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Topological Properties of the Optical Operator Reconfiguration Network

Wang Xianchao[1,3,*] *and Zuo Kaizhong*[2,3]

[1] School of Mathematics & Computational Science, Fuyang Normal College, Fuyang 236041, China
[2] School of Mathematics & Computer Science, Anhui Normal University, Wuhu 241000, China
[3] School of Computer Engineering and Science, Shanghai University, Shanghai 200072, China

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Abstract: We present a first study on the reconfigurability of optical operators in the optical computing platform, ternary optical computer (TOC), from the viewpoint of complex network. In the optical operator reconfiguration network (OORN), vertexes stand for the basic operating units (BOUs) and the optical operators, and directed edges indicate the dynamic reconfiguration relations between BOUs and operators. We find that the OORN has small-world pattern and scale-free feature as other complex networks. In order to describe the clustering property of the OORN, we propose an approach for characterizing the OORN by introducing a new numerical feature, density of vertex. Its density distribution follows power-law distribution as its cumulative degree distribution. In addition, we find that it is reasonable and optimal to use 50 kinds of BOUs in real TOC system by comparing the OORNs with different kinds of BOUs.

Keywords: Ternary optical computer, optical operator reconfiguration network, basic operating unit, density

1 Introduction

The solution to the Königsberg bridge problem by the Swiss mathematician Leonhard Euler started the method to describe the objective world by use of network. Large and complex stochastic networks are conspicuous in science and everyday life, and have attracted a great deal of interest. In these networks, the individuals or organizations are looked upon as nodes and their relationships as edges. If the edges are directed in a network, it is called directed one. Otherwise, it is called undirected one.

Biological [1,2,3,4,5,6,7] and chemical systems [8, 9], neural networks [10,11], social interacting species [12,13,14], the Internet [15], the World Wide Web [16], transportation systems [17,18,19], communication networks [20,21,22], natural language [23,24,25] and disease transmission networks [26,27,28] are only a few examples of complex systems composed by a large number of highly interconnected units. Obviously, the communication networks and disease transmission networks are directed. People have found that there are some features, such as small-world property [1,3,4,15, 21,29,30] and scale-free nature [10,21,30,31] in these real networks. In recent years, some dynamic reconfiguration networks have attracted some researchers' attentions [2,3,10,11,32]. In this paper, we'll study another dynamic reconfiguration network and its topological properties.

On the other hand, Jin et al. proposed the principle and architecture of a ternary optical computer(TOC) [33, 34]. Many achievements have been obtained in the past one decade, especially in recent years. For instance, the decrease radix design principle(DRDP) [35], which discussed how to build the configurable optical processor, was proposed. And a TOC experimental platform was built according to the principle. Based on MSD number system, the optical three-step addition and optical vector-matrix multiplication [36] were performed on the experimental platform. Meanwhile, the principle of adder in the TOC was proposed [37]. A one-step MSD optical adder, which improved the computation speed of the TOC in some degree, was designed and implemented [38]. A novel TOC experimental platform [39] was built in 2011, according to the DRDP. It had some good features. For example, it had high computation accuracy for it was

* Corresponding author e-mail: wxcdx@126.com

digital; it had computation flexibility for it could reconfigure dynamically optical processor according to user requirement; it had high computation speed for the MSD adder was carry-free and the TOC was a multiple-instruction multiple-data system [39]. In order to make better use of these features and manage efficiently these optical operators, we will focus on the optical operator reconfiguration network(OORN) and their principal topological properties.

This paper is organized as follows. Section 2 briefs the related work, including the DRDP and principal properties of complex networks. Section 3 presents the reconfigurability of optical operators in the TOC from the viewpoint of complex networks. In the OORN, nodes stand for the basic operating units (BOUs) and the optical operators, and directed edges indicate the dynamic reconfiguration relations between BOUs and operators. Section 4 focuses on studying the key topological properties of the OORN. The results show that the OORN is scale-free, small-world, and so on. At the same time, in order to adequately describe the OORN, it presents a novel idea, density and density distribution. In addition, it compares the OORNs with different numbers of BOUs. Section 5 illustrates the concluding remarks and the consideration of future work.

2 Related work

In this section we discuss the related work, including the DRDP and principal properties of complex networks.

2.1 Decrease radix design principle

Obviously, among these achievements about the TOC, the most important one is the DRDP. According to it, any of the n^{n^2} two-input n-valued logic operations can be implemented by combination of some BOUs. And to n-valued logic, there are $n^2(n-1)$ different BOUs. The implementation of an operation by composing some BOUs is called reconfiguration[35].

If $n=3$, it can be easily seen that there are altogether 19,683 kinds of two-input tri-valued logic operations and 18 kinds of the most fundamental BOUs. To make full use of the TOC hardware, these fundamental BOUs can be merged functionally according to some rules. After being merged, there are 50 kinds of BOUs altogether[39]. For convenience, these BOUs are numbered, the BOU with No. p written as BOU$_p$, the BOUs with No. from p to q as BOU$_{p-q}$, and the BOUs with No. p and q as BOU$_{p,q}$. After being numbered, BOU$_{1-18}$ are the most fundamental BOUs. Meantime, each of BOU$_{21-44}$ and BOU$_{51-58}$ is merged functionally by two and three of BOU$_{1-16}$, respectively. For example, BOU$_{21}$ is merged by BOU$_1$ and BOU$_3$, and BOU$_{51}$ by BOU$_1$, BOU$_3$ and BOU$_5$[39]. Nonetheless, all of the BOUs are the same in hardware structure, shown in FIG. 1. In the structure, a liquid crystal cell (LCC) was sandwiched by two pieces of polarizer, P1 and P2. A nonenergized LCC could twist the polarized light entering it by 90^0 on exit and an electric field applied across the LCC could make the polarized light go through without being twisted. Moreover, P1 and P2 could be a piece of horizontal or vertical polarizer.

Aggregating all the BOUs with the same polarizers, we set up the optical operators of the TOC at Shanghai University in 2011. Obviously, these operators were made up of four parts, called VV, VH, HH and HV, respectively. Each part had 24×24 pixels i.e. 576 BOUs and an experimental system was designed and implemented to mange these operators [39]. Based on the DRDP, the system was also a dynamically reconfigurable optical computing platform. In other words, any one-bit two-input tri-valued logic processor could be dynamically reconfigured at runtime by no more than 6 BOUs in total, and no more than 3 BOUs were needed in each part.

2.2 Principal properties of complex networks

In this subsection, we describe some significant topological properties, such as average path length, degree distribution, clustering coefficient [29,40], which appear to be common to real networks of many different types.

The path length d_{ij} is the number of the edges or the length of the geodesic on the shortest path from node i to node j in real networks. And the average path length L of a network can be obtained according to the following formula:

$$L=\frac{1}{\frac{1}{2}n(n-1)}\sum_{i<j}d_{ij}, \tag{1}$$

where n is the number of the nodes. In most real networks, L is far less than n. The property is called small-world pattern [19,40,41,42,43,44,45,46].

The degree k_i of node i is the number of edges connected to it. Average degree $\overline{k}$ of a network is the mean of degrees over all of the nodes. And $p(k)$ is the probability that a node chosen uniformly at random has

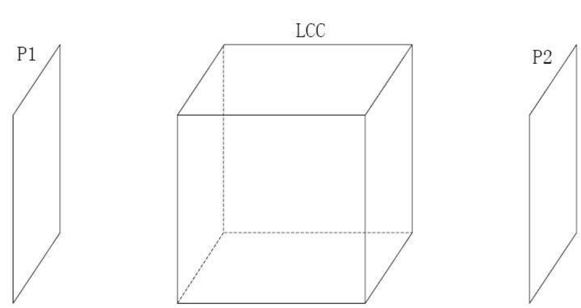

Fig. 1: Structure of a BOU.

degree k. Thus, the degree distribution of a network can be presented with $p(k)$. An alternative way of presenting degree data is to use the cumulative degree function

$$P(k) = \sum_{k'=k}^{\infty} p(k'). \tag{2}$$

It can describe the real networks which have great degree nodes. In most of real networks, $P(k)$ follows power-law distributions, that is, $P(k) \sim k^{-\gamma}, \gamma > 0$. Networks with power-law degree distributions are referred to as scale-free networks [16,22,45,46].

Clustering coefficient C describes the clustering level of nodes in a network [19,29,31,40,43]. The way of calculating the clustering coefficient C_i of node i is as follows:

$$C_i = \frac{\Delta_i}{\Lambda_i}, \tag{3}$$

where Δ_i and Λ_i are the numbers of triangles and transitive triples connected to node i, respectively. Obviously, the number of the former is less than or equal to the one of the latter. In other words, $0 \le C_i \le 1$. The clustering coefficient C of a network is defined as the mean of clustering coefficients over all nodes. That is to say,

$$C = \frac{1}{n}\sum_i C_i. \tag{4}$$

These properties are foundation to study many real networks. Besides them, there are some other properties, such as degree correlation [21], network resilience, community structure [47] and mixing pattern [40].

3 Optical operator reconfiguration network in the ternary optical computer

As mentioned above, any two-input tri-valued logic operation can be implemented by use of 50 kinds of BOUs. At the same time, there are three stable light states, no-intensity light, horizontally polarized light and vertically polarized light, to present information in the TOC. In order to achieve these logic operations, they must be firstly mapped into the 8311 kinds of physical operators which can be reconfigured with the 50 kinds of BOUs. There are still 8310 kinds of physical operators except for the operator whose optical states are all no-intensity light. These physical operators, including 50 kinds of BOUs, are numbered from 1 to 8310 to distinguish them. Thus, each BOU has two Nos.. For example, the operator No. of the BOU_{25} is 2227. However, for each BOU, we don't use its operator No. but its BOU No..

The first approach to capture the global properties of a complex system is to model it as a network where nodes represent the dynamic units, and edges stand for the interactions between nodes. Therefore, to research the

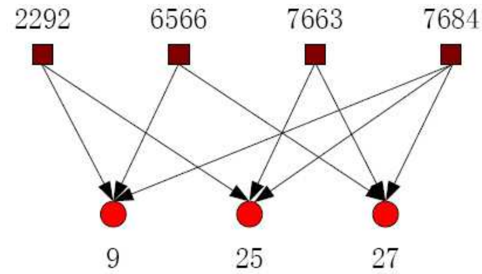

Fig. 2: Topology of the optical operator reconfiguration network composed by operators and BOUs in Table 1.

topological properties of the optical operator reconfiguration network in the TOC, we also model it as a network where nodes represent optical operators and BOUs, and directed edges stand for the reconfigurable relations between them. For instance, we consider a simple optical operator reconfiguration network. In this network, we investigate the operators with No. 2292, 6566, 7663 and 7684. The BOU usage of these operators is shown in Table 1, where the digits stand for the Nos. of operators and BOUs. In other words, the table shows the reconfiguration relations between these optical operators and $BOU_{9,25,27}$. For example, the operator with No.2292 is dynamically reconfigured with the $BOU_{9,25}$.

Fig. 2 illustrates a simple optical operator reconfiguration network according to the reconfiguration information in Table 1. Here the directed edges stand for the reconfiguration relations with which the operators can be dynamically reconfigured by different BOUs. Obviously, square and circle nodes stand for operators and BOUs, respectively.

There are some distinct features in the optical operator reconfiguration network as follows:

♦1)There is no edge between BOU nodes or between operator nodes. In other words, it is a bipartite graph.

♦2)It is directed.

♦3)There is no node whose degree is 0 or 1 in the network.

In order to study the topological properties of OORN, we must construct the OORN with all physical operators and BOUs. Fig. 3 illustrates the OORN with all operators and BOUs. Here circles stand for BOU nodes and squares for operator nodes, and the directed edges similarly stand

Table 1: Operators and BOUs to reconfigure a simple optical operator reconfiguration network.

Operators	BOUs
2292	9 25
6566	9 27
7663	25 27
7684	9 25 27

for the reconfiguration relations between operators and BOUs. It can be easily seen that the operator nodes have small out-degrees and the BOU nodes have terribly great in-degrees. To obtain the in-degree of each BOU node, we firstly count each BOU usage, shown in Table 2. Where ’Frequency’ means the times of each BOU when 8310 kinds of optical operators are reconfigured dynamically with different BOUs. For example, it is 707 times for BOU_2 to reconfigure different optical operators.

At the same time, in Table 2, the frequency of each BOU includes the time it uses itself. In other words, the digits, decreased by one, in the second and the fourth columns are the in-degrees of relevant BOUs in the OORN. For example, the in-degree of BOU_2 is 706.

On the other hand, we also count the numbers of optical operators which can be reconfigured dynamically with different numbers of BOUs, shown in Table 3. For example, there are 652 optical operators which can be reconfigured dynamically with 2 BOUs.

As mentioned above, there is no node whose degree is 0 or 1. Therefore, except for the first row, the digits in the first column of Table 3 are the out-degrees of operator nodes and the digits in the second column are the numbers of operator nodes with relevant out-degrees. For example, the second row illustrates that there are 652 operator nodes with out-degree 2 in the OORN with all physical operators and BOUs.

According to Table 2 and Table 3, we can obtain the node degree information, shown in Table 4, of the OORN. In the table, we don’t distinguish out-degree and in-degree.

4 Topological properties of the optical operator reconfiguration network

In this section, we discuss some principal topological properties of the OORN modeled with all physical operators and BOUs.

4.1 Density distribution

As mentioned above, there is no edge to connect any two BOU nodes or any two operator nodes in the OORN. In other words, for each node i, Δ_i is equal to zero. Therefore, according to Eq. (3), its clustering coefficient C_i is zero, and the clustering coefficient C of the OORN is also zero, according to Eq. (4). Thus, clustering coefficient can’t adequately describe the clustering property of the OORN.

In order to better describe the clustering property of the OORN, we propose an idea of the density. Density D_i of node i represents the clustering level of the edges which are connected to it. In other words, D_i is involved with not only the degree k_i of node i but also the number of the edges between its adjacent nodes. The way of

Table 2: BOU usage in the OORN with all operators and BOUs.

No.	Frequency	No.	Frequency
1	707	28	400
2	707	29	400
3	809	30	262
4	809	31	400
5	1309	32	268
6	1309	33	274
7	815	34	400
8	815	35	280
9	917	36	160
10	917	37	280
11	1429	38	268
12	1429	39	274
13	1441	40	400
14	1441	41	280
15	1561	42	160
16	1561	43	280
17	2187	44	268
18	2187	51	78
21	394	52	78
22	400	53	78
23	400	54	78
24	262	55	78
25	400	56	78
26	268	57	78
27	394	58	78

Table 3: Number of operators which are reconfigured with different numbers of BOUs in the OORN with all operators and BOUs.

Number of BOUs	Number of operators
1	50
2	652
3	2674
4	3584
5	1266
6	84

Table 4: Degree information of the OORN with all operators and BOUs.

Degree	Number of nodes	Degree	Number of nodes
2	652	814	2
3	2674	808	2
4	3584	706	2
5	1266	399	8
6	84	393	2
2186	2	279	4
1560	2	273	2
1440	2	267	4
1428	2	261	2
1308	2	159	2
916	2	77	8

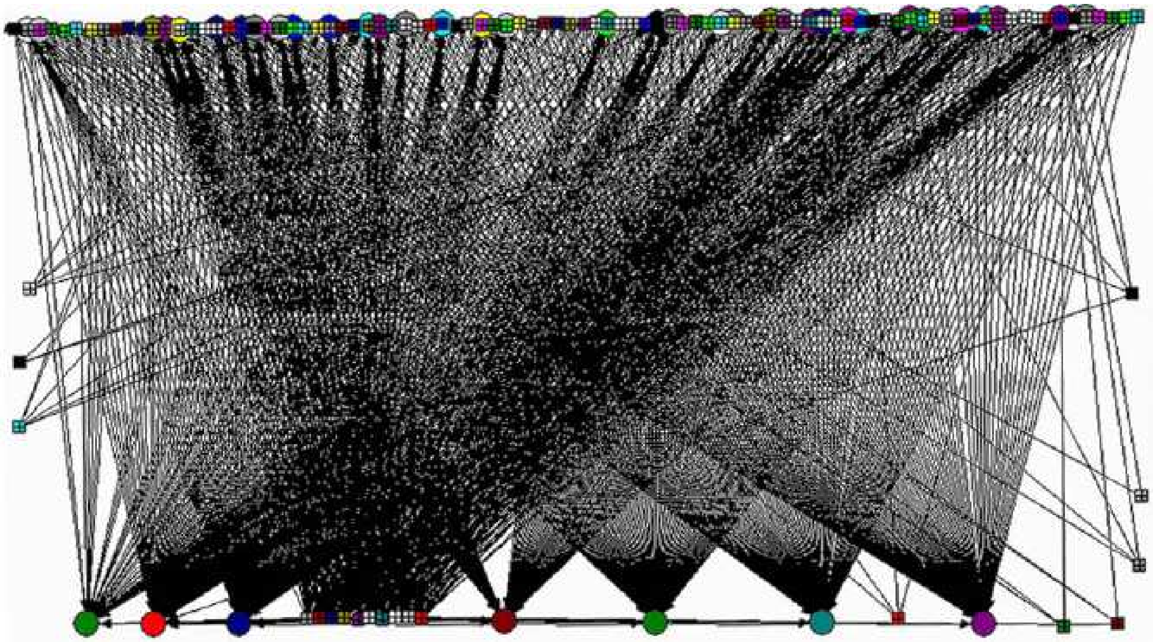

Fig. 3: OORN with all operators and BOUs.

calculating D_i is similar to the one of calculating C_i. Supposing that there are k_i nodes connected to the node i, the way of calculating D_i is shown in Eq. (5):

$$D_i = \frac{E_i}{\frac{k_i(k_i+1)}{2}}, \tag{5}$$

where $k_i(k_i+1)/2$ represents the number of all possible edges between the k_i+1 nodes, and E_i stands for the actual edges between them. Obviously, if the degree k_i of node i is equal to 1, its D_i is 1. Similarly, there is a regulation that D_i is 0 if k_i is equal to 0. The density $D(k_i)$ is defined as the mean of densities over all nodes with degree k_i in a network, and the density D as the mean of densities over all nodes.

In bipartite network, E_i is equal to the degree k_i of node i since there is no edge between k_i BOU nodes or between operator nodes. Thus, Eq. (5) is changed into Eq. (6):

$$D_i = \frac{2}{(k_i+1)}. \tag{6}$$

According to the formula, it can be easily seen that the density D_i of each BOU node in Fig. 2 is 0.5 since its degree k_i is equal to 3. However, the clustering coefficient C_i of each node in Fig. 2 is zero.

After each $D(k_i)$ being calculated, the density $D(k_i)$ distribution of the OORN with all physical operators and BOUs is shown in Fig. 4. Here the horizontal axis for each panel denotes vertex degree k_i (in-degrees for BOUs and out-degrees for operators) and the vertical axis indicates density $D(k_i)$. At the same time, Fig. 4(a) is

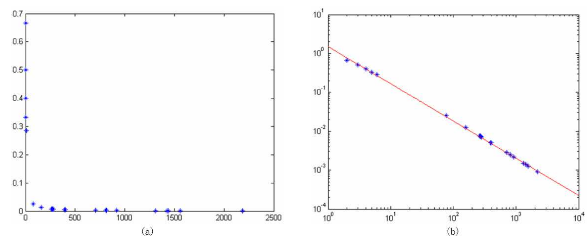

Fig. 4: Density $D(k_i)$ distribution of the OORN with all operators and BOUs.

shown on normal scales and Fig. 4(b) shown on logarithmic scales. The line in Fig. 4(b) is the nonlinear regression of density $D(k_i)$. In addition, its equation is $y = 1.4936x^{0.955}$, and their linear correlation coefficient is 0.9995. In Fig. 4(a), it can be seen that the $D(k_i)$ follows power-law distribution. Moreover, according to the D_i of each node, we can easily obtain the density D, which is equal to 0.4394, of the OORN.

4.2 Other important properties

In order to investigate other important properties of the OORN, it is looked upon as an undirected network. Thus, the average path length L is equal to 27.2537. It can be easily found that L is terribly less than the number of nodes, 8310, in the OORN with all physical operators and BOUs. In other words, the OORN has the small-world property.

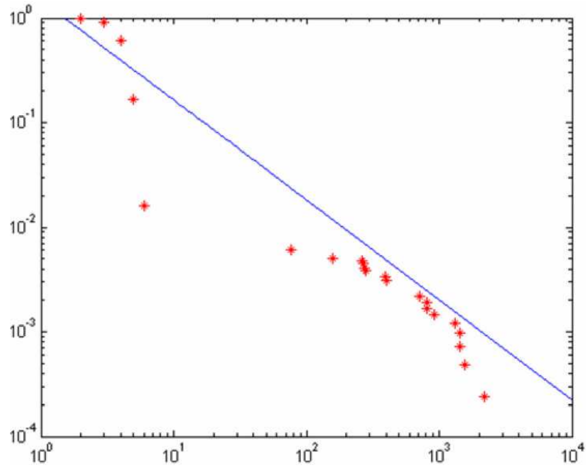

Fig. 5: Cumulative degree $P(k)$ distribution for the OORN in the TOC system.

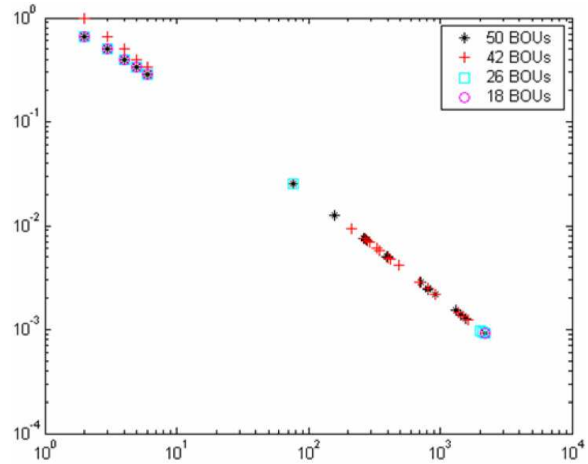

Fig. 6: Density $D(k_i)$ distributions for the OORNs with various BOUs.

Meanwhile, the average degree $\bar{k}$, obtained according to Table 4, is 3.6698. Obviously, the clustering coefficient of each node in the OORN is zero and its clustering coefficient C is zero. And Fig. 5 shows the cumulative degree distribution $P(k)$ on logarithmic scales. Here the horizontal axis is vertex degree k_i and the vertical axis is the cumulative probability distribution of degrees, i.e., the fraction of vertices that have degree greater than or equal to k_i. And the line is the nonlinear regression of cumulative degree $P(k)$. Moreover, its equation is $y = 1.0296x^{0.9921}$, and their linear correlation coefficient is 0.9171. It can be seen that the cumulative degrees approximately follow power-law distribution. Therefore, the OORN with all physical operators and BOUs is nearly scale-free.

4.3 Comparison of the optical operator reconfiguration network with various kinds of BOUs

As mentioned above, the most fundamental BOUs can be emerged functionally to generate other kinds of BOUs, BOU_{21-44} and BOU_{51-58}. Thus, the dynamic reconfiguration of operators can be based on various BOUs, such as 18 kinds of the most fundamental BOUs, 26 kinds of BOUs (including BOU_{1-18} and BOU_{51-58}), 42 kinds of BOUs (including BOU_{1-18} and BOU_{21-44}) and 50 kinds of BOUs (including BOU_{1-18}, BOU_{21-44} and BOU_{51-58}). Therefore, different OORNs with various BOUs can be constructed.

Table 5 shows the comparison of the OORNs with various BOUs. Where 'BOU' is the kinds of BOUs which are used to construct the OORNs, and 'Operator', 'Edge', 'C', 'D', 'L', and '$\bar{k}$' are the number of physical operators(including BOUs), the number of edges, clustering coefficient, density, average path length, average degree of the OORNs, respectively.

From Table 5, we can see that there are the same number of optical operators and the clustering coefficients of these OORNs are all zero. At the same time, the densities and average path lengths increase and average degrees decrease with the increase of the number of BOUs. The reason is that the number of nodes is unchangeable while the number of edges decreases with the increase of the number of BOUs.

On the other hand, the number of operators provided by the TOC is unchangeable in real application. Therefore, the TOC can provide more data-bits, and process more data in parallel if more kinds of BOUs are used in real system. In other words, if density D and average path length L are greater and average degree $\bar{k}$ is smaller, the chosen BOUs can make better use of the parallelism of the TOC. However, there are up to 50 kinds of BOUs to use in the TOC system. Consequently, it is reasonable and optimal to use 50 kinds of BOUs in real TOC system. Fig. 6 shows the density $D(k_i)$ distributions for the OORNs with various kinds of BOUs. Similarly, the horizontal axis is vertex degree k_i and the vertical axis is density $D(k_i)$. And they are both shown on logarithmic scales. It can be seen that their density distributions all follow power-law distribution, regardless of the kinds of BOUs used in the TOC system.

Table 5: Comparison of different OORNs with various BOUs.

BOU	Operator	Edge	C	D	L	$\bar{k}$
18	8310	39348	0	0.358	18.855	4.735
26	8310	38092	0	0.371	20.046	4.584
42	8310	31032	0	0.433	26.745	3.734
50	8310	30496	0	0.439	27.254	3.670

5 Conclusions

In this paper, we have investigated the reconfigurability of optical operators in the TOC from the viewpoint of complex networks. With the help of complex networks, we have obtained some important and interesting topological characteristics of the optical operator reconfiguration network, such as average path length, clustering coefficient, average degree and degree distribution. These numerical results have shown that the OORN simultaneously exhibits small-world effect and scale-free degree distribution, and clustering coefficient can't adequately show the features of the networks. In addition, we have proposed a novel method, density of node, to illustrate the features of the networks, studied their density distributions, and found that both its density distribution and degree distribution follow power-law distribution.

Moreover, we have compared the optical operator reconfiguration network with various kinds of BOUs. On the basis of the comparison, we have drawn a conclusion that it is reasonable and optimal to use 50 kinds of BOUs in real TOC system. To some degree, the conclusion provides theoretical foundation for selecting the kinds of BOUs in the TOC system. In the future, we will continue investigating the other topological properties, such as network resilience, degree correlation, community structure and mixing pattern.

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Wang Xianchao received his Ph.D. degree in computer science and technology from School of Computer Engineering and Science of Shanghai University, China, in 2011. He is now an assistant professor and an assistant dean of School of Mathematics and Statistics at the Fuyang Normal College, China. And he is both a member of ACM and a senior of China Computer Federation. His research interests are in applied mathematics including the mathematical methods and models for complex systems, optical computing, complex network, big data and embedded system. He is a reviewer of Applied Optics and Optics Letters.

Zuo Kaizhong received his Ph. D.degree in computer science and technology from the Shanghai University, China, in 2012. He is now a Professor at Anhui Normal University. His research interests include ternary optical computer, ternary polarization hologram storage, and security and privacy in internet of things. Dr. Zuo is a member of ACM.