued analysis of the trends following the proposed methodology and using the tools created for this study. As one can readily expand our dataset with more publications from other conferences and leading journals and bring in additional research subjects like *memory system design, accelerators, etc.* for analysis and prediction purposes, more meaningful and influential results shall be obtained to meet specific research and development needs.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

Last but not least, the data analytical tools are released at https://github.com/FCAS-SCUT/Science_of_Science_NoC, and the website for all the data plots is available at https://www.sci-sci.com. Researchers, not limited to those working in the NoC area, can adopt this methodology to understand and gauge all scientific research areas of their interest and make sound predictions about the future.

APPENDIX.

A. THE PROPOSED SUBJECT LABELING ALGORITHM

In order to automatically select a subject or subjects for each paper, we have developed an algorithm based on supervised learning. Part of speech, word frequency, location (when a word first appears in an article), external feature (word vectored trained from glove [75]), and tf-idf are selected as the features. SVM is used as the classification algorithm. Half of the labeled publications are used as the training dataset, and the rest are for inference. To improve the algorithm performance, a synonym table is used to record the synonyms (*e.g.*, NoC, networks-on-chip, and network-on-chip are included into the table and they have the same meaning). A dictionary is also built which is composed by the leaf nodes in the subject tree. The proposed algorithm works as follows. It first extracts the candidate subject set by scanning the title, abstract, keywords, and full text of a paper to match with entries in the synonym table and the dictionary. Next, SVM is used to choose the final subjects from the candidate set.

Three unsupervised learning (KNN-based clustering [76], LDA [77], and textRank [78]) algorithms, and a supervised learning algorithm are compared against the proposed subject labeling algorithm. KNN-based clustering, LDA, and textRank can extract keywords from a document without going through training. The supervised learning algorithm uses SVM directly on the title, abstract, keywords, and full text of each paper without the help of the dictionary and the synonym table. Half of the labeled publications are reserved for training, and the rest for inference in the supervised learning algorithm. Tables 12 and 13 show the results of the unsupervised and supervised learning algorithms. Generally, these algorithms lead to unsatisfactory results for reasons below.

- Unsupervised learning is biased to plow the keyphrases of each paper, which are not necessarily the same as the research subject. For example, in the case of the paper [79], textRank outputs "SMART, SMART++, and multi-hop". The reason is that this article coins the name SMART for the proposed router architecture, and the algorithm mistakenly takes SMART as an NoC subject, not "'router design" as expected.
- Supervised learning also has a low precision, since there are many sources of noise. For example, a paper on router design that uses XY routing may be incorrectly labeled as a paper on NoC routing.
- Our proposed scheme achieves the best performance, as it takes advantage of the NoC subject tree and the supervised learning. The candidate subjects are generated by scanning the title, abstract, keywords, and full text first by string matching. The supervised learning is applied on top of the candidate subjects to minimize the impact of noise.

TABLE 12. Results of the unsupervised learning algorithm

Method	Without dictionary		
	Precision	Recall	F1-Measure
KNN-based clustering	0.125	0.297	0.175
LDA	0.106	0.288	0.155
TextRank	0.110	0.253	0.153
	With dictionary*		
Clustering	0.134	0.318	0.188
LDA	0.114	0.306	0.165
TextRank	0.120	0.266	0.165

*The unsupervised learning with dictionary means that the results are string matched with the dictionary and synonym table after these algorithms are performed.

TABLE 13. Results of the supervised learning and the proposed method

Method	Precision	Recall	F1-Measure
supervised learning	0.364	0.101	0.170
proposed	0.878	0.729	0.796

B. EFFICIENCY TEST OF PREDICTION MODEL

We use an autoregressive model of order n to predict the number of papers to be published in year t, denoted as X_t. In this case, X_t is estimated by taking into account of the publication numbers over the preceding n years (X_{t-n},X_{t-n-1},...,X_{t-1}).

$$X_t = \sum_{i=1}^{n} \beta_i X_{t-i} + \varepsilon_t$$

where β_i's are the regression coefficients, and ϵ_t is the white noise in year t. This model is trained and fitted using the maximum likelihood estimation method [80] to minimize the regression error. To verify the accuracy of the model, we use the number of publications in year 2001-2019 to train the model and measure the error of forecasting the number of publications in 2020. The relative error is defined as

$$\delta = |X'_{2020} - X_{2020}| / X_{2020}$$

where X'_{2020} is the predicted number of publications. Table 14 shows the relative errors of the prediction model. One can see that the model produces fairly accurate predictions.

TABLE 14. The relative errors of predicting publications in different NoC subjects in Y2020.

All Subjects	1.69%
Topology	0.48%
Routing	1.36%
Flow control	4.10%
Router design	3.27%
Mapping	2.45%
Emerging technology	2.23%

C. SUPPLEMENTARY TABLES

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 15. The subject distribution of the communities in the NoC citation network with resolution=1. The percentage of main subjects are shown in each main community.*

Communities	Subjects				
Community_id:102 45 papers	*emerging technology*	*testing and diagnosis*	*topology*	*routing*	
	49%	18%	16%	13%	
Community_id:123 383 papers	*flow control*	*routing*	*topology*	*router design*	*reliability*
	21%	18%	18%	16%	13%
Community_id:142 247 papers	*mapping*	*flow control*	*routing*	*topology*	*modeling*
	23%	21%	10%	10%	9%
Community_id:184 35 papers	*NoC for memory*	*security*	*emerging technology*		
	26%	23%	17%		
Community_id:190 95 papers	*emerging technology*	*topology*	*routing*	*flow control*	
	56%	26%	11%	9%	

* If a paper touches more than one NoC subject, it will be counted more than once in the table. As a result, the sum of the percentages of different subjects might be greater than 100%, as the case in community 190.

TABLE 16. Top five most cited papers in each calendar year between 2002 and 2020

2002	[81]				
2003	[82]	[17]	[83]	[84]	[81]
2004	[17]	[82]	[85]	[86]	[87]
2005	[17]	[82]	[85]	[86]	[88]
2006	[17]	[89]	[90]	[91]	[92]
2007	[17]	[93]	[18]	[94]	[82]
2008	[95]	[17]	[96]	[42]	[97]
2009	[95]	[18]	[17]	[98]	[42]
2010	[41]	[17]	[43]	[99]	[42]
2011	[17]	[41]	[43]	[45]	[100]
2012	[41]	[42]	[17]	[101]	[102]
2013	[41]	[40]	[103]	[20]	[42]
2014	[104]	[105]	[43]	[42]	[106]
2015	[107]	[108]	[109]	[110]	[111]
2016	[104]	[40]	[43]	[109]	[112]
2017	[104]	[113]	[105]	[109]	[17]
2018	[40]	[105]	[104]	[114]	[17]
2019	[115]	[104]	[116]	[40]	[40]
2020	[117]	[40]	[118]	[119]	[103]

TABLE 17. Citation counts in each calendar year between 2002 and 2020 of the five most cited papers. [17] is a pioneering work in NoC. [42] is a milestone NoC design. [43] reports an NoC used in a commercial processor chip from Intel. Two NoC simulators widely used in academia research are detailed in [40] and [41], respectively.

Article / Year	[17]	[42]	[43]	[40]	[41]
Total	85	46	43	39	38
2002	0	0	0	0	0
2003	1	0	0	0	0
2004	8	1	0	0	0
2005	7	1	0	0	0
2006	3	0	0	0	0
2007	13	1	0	0	0
2008	9	8	2	0	0
2009	5	5	5	1	0
2010	9	5	6	2	10
2011	8	3	7	3	7
2012	6	8	3	4	10
2013	3	4	2	5	5
2014	3	4	5	4	2
2015	1	1	2	2	1
2016	2	3	5	5	1
2017	3	0	2	2	0
2018	4	2	2	6	1
2019	0	0	1	2	1
2020	0	0	1	3	0

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

TABLE 18. Main communities of the citation networks in 2005, 2010, 2015 and 2020

Year	2005		2010		2015		2020	
Number of Nodes	65		462		801		997	
Number of communities	24		23		19		14	
Communities	ID	percentage	ID	percentage	ID	percentage	ID	percentage
	1	7.32%	1	7.22%	1	13.54%	1	16.05%
	2	5.42%	2	6.92%	2	11.33%	2	10.03%
	3	5.22%	3	5.82%	3	7.02%	3	8.43%
	4	4.71%	4	4.91%	4	6.72%	4	7.92%
	5	4.31%	5	4.61%	5	5.02%	5	6.52%
	6	4.01%	6	4.51%	6	4.61%	6	5.62%
	7	3.91%	7	4.41%	7	3.81%	7	5.32%
	8	2.61%	8	2.71%	8	3.51%	8	5.22%
	9	2.61%	9	2.61%	9	3.41%	9	3.81%
	10	2.41%	10	2.61%	10	3.01%	10	3.21%
	11	2.31%	11	2.51%	11	2.61%	11	3.01%
	12	2.31%	12	2.51%	12	2.41%	12	2.61%
	13	2.31%	13	2.31%	13	2.31%	13	1.60%
	14	2.31%	14	2.31%	14	1.40%	14	1.10%
	15	2.31%	15	2.31%	15	1.20%		
	16	1.91%	16	1.91%	16	1.10%		
	17	1.91%	17	1.91%	17	1.00%		
	18	1.81%	18	1.91%	18	1.00%		
	19	1.71%	19	1.81%	19	1.00%		
	20	1.40%	20	1.50%				
	21	1.40%	21	1.40%				
	22	1.30%	22	1.20%				
	23	1.10%	23	1.20%				
	24	1.10%						

TABLE 19. Main communities of the co-authorship networks in 2005, 2010, 2015 and 2020

Year	2005		2010		2015		2020	
Number of Nodes	206		922		1642		2194	
Number of communities	23		20		18		13	
Communities	ID	Percentage	ID	Percentage	ID	Percentage	ID	Percentage
	1	7.11%	1	7.11%	1	7.02%	1	11.76%
	2	5.74%	2	5.65%	2	6.20%	2	11.08%
	3	4.83%	3	4.79%	3	5.42%	3	6.93%
	4	3.10%	4	4.69%	4	4.42%	4	4.97%
	5	2.64%	5	3.05%	5	4.28%	5	4.97%
	6	2.37%	6	3.01%	6	3.65%	6	4.65%
	7	2.32%	7	2.87%	7	2.96%	7	4.56%
	8	2.32%	8	2.83%	8	2.19%	8	3.65%
	9	2.19%	9	2.51%	9	2.05%	9	1.96%
	10	2.05%	10	2.37%	10	2.01%	10	1.96%
	11	2.05%	11	2.32%	11	1.87%	11	1.69%
	12	1.91%	12	2.19%	12	1.64%	12	1.32%
	13	1.78%	13	1.87%	13	1.60%	13	1.05%
	14	1.69%	14	1.73%	14	1.41%	~	~
	15	1.28%	15	1.60%	15	1.41%	~	~
	16	1.19%	16	1.37%	16	1.23%	~	~
	17	1.19%	17	1.19%	17	1.19%	~	~
	18	1.14%	18	1.09%	18	1.00%	~	~
	19	1.14%	19	1.05%	~	~	~	~
	20	1.14%	20	1.00%	~	~	~	~
	21	1.14%	~	~	~	~	~	~
	22	1.14%	~	~	~	~	~	~
	23	1.09%	~	~	~	~	~	

REFERENCES

[1] Amit Kumar Singh, Muhammad Shafique, Akash Kumar, and Jörg Henkel. "Mapping on multi/many-core systems: survey of current and emerging trends". In Proc. Design Automation Conf, pages 1–10, 2013.

[2] Pradip Kumar Sahu and Santanu Chattopadhyay. "A survey on application mapping strategies for network-on-chip design". J. Systems Architecture, 59(1):60–76, 2013.

[3] Nassima Kadri and Mouloud Koudil. "A survey on fault-tolerant application mapping techniques for network-on-chip". J. Systems Architecture, 92:39–52, 2019.

[4] Yue Wu, Chao Lu, and Yunji Chen. "A survey of routing algorithm for mesh Network-on-Chip". Frontiers of Computer Science in China, 10(4):591–601, 2016.

[5] Martin Radetzki, Chaochao Feng, Xueqian Zhao, and Axel Jantsch. "Methods for fault tolerance in networks-on-chip". ACM Computing Surveys (CSUR), 46(1):1–38, 2013.

[6] Janibul Bashir, Eldhose Peter, and Smruti R Sarangi. "A survey of on-chip optical interconnects". ACM Computing Surveys (CSUR), 51(6):1–34, 2019.

[7] Sebastian Werner, Javier Navaridas, and Mikel Luján. "A survey on optical network-on-chip architectures". ACM Computing Surveys (CSUR), 50(6):1–37, 2017.

[8] Emmanuel Ofori-Attah and Michael Opoku Agyeman. "A survey of low power noc design techniques". In Proc. Int'l Workshop Advanced Interconnect Solutions and Technologies for Emerging Computing Systems, pages 22–27, 2017.

[9] Axel Jantsch, Nikil Dutt, and Amir M Rahmani. "Self-awareness in systems on chip—a survey". IEEE Design & Test, 34(6):8–26, 2017.

[10] Salma Hesham, Jens Rettkowski, Diana Göhringer, and Mohamed A Abd El Ghany. "Survey on real-time network-on-chip architectures". In Proc. Int'l Symp. Applied Reconfigurable Computing, pages 191–202, 2015.

[11] Salma Hesham, Jens Rettkowski, Diana Goehringer, and Mohamed A Abd El Ghany. "Survey on real-time networks-on-chip". IEEE Trans. Parallel & Distributed Systems, 28(5):1500–1517, 2016.

[12] Babak Aghaei, Ahmad Khademzadeh, Midia Reshadi, and Kambiz Badie. "Link testing: a survey of current trends in network on chip". J. Electronic Testing, 33(2):209–225, 2017.

[13] Sarzamin Khan, Sheraz Anjum, Usman Ali Gulzari, and Frank Sill Torres. "Comparative analysis of network-on-chip simulation tools". IET Computers & Digital Techniques, 12(1):30–38, 2017.

[14] Gu Haiyun. "Survey of dynamically reconfigurable network-on-chip". In Proc. Int'l Conf. Future Computer Sciences & Application, pages 200–203, 2011.

[15] Santo Fortunato, Carl T Bergstrom, Katy Börner, James A Evans, Dirk Helbing, Staša Milojević, Alexander M Petersen, Filippo Radicchi, Roberta Sinatra, Brian Uzzi, et al. "Science of science". Science, 359(6379):1007–1007, 2018.

[16] William J Dally and Brian Towles. "Route packets, not wires: on-chip inteconnection networks". In Proc. Design Automation Conf., pages 684–689, 2001.

[17] Luca Benini and Giovanni De Micheli. "Networks on chips: a new SoC paradigm". Computer, 35(1):70–78, 2002.

[18] Tobias Bjerregaard and Shankar Mahadevan. "A survey of research and practices of network-on-chip". ACM Computing Surveys (CSUR), 38(1):1–51, 2006.

[19] Jongman Kim, Chrysostomos Nicopoulos, Dongkook Park, Reetuparna Das, Yuan Xie, Vijaykrishnan Narayanan, Mazin S Yousif, and Chita R Das. "A novel dimensionally-decomposed router for on-chip communication in 3D architectures". In Proc. Int'l Symp. Computer Architecture, pages 138–149, 2007.

[20] Amit Kumar, Li-Shiuan Peh, Partha Kundu, and Niraj K Jha. "Express virtual channels: towards the ideal interconnection fabric". ACM SIGARCH Computer Architecture News, 35(2):150–161, 2007.

[21] Changyun Zhu, Zhenyu Gu, Li Shang, Robert P Dick, and Russ Joseph. "Three-dimensional chip-multiprocessor run-time thermal management". IEEE Trans. Computer-Aided Design of Integrated Circuits and Systems, 27(8):1479–1492, 2008.

[22] Hiroki Matsutani, Paul Bogdan, Radu Marculescu, Yasuhiro Take, Daisuke Sasaki, Hao Zhang, Michihiro Koibuchi, Tadahiro Kuroda, and Hideharu Amano. "A case for wireless 3D NoCs for CMPs". In Proc. Asia and South Pacific Design Automation Conf., pages 23–28, 2013.

[23] A. J Karkar, J. E Turner, K Tong, and R Ai-Dujaily. "Hybrid wire-surface wave interconnects for next-generation networks-on-chip". IET Computers & Digital Techniques, 7(6):294–303, 2013.

[24] Ammar Karkar, Terrence Mak, Kin-Fai Tong, and Alex Yakovlev. "A survey of emerging interconnects for on-chip efficient multicast and broadcast in many-cores". IEEE Circuits and Systems Magazine, 16(1):58–72, 2016.

[25] Assad Abbas, Mazhar Ali, Ahmad Fayyaz, Ankan Ghosh, Anshul Kalra, Samee U Khan, Muhammad Usman Shahid Khan, Thiago De Menezes, Sayantica Pattanayak, and Alarka Sanyal. "A survey on energy-efficient methodologies and architectures of network-on-chip". Computers & Electrical Engineering, 40(8):333–347, 2014.

[26] An Zeng, Zhesi Shen, Jianlin Zhou, Jinshan Wu, Ying Fan, Yougui Wang, and H Eugene Stanley. "The science of science: From the perspective of complex systems". Physics Reports, 714:1–73, 2017.

[27] Steven H Strogatz. "Exploring complex networks". Nature, 410(6825):268–276, 2001.

[28] Sergey N Dorogovtsev, Alexander V Goltsev, and José FF Mendes. "Critical phenomena in complex networks". Reviews of Modern Physics, 80(4):1275, 2008.

[29] Stefano Boccaletti, Vito Latora, Yamir Moreno, Martin Chavez, and D-U Hwang. "Complex networks: structure and dynamics". Physics Reports, 424(4-5):175–308, 2006.

[30] Réka Albert and Albert-László Barabási. "Statistical mechanics of complex networks". Reviews of Modern Physics, 74(1):47, 2002.

[31] Sven Bilke and Carsten Peterson. "Topological properties of citation and metabolic networks". Physical Review E, 64(3):036106, 2001.

[32] Lovro Šubelj, Dalibor Fiala, and Marko Bajec. "Network-based statistical comparison of citation topology of bibliographic databases". Scientific Reports, 4(1):1–10, 2014.

[33] Mark EJ Newman. "The structure of scientific collaboration networks". Proc. National Academy of Sciences, 98(2):404–409, 2001.

[34] Mark EJ Newman. "Coauthorship networks and patterns of scientific collaboration". Proc. National Academy of Sciences, 101(1):5200–5205, 2004.

[35] Min Song, Go Eun Heo, and Su Yeon Kim. "Analyzing topic evolution in bioinformatics: investigation of dynamics of the field with conference data in DBLP". Scientometrics, 101(1):397–428, 2014.

[36] Xiaoling Sun, Kun Ding, and Yuan Lin. "Mapping the evolution of scientific fields based on cross-field authors". Journal of Informetrics, 10(3):750–761, 2016.

[37] Albert-Laszlo Barabâsi, Hawoong Jeong, Zoltan Néda, Erzsebet Ravasz, Andras Schubert, and Tamas Vicsek. "Evolution of the social network of scientific collaborations". Physica A: Statistical Mechanics and Its Applications, 311(3-4):590–614, 2002.

[38] Yan Wu, Srinivasan Venkatramanan, and Dah-Ming Chiu. "A population model for academia: case study of the computer science community using dblp bibliography 1960-2016". IEEE Trans. Emerging Topics in Computing, pages 228–235, 2018.

[39] C. Pizzuti. "A multi-objective genetic algorithm for community detection in networks". In Proc. IEEE Int'l Conf. Tools with Artificial Intelligence, pages 379–386, 2009.

[40] Niket Agarwal, Tushar Krishna, Li-Shiuan Peh, and Niraj K Jha. "GARNET: A detailed on-chip network model inside a full-system simulator". In Proc. IEEE Int'l Symp. Performance Analysis of Systems and Software, pages 33–42, 2009.

[41] Andrew B Kahng, Bin Li, Li-Shiuan Peh, and Kambiz Samadi. "ORION 2.0: A fast and accurate NoC power and area model for early-stage design space exploration". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 423–428, 2009.

[42] Li-Shiuan Peh and William J Dally. "A delay model and speculative architecture for pipelined routers". In Proc. Int'l Symp. High-Performance Computer Architecture, pages 255–266, 2001.

[43] Yatin Hoskote, Sriram Vangal, Arvind Singh, Nitin Borkar, and Shekhar Borkar. "A 5-GHz mesh interconnect for a teraflops processor". IEEE Micro, 27(5):51–61, 2007.

[44] Hengyi Liang, Zhilu Wang, Bowen Zheng, and Qi Zhu. "Addressing extensibility and fault tolerance in can-based automotive systems: Special session paper". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 1–8, 2017.

[45] Samuel Rodrigo, Jose Flich, Antoni Roca, Simone Medardoni, Davide Bertozzi, J Camacho, Federico Silla, and Jose Duato. "Addressing manufacturing challenges with cost-efficient fault tolerant routing". In Proc. Int'l Symp. Networks-on-Chip, pages 25–32, 2010.

[46] Sorin Manolache, Petru Eles, and Zebo Peng. "Fault and energy-aware communication mapping with guaranteed latency for applications

implemented on NoC". In Proc. Design Automation Conf., pages 266–269, 2005.

[47] Mario Lodde, Jose Flich, and Manuel E Acacio. "Heterogeneous NoC design for efficient broadcast-based coherence protocol support". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 59–66, 2012.

[48] Jose Flich, Andres Mejia, Pedro López, and José Duato. "Region-based routing: An efficient routing mechanism to tackle unreliable hardware in network on chips". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 183–194, 2007.

[49] Mohammad Fattah, Maurizio Palesi, Pasi Liljeberg, Juha Plosila, and Hannu Tenhunen. "SHIFA: System-level hierarchy in run-time fault-aware management of many-core systems". In Proc. Design Automation Conf., pages 1–6, 2014.

[50] Pirretti, Matthew and Link, Greg M and Brooks, Richard R and Vijaykrishnan, Narayanan and Kandemir, Mahmut and Irwin, Mary Jane. "fault tolerant algorithms for network-on-chip interconnect". In IEEE Symp. VLSI, pages 46–51, 2004.

[51] Igor Loi, Subhasish Mitra, Thomas H Lee, Shinobu Fujita, and Luca Benini. "A low-overhead fault tolerance scheme for TSV-based 3D network on chip links". In Proc. Int'l Conf. Computer-Aided Design, pages 598–602, 2008.

[52] Antonio Pullini, Federico Angiolini, Davide Bertozzi, and Luca Benini. "Fault tolerance overhead in network-on-chip flow control schemes". In Proc. Symp. Integrated Circuits and Systems Design, pages 224–229, 2005.

[53] Adán Kohler, Gert Schley, and Martin Radetzki. "Fault tolerant network on chip switching with graceful performance degradation". IEEE Trans. Computer-Aided Design of Integrated Circuits and Systems, 29(6):883–896, 2010.

[54] Yung-Chang Chang, Ching-Te Chiu, Shih-Yin Lin, and Chung-Kai Liu. "On the design and analysis of fault tolerant NoC architecture using spare routers". In Proc. Asia and South Pacific Design Automation Conf., pages 431–436, 2011.

[55] Sadia Moriam and Gerhard P Fettweis. "Reliability assessment of fault tolerant routing algorithms in networks-on-chip: An analytic approach". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 61–66, 2017.

[56] Dominic DiTomaso, Avinash Kodi, and Ahmed Louri. "QORE: A fault tolerant network-on-chip architecture with power-efficient quad-function channel (QFC) buffers". In Proc. IEEE Int'l Symp. High Performance Computer Architecture, pages 320–331, 2014.

[57] Qiaoyan Yu, Meilin Zhang, and Paul Ampadu. "A comprehensive Networks-on-Chip simulator for error control explorations". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 263–264, 2011.

[58] Yiyuan Xie, Mahdi Nikdast, Jiang Xu, Wei Zhang, Qi Li, Xiaowen Wu, Yaoyao Ye, Xuan Wang, and Weichen Liu. "Crosstalk noise and bit error rate analysis for optical network-on-chip". In Proc. Design Automation Conf., pages 657–660, 2010.

[59] Qiaoyan Yu, Meilin Zhang, and Paul Ampadu. "Exploiting inherent information redundancy to manage transient errors in NoC routing arbitration". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 105–112, 2011.

[60] Qiaoyan Yu and Paul Ampadu. "Transient and permanent error co-management method for reliable networks-on-chip". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 145–154, 2010.

[61] Heiko Zimmer and Axel Jantsch. "A fault model notation and error-control scheme for switch-to-switch buses in a network-on-chip". In Proc. IEEE/ACM/IFIP Int'l Conf. Hardware/software Codesign and System Synthesis, pages 188–193, 2003.

[62] Melinda Y Agyekum and Steven M Nowick. "Error-correcting unordered codes and hardware support for robust asynchronous global communication". IEEE Trans. Computer-Aided Design of Integrated Circuits and Systems, 31(1):75–88, 2011.

[63] Vladimir Pasca, Lorena Anghel, Claudia Rusu, Riccardo Locatelli, and Marcello Coppola. "Error resilience of intra-die and inter-die communication with 3D spidergon STNoC". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 275–278, 2010.

[64] Ramakrishna Vadlamani, Jia Zhao, Wayne Burleson, and Russell Tessier. "Multicore soft error rate stabilization using adaptive dual modular redundancy". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 27–32, 2010.

[65] Alexandre Coelho, Amir Charif, Nacer-Eddine Zergainoh, Juan Fraire, and Raoul Velazco. "A soft-error resilient route computation unit for 3D networks-on-chips". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 1357–1362, 2018.

[66] Sourav Das, Kanad Basu, Janardhan Rao Doppa, Partha Pratim Pande, Ramesh Karri, and Krishnendu Chakrabarty. "Abetting planned obsolescence by aging 3D networks-on-chip". In Proc. IEEE/ACM Int'l Symp. Networks-on-Chip, pages 1–8, 2018.

[67] Venkata Yaswanth Raparti, Nishit Kapadia, and Sudeep Pasricha. "ARTEMIS: An aging-aware runtime application mapping framework for 3D NoC-based chip multiprocessors". IEEE Trans. Multi-Scale Computing Systems, 3(2):72–85, 2017.

[68] Kshitij Bhardwaj, Koushik Chakraborty, and Sanghamitra Roy. "Towards graceful aging degradation in NoCs through an adaptive routing algorithm". In Proc. DAC Design Automation Conf., pages 382–391, 2012.

[69] Kshitij Bhardwaj, Koushik Chakraborty, and Sanghamitra Roy. "An MILP-based aging-aware routing algorithm for NoCs". In Proc. Design, Automation and Test in Europe Conf. Exhibition, pages 326–331, 2012.

[70] Dean Michael Ancajas, Koushik Chakraborty, and Sanghamitra Roy. "Proactive aging management in heterogeneous NoCs through a criticality-driven routing approach". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 1032–1037, 2013.

[71] Zana Ghaderi, Ayed Alqahtani, and Nader Bagherzadeh. "Online monitoring and adaptive routing for aging mitigation in NoCs". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 67–72, 2017.

[72] Eigenvector centrality, 2000.

[73] Ye Sun and Vito Latora. "The evolution of knowledge within and across fields in modern physics". Scientific Reports, 10(1):1–9, 2020.

[74] Albert-László Barabási. Network science. Cambridge university press, 2016.

[75] Jeffrey Pennington, Richard Socher, and Christopher D Manning. "Glove: global vectors for word representation". In Proc. Conf. Empirical Methods in Natural Language Processing, pages 1532–1543, 2014.

[76] Jung-Yi Jiang, Shian-Chi Tsai, and Shie-Jue Lee. "FSKNN: multi-label text categorization based on fuzzy similarity and k nearest neighbors". Expert Systems with Applications, 39(3):2813–2821, 2012.

[77] David M Blei, Andrew Y Ng, and Michael I Jordan. "Latent dirichlet allocation". J. Machine Learning Research, 3:993–1022, 2003.

[78] Rada Mihalcea and Paul Tarau. "Textrank: bringing order into text". In Proc. Conf. Empirical Methods in Natural Language Processing, pages 404–411, 2004.

[79] Iván Pérez, Enrique Vallejo, and Ramón Beivide. "Smart++ reducing cost and improving efficiency of multi-hop bypass in noc routers". In Proc. Int'l Symp. Networks-on-Chip, pages 1–8, 2019.

[80] K. Najarian and A. Darvish. "Maximum likelihood estimation". Wiley Encyclopedia of Biomedical Engineering, 2006.

[81] Marco Sgroi, Michael Sheets, Andrew Mihal, Kurt Keutzer, Sharad Malik, Jan Rabaey, and Alberto Sangiovanni-Vincentelli. "Addressing the system-on-a-chip interconnect woes through communication-based design". In Proc. Design Automation Conf., pages 667–672, 2001.

[82] Shashi Kumar, Axel Jantsch, J-P Soininen, Martti Forsell, Mikael Millberg, Johny Oberg, Kari Tiensyrja, and Ahmed Hemani. "A network on chip architecture and design methodology". In Proc. IEEE Symp. VLSI, pages 117–124, 2002.

[83] Jingcao Hu and Radu Marculescu. "Exploiting the routing flexibility for energy/performance aware mapping of regular NoC architectures". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 688–693, 2003.

[84] Kees Goossens, Jef van Meerbergen, Ad Peeters, and R Wielage. "Networks on silicon: combining best-effort and guaranteed services". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 423–425, 2002.

[85] Edwin Rijpkema, Kees Goossens, Andrei Rădulescu, John Dielissen, Jef van Meerbergen, Paul Wielage, and Erwin Waterlander. "Trade-offs in the design of a router with both guaranteed and best-effort services for networks on chip". IEE Computers and Digital Techniques, 150(5):294–302, 2003.

[86] Jingcao Hu and Radu Marculescu. "Energy-aware mapping for tile-based NoC architectures under performance constraints". In Proc. Asia and South Pacific Design Automation Conf., pages 233–239, 2003.

[87] Evgeny Bolotin, Israel Cidon, Ran Ginosar, and Avinoam Kolodny. "QNoC: QoS architecture and design process for network on chip". J. systems architecture, 50(2-3):105–128, 2004.

[88] Matteo Dall'Osso, Gianluca Biccari, Luca Giovannini, Davide Bertozzi, and Luca Benini. "Xpipes: a latency insensitive parameterized network-

on-chip architecture for multi-processor SoCs". In Proc. IEEE Int'l Conf. Computer Design, pages 45–48, 2012.

[89] Srinivasan Murali and Giovanni De Micheli. "Bandwidth-constrained mapping of cores onto NoC architectures". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, volume 2, pages 896–901, 2004.

[90] Krishnan Srinivasan, Karam S Chatha, and Goran Konjevod. "Linear-programming-based techniques for synthesis of network-on-chip architectures". IEEE Trans. Very Large Scale Integration Systems, 14(4):407–420, 2006.

[91] Jongman Kim, Dongkook Park, Theo Theocharides, Narayanan Vijaykrishnan, and Chita R Das. "A low latency router supporting adaptivity for on-chip interconnects". In Proc. Design Automation Conf., pages 559–564, 2005.

[92] Sudeep Pasricha, Nikil Dutt, Elaheh Bozorgzadeh, and Mohamed Ben-Romdhane. "Floorplan-aware automated synthesis of bus-based communication architectures". In Proc. Design Automation Conf., pages 565–570, 2005.

[93] Jingcao Hu and Radu Marculescu. "DyAD: smart routing for networks-on-chip". In Proc. Design Automation Conf., pages 260–263, 2004.

[94] Mikael Millberg, Erland Nilsson, Rikard Thid, and Axel Jantsch. "Guaranteed bandwidth using looped containers in temporally disjoint networks within the Nostrum network on chip". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, volume 2, pages 890–895, 2004.

[95] Robert Mullins, Andrew West, and Simon Moore. "Low-latency virtual-channel routers for on-chip networks". In Proc. Int'l Symp. Computer Architecture, pages 188–197, 2004.

[96] Hangsheng Wang, Li-Shiuan Peh, and Sharad Malik. "Power-driven design of router microarchitectures in on-chip networks". In Proc. Int'l Symp. Microarchitecture, pages 105–116, 2003.

[97] Robert Mullins, Andrew West, and Simon Moore. "The design and implementation of a low-latency on-chip network". In Proc. Asia and South Pacific Conf. Design Automation, pages 6–12, 2006.

[98] Luca Benini and Giovanni De Micheli. "Networks on chip: a new paradigm for systems on chip design". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 418–419, 2002.

[99] John D Owens, William J Dally, Ron Ho, DN Jayasimha, Stephen W Keckler, and Li-Shiuan Peh. "Research challenges for on-chip interconnection networks". IEEE micro, 27(5):96–108, 2007.

[100] David Fick, Andrew DeOrio, Gregory Chen, Valeria Bertacco, Dennis Sylvester, and David Blaauw. "A highly resilient routing algorithm for fault-tolerant NoCs". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 21–26, 2009.

[101] Paul Gratz, Boris Grot, and Stephen W Keckler. "Regional congestion awareness for load balance in networks-on-chip". In Proc. Int'l Symp. High Performance Computer Architecture, pages 203–214, 2008.

[102] Sheng Ma, Natalie Enright Jerger, and Zhiying Wang. "DBAR: an efficient routing algorithm to support multiple concurrent applications in networks-on-chip". In Proc. Int'l Symp. Computer Architecture, pages 413–424, 2011.

[103] Thomas Moscibroda and Onur Mutlu. "A case for bufferless routing in on-chip networks". In Proc. Int'l Symp. Computer Architecture, pages 196–207, 2009.

[104] Chen Sun, Chia-Hsin Owen Chen, George Kurian, Lan Wei, Jason Miller, Anant Agarwal, Li-Shiuan Peh, and Vladimir Stojanovic. "DSENT-a tool connecting emerging photonics with electronics for opto-electronic networks-on-chip modeling". In Proc. Int'l Symp. Networks-on-Chip, pages 201–210, 2012.

[105] Nan Jiang, Daniel U Becker, George Michelogiannakis, James Balfour, Brian Towles, David E Shaw, John Kim, and William J Dally. "A detailed and flexible cycle-accurate network-on-chip simulator". In Proc. IEEE Int'l Symp. Performance Analysis of Systems and Software, pages 86–96, 2013.

[106] Chrysostomos A Nicopoulos, Dongkook Park, Jongman Kim, Narayanan Vijaykrishnan, Mazin S Yousif, and Chita R Das. "ViChaR: a dynamic virtual channel regulator for network-on-chip routers". In Proc. Int'l Symp. Microarchitecture, pages 333–346, 2006.

[107] Sujay Deb, Amlan Ganguly, Partha Pratim Pande, Benjamin Belzer, and Deukhyoun Heo. "Wireless NoC as interconnection backbone for multicore chips: Promises and challenges". IEEE J. Emerging and Selected Topics in Circuits and Systems, 2(2):228–239, 2012.

[108] Amlan Ganguly, Kevin Chang, Sujay Deb, Partha Pratim Pande, Benjamin Belzer, and Christof Teuscher. "Scalable hybrid wireless network-on-chip architectures for multicore systems". IEEE Trans. Computers, 60(10):1485–1502, 2010.

[109] David Wentzlaff, Patrick Griffin, Henry Hoffmann, Liewei Bao, Bruce Edwards, Carl Ramey, Matthew Mattina, Chyi-Chang Miao, John F Brown III, and Anant Agarwal. "On-chip interconnection architecture of the tile processor". IEEE micro, 27(5):15–31, 2007.

[110] Bhavya K Daya, Chia-Hsin Owen Chen, Suvinay Subramanian, Woo-Cheol Kwon, Sunghyun Park, Tushar Krishna, Jim Holt, Anantha P Chandrakasan, and Li-Shiuan Peh. "SCORPIO: A 36-core research chip demonstrating snoopy coherence on a scalable mesh NoC with in-network ordering". In Proc. Int'l Symp. Computer Architecture, pages 25–36, 2014.

[111] Sujay Deb, Kevin Chang, Xinmin Yu, Suman Prasad Sah, Miralem Cosic, Amlan Ganguly, Partha Pratim Pande, Benjamin Belzer, and Deukhyoun Heo. "Design of an energy-efficient CMOS-compatible NoC architecture with millimeter-wave wireless interconnects". IEEE Trans. Computers, 62(12):2382–2396, 2012.

[112] Eberle A Rambo and Rolf Ernst. "Worst-case communication time analysis of networks-on-chip with shared virtual channels". In Proc. Design, Automation and Test in Europe Conf. and Exhibition, pages 537–542, 2015.

[113] Reetuparna Das, Satish Narayanasamy, Sudhir K Satpathy, and Ronald G Dreslinski. "Catnap: energy proportional multiple network-on-chip". ACM SIGARCH Computer Architecture News, 41(3):320–331, 2013.

[114] Chris Fallin, Chris Craik, and Onur Mutlu. "CHIPPER: a low-complexity bufferless deflection router". In Proc. Int'l Symp. High Performance Computer Architecture, pages 144–155, 2011.

[115] Jae-Yeon Won, Xi Chen, Paul Gratz, Jiang Hu, and Vassos Soteriou. "Up by their bootstraps: online learning in artificial neural networks for CMP uncore power management". In Proc. Int'l Symp. High Performance Computer Architecture, pages 308–319, 2014.

[116] Ali Bakhoda, John Kim, and Tor M Aamodt. "Throughput-effective on-chip networks for manycore accelerators". In Proc. Int'l Symp. Microarchitecture, pages 421–432, 2010.

[117] Jieming Yin, Zhifeng Lin, Onur Kayiran, Matthew Poremba, Muhammad Shoaib Bin Altaf, Natalie Enright Jerger, and Gabriel H Loh. "Modular routing design for chiplet-based systems". In Proc. Int'l Symp. Computer Architecture, pages 726–738, 2018.

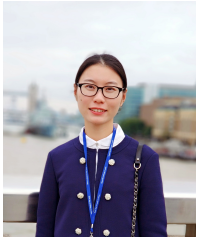
[118] Youjie Li, Iou-Jen Liu, Yifan Yuan, Deming Chen, Alexander Schwing, and Jian Huang. "Accelerating distributed reinforcement learning with in-switch computing". In Proc. Int'l Symp. Computer Architecture, pages 279–291, 2019.

[119] Mario Badr and Natalie Enright Jerger. "SynFull: synthetic traffic models capturing cache coherent behaviour". ACM SIGARCH Computer Architecture News, 42(3):109–120, 2014.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123106, IEEE Access

WEILONG CHEN was born in 2000, currently studying in South China University of Technology, majoring in software engineering. He loves scientific research, likes to explore the unknown and deeply marvels at the charm of science.

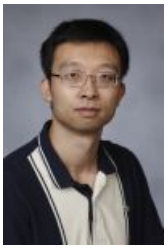
XIAOHANG WANG received the B.Eng. and Ph.D degree in communication and electronic engineering from Zhejiang University in 2006 and 2011. He is currently an associate professor at South China University of Technology. He was the receipt of PDP 2015 and VLSI-SoC 2014 Best Paper Awards. His research interests include many-core architecture, power efficient architectures, optimal control, and NoC-based systems.



YE SUN received the master degree in system science in Beijing Normal University in 2014 and 2017. She is currently a Ph.D student in Queen Mary University of London.

QIAO HU receive the MS degree in Building structure reasearch institute in China Metallurgical Construction Group. He is currently an algorithm engineer of Swarma Campus (Beijing) Technology Co. , Ltd. His research interests include science of science, knowledge graph and complex networks.

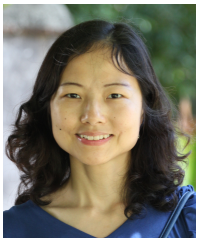
LETIAN HUANG received the MS and PhD degrees in communication and information system from the University of Electronic Science and Technology of China (UESTC), Chengdu, China in 2009 and 2016, respectively. He is an associate professor with UESTC. His scientific work contains more than 40 publications including book chapters, journal articles and conference papers. His research interests include heterogeneous multi-core system-on-chips, network-on-chips, and mixed signal IC design



YINGTAO JIANG joined the Department of Electrical and Computer Engineering, University of Nevada, Las Vegas in Aug. 2001, upon obtaining his Ph.D degree in Computer Science from the University of Texas at Dallas. He has been a full professor since July 2013 at the same university, and served as the Department Chair between 2015 & 2018. Since July 2018, he has began serving as an associate dean of the College of Engineering. His research interests include algorithms, computer architectures, VLSI, networking, nanotechnologies, etc.

AMIT KUMAR SINGH received the B.Tech. degree in Electronics Engineering from Indian Institute of Technology (Indian School of Mines), Dhanbad, India, in 2006, and the Ph.D degree from the School of Computer Engineering, Nanyang Technological University(NTU), Singapore, in 2013. He was with HCL Technologies, India for year and half before starting his PhD at NTU, Singapore, in 2008. He worked as a post-doctoral researcher at National University of Singapore (NUS) from 2012 to 2014 and at University of York, UK from 2014 to 2016. Currently, he is working as senior research fellow at University of Southampton, UK. His current research interests include system level design-time and run-time optimizations of 2D and 3D multi-core systems with focus on performance, energy, temperature, and reliability. He has published over 45 papers in the above areas in leading international journals/conferences.

TERRENCE MAK is an Associate Professor at Electronics and Computer Science, University of Southampton. Previously, He worked with Turing Award holder Prof. Ivan Sutherland, at Sun Lab in California and has awarded Croucher Foundation scholar. His newly proposed approaches, using runtime optimisation and adaptation, strengthened network reliability, reduced power dissipations and significantly improved overall on-chip communication performances. Throughout a spectrum of novel methodologies, including regulating traffic dynamics using network-on-chips, enabling unprecedented MTBF and to provide better on-chip efficiencies, and proposed a novel garbage collections methods, defragmentation, together led to three prestigious best paper awards at DATE 2011, IEEE/ACM VLSI-SoC 2014 and IEEE PDP 2015, respectively. He has published more than 100 papers in both conferences and journals and jointly published 4 books.



MEI YANG received her Ph.D in Computer Science from the University of Texas at Dallas in Aug. 2003. She has been a full professor in the Department of Electrical and Computer Engineering, University of Nevada, Las Vegas since 2016. Her research interests include computer architectures, networking, and embedded systems.