A Framework for Network Self-evolving based on Distributed Swarm Intelligence⋆

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Abstract. More and more users are attracted by P2P networks characterized by decentralization, autonomy and anonymity. The management and optimization of P2P networks have become the important research contents. This paper presents a framework for network self-evolving problem based on distributed swarm intelligence, which is achieved by the collaboration of different nodes. Each node, as an independent agent, only has the information of its local topology. Through the consensus method, each node searches for an evolving structure to evolve its local topology. The self-evolving of each node's local topology makes the whole topology converge to the optimal topology model. In the experiments, two simulated examples under different network topologies illustrate the feasibility of our approach.

Keywords: Self-evolving Network · Swarm Intelligence · Distributed Optimization · Distributed Computing · Distributed Consensus.

1 Introduction

Benefitted from the decentralization, scalability, autonomy and anonymity, P2P network has been extensively applied in many fields, such as file exchange, peer-to-peer computing, cooperative work, instant communication, search engine and so on. That applications and users based on P2P network rapidly increase has raised a new challenge to the management and optimization of P2P network. Many technologies can be used to achieve the optimization of P2P network, such as game theory[1, 2], neural network[3, 4], distributed computation[5–7] and so on. But in practical applications, many approaches confront with the problem about computational complexity, optimization effectiveness, computational convergence and so on.

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In dynamic network environment, each node in P2P network is allowed to join or exit the network freely. In addition, in some special applications, such as anti-tracking network, anonymous network, et al, the topology structures of such networks need to be hidden for the purpose of security and privacy that brings a big challenge to the network self-optimization. To address this problem, we present a framework for network self-evolving based on distributed swarm intelligence. Each node acts as an independent agent to collaborate with other nodes and searches for the optimal local topology which is beneficial to all relevant nodes. Then, according to the consensus results, the relevant nodes evolve the local topology. Our approach also designs an optimal topology model to guide each node's local topology evolving to guarantee the convergence of their evolving processes.

2 Model of Self-evolving Network

Based on an unstructured P2P network, our approach achieves the topology self-evolving towards the optimal topology through the distributed swarm intelligence. We denote the self-evolving network as an undirected graph $G(V, E)$, in which V denotes the node collection and E denotes the edge collection. Assume graph G has N nodes, each node $v_i (1 \leq i \leq N)$ is regarded as a biological species having a fitness value f_i which directly reflects node v_i' local topology's status. Node v_i collaborates with its neighboring nodes and adjusts its local topology to search for a local optimal f_i.

The optimal topology model is defined as a kind of network topology which has the uniform distribution of all nodes' degrees. We set a degree threshold τ to limit the density of each node's degree. Formally, the optimal topology T_o can be defined as shown in Eq. 1 in which $D(v_i)$ denotes the degree of node v_i.

$$T_o = \{v_i \in V | D(v_i) \rightarrow \tau\} \tag{1}$$

For node v_i, its local clustering coefficient c_i can be calculated by Eq. 2 in which Z_i denotes the edge number in the group of node v_i and its neighboring nodes.

$$c_i = \frac{2 \times Z_i}{d_i(d_i - 1)} \tag{2}$$

Assume node v_i has the degree of τ, we consider two extreme cases, one is that any two neighboring nodes of node v_i has no links, the other is that node v_i and its neighboring nodes form a full-connected graph. Then, we can calculate the lowest and highest local clustering coefficients of node v_i with the degree τ, separately denoted as $c_i^l = \frac{2}{\tau - 1}$ and $c_i^h = 1$.

Combined with the node degree and local clustering coefficient, the fitness value f_i of each node v_i can be calculated by Eq. 3, in which $\bar{c}_i$ denotes the average local clustering coefficient of node v_i' neighboring nodes, α and β denote the normalized coefficients. The average local clustering coefficient $\bar{c}_i$ can be

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calculated by Eq. 4 in which n_i denotes the number of node v_i' neighboring nodes, N_i denotes the neighboring node collection of node v_i, c_v denotes the local clustering coefficient of the neighboring node v.

$$f_i = F_i(N_i) = \frac{|d_i - \tau|}{\alpha} + \frac{|c_i - \bar{c_i}|}{\beta} \tag{3}$$

$$\bar{c_i} = \frac{1}{n_i} \sum_{v \in N_i} c_v \tag{4}$$

3 Self-evolving Architecture

3.1 Distributed Swarm Intelligence Algorithm

Assume P2P network contains n nodes, $V = \{v_1, v_2, \cdots, v_n\}$. Each node $v_i (1 \leq i \leq n)$ independently executes the swarm intelligence algorithm, searches for its optimal local topology which minimizes the fitness value calculated by Eq. 3 according to node v_i' neighboring nodes set N_i. As shown in Eq. 5, the neighboring nodes set N_i^* of node v_i represents its optimal local topology. All nodes collaborate with its neighboring nodes to search for the global optimal topology. Based on the distributed swarm intelligence algorithm, the objective function F_G of the global topology can be shown as Eq. 6.

$$N_i^* = arg \min_{N_i \subseteq V} F_i(N_i) \tag{5}$$

$$F_G \triangleq \frac{1}{n} \sum_{i=1}^{n} F_i(N_i) \tag{6}$$

Since each node v_i observes only one component of the objective function F_G while exchanging the information with its neighboring nodes, each node v_i estimates a local optimal topology Lo_i with its own swarm intelligence algorithm separately. We define the evolving area of each node v_i as $D_i = \{u | u \in V \ and \ dst(u, v_i) \leq 2\}$,in which $dst(v, u)$ denotes the distance of node v and u. Each node v_i collaborates with all nodes in its evolving area D_i to evolve its local topology. Each node only has two atomic operations in the optimization of its local topology: (1)breaks connection with its neighboring nodes and (2)builds connection with other nodes.

$$\begin{cases} f_i^1 = F_i(N_i^1) \ , \ N_i^1 \leftarrow AO_1(n_i, u_1) \\ f_i^2 = F_i(N_i^2) \ , \ N_i^2 \leftarrow AO_2(n_i, u_2) \\ \qquad \vdots \\ f_i^m = F_i(N_i^m) \ , N_i^m \leftarrow AO_m(n_i, u_2) \end{cases} \tag{7}$$

Assume that there are m nodes in the evolving area D_i of node v_i, which are labelled as $u_1, u_2, \cdots, u_m$. For each node $u_j (1 \leq j \leq m)$, node v_i evaluates the fitness value after it implements the atomic operation. Here, $AO(x, y)$ denotes the

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atomic operation between node x and y, N_i^j denotes node v_i's new neighboring nodes set after the implementation of $AO(v_i, u_j)$, f_i^0 denotes the fitness value without any atomic operations. Then, node v_i can get m fitness values, as shown in Eq. 7.

Node v_i minimizes the fitness value to search for its optimal local topology, but cannot be at the cost of the relevant nodes' local topology. So, node v_i firstly chooses the "better" fitness values and collaborates with relevant nodes to make a consensus. We define the candidate set which is consist of fitness value f_i^j, candidate node u_j and the relevant atomic operation AO_j as shown in Eq. 8. Each node $u_j(1 \leq j \leq m)$ in the evolving area D_i will also get its own Vec_j. Then, node v_i needs to search for an atomic operation which minimizes fitness values of both sides to make a consensus.

$$Vec_i = \{(f_i^j, C_i, AO_j(n_i, u_j))|f_i^j > f_i^0, 1 \leq j \leq m\} \tag{8}$$

3.2 Consensus Search

For each node v_i and its candidate set Vec_i, node v_i needs to implement the following steps to make consensuses with the candidate nodes in Vec_i.

(1) *Target node search.* Node v_i searches for the target nodes of which the candidate sets also contains the atomic operation related with node v_i.
(2) *Atomic operation evaluation.* Node v_i evaluates the effects of the atomic operations on the relevant target nodes' fitness values and searches for the atomic operations which minimize the fitness values of both sides.
(3) *Local topology evolution.* Node v_i and its target node exchange the information with each other to make consensuses for local topology evolution.

At first, each node v_i iterates the candidate nodes in C, and requests that if node u_j's candidate nodes set also contains v_i. If so, it means that the atomic operation between node v_i and u_j benefits both parties. Then, node v_i chooses node u_j as target node for further atomic operation. At the same time, node u_j sends its fitness value about its current local topology to node v_i. After the step of *target node search*, node v_i will get two important sets: the target nodes set T and the corresponding fitness values set FV.

Secondly, node v_i evaluates the effect of the atomic operation with each target node and calculates the evaluation value ev for quantitative evaluation of the local topology evolution. The calculation of evaluation value ev is shown in Eq. 9, in which, α and β are weight coefficients, f_u and f_v separately denote the fitness values of the current local topology of node u_j and v_i, f_u^0 and f_v^0 separately denote the fitness values of the evolved local topology of node u_j and v_i after the corresponding atomic operation. In general, the values of α and β are 0.5.

$$ev = \alpha * (f_u^0 - f_u) + \beta * (f_v^0 - f_v) \tag{9}$$

The evaluation value ev measures the effect of an atomic operation on the change of the fitness values of the relevant nodes. Node v_i searches for the

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min evaluation value, and evolves its local topology based on the corresponding atomic operation to make sure that the topology evolution approaches to the optimal topology T_o defined in Eq. 1. After the step of *atomic operation evaluation*, node v_i get the evaluation values set EV.

Node v_i sorts the evaluation values set EV according to the evaluation value ev from the big to small. Node v_i chooses the biggest one and negotiates with the corresponding target node for the implementation of the atomic operation. If the target node makes a consensus with node v_i, they collaborate to evolve the local topology based on the corresponding atomic operation. If not, node v_i chooses the next target node in the sorted evaluation values set EV for the negotiation of the local topology evolution until node v_i succeeds in making a consensus with one target node, or the iteration of EV is completed.

3.3 Topology Self-evolving

In a n-nodes P2P network, a stable condition is introduced for each node to estimate necessity of consensus search and local topology evolving. For each node $v_i(1 \leq i \leq n)$, the criterion of the stable condition can be defined as σ, which can be calculated as Eq. 10. In Eq. 10, m denotes the node number in node v_i' evolving area, $EA(v_i)$ denotes the node set of node v_i' evolving area, f_{v_i} and f_u separately denote the fitness values of node v_i and u in the current local topology.

$$\sigma = \frac{1}{m} \sum_{u \in EA(v_i)} |f_{v_i} - f_u| \tag{10}$$

According to the optimal topology definition shown in Eq. 1, the optimal topology has the uniform distribution of all nodes' degree and each node's degree is close to the degree threshold τ. So, with the determined value τ, the fitness value of each node also approaches to a determined value. Because an absolute uniform distribution of nodes' degree can not be achieved, we set an optimal fitness value interval $< f_{down}, f_{up} >$ to conduct each node to evolve its local topology. If in node v_i's evolving area, every node's fitness value is in the interval, we believe node v_i is in stable condition. Every node in stable condition will not implement evolving calculation and topology optimizing except its local topology has been changed.

Based on the interval $< f_{down}, f_{up} >$ and Eq. 10, the max value of criterion value σ is $(f_{up} - f_{down})/m$, and the min value is 0. So, the stable condition can be defined as that each node v_i' criterion value σ is in the interval $< 0, (f_{up} - f_{down})/m >$ for a given optimal fitness value interval $< f_{down}, f_{up} >$. In other words, the optimal fitness value interval $< f_{down}, f_{up} >$ determined the eventual status of network self-evolving. The fitness value interval can be calculated by the optimal topology' status.

For example, in our previous work[8], we conceived a topology model, named convex-polytope topology(CPT). When CPT reaches the maximum connectivity, the average degree of all nodes in CPT approaches to 6. We take CPT as an

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example, then $\tau = 6$. In the optimal structure of CPT, the degree interval is $< 5, 7 >$. According to the CPT's property and Eq. 2, the corresponding clustering coefficient interval is $< 2/3, 1 >$. Then, according to Eq. 3 in which we set $\alpha = 1$ and $\beta = 1$, we can calculate the optimal fitness value interval is $< 0, 4/3 >$.

4 Performance Evaluation

To evaluate the performance of network self-evolving of our proposal, we use ring topology and centralized topology to construct two networks with 100 nodes, and deploy our algorithm on each node for network self-evolving. We use d_{min}, d_{max} and d_{avg} to denote the minimum node degree, maximum node degree and average node degree respectively. We define the degree threshold τ of the optimal topology model T_o as 6 for our proposal to calculate the fitness value.

As illustrated in Fig. 1(a), the network is constructed in ring topology initially, in which each node has the degree of 2. So, the values of d_{max}, d_{min} and d_{avg} are same with 2 at the beginning. After each round of network self-evolving, d_{max} increases until its value reaches to 7. Because we set the degree threshold $\tau = 6$, when one node's degree is bigger than 6, its fitness value will be decreased. The value of d_{min} increases until it reaches to 5, because our proposal cannot achieve the absolute uniform distribution of nodes' degree. But, the value of d_{avg} finally reaches to 5.3 which is very close to the degree threshold.

As illustrated in Fig. 1(b), the network is constructed in centralized topology initially. The central node connects with all other nodes which has the degree of 99, and the other nodes only have one connection with central node which have the degree of 1. So, the d_{max} and d_{min} is 99 and 1 at the beginning. The value of d_{max} decreases until it approaches to 9, the value of d_{min} increases until it reaches to 5. After the network self-evolving, the node degree of this network inclines to balanced, and the degree of all nodes is in the interval $< 5, 9 >$. Experiments on different topologies show the effectiveness of our proposal on the network self-evolving. In both of centralized and ring topologies, our proposal can achieve the topology self-evolving towards the optimal topology model T_o.

5 Conclusion

In this paper, we present a framework for network self-evolving based on distributed swarm intelligence to solve the management and optimization problem of dynamic network topology without the global view of the whole P2P network. Each node, as an independent agent, evaluates the atomic operations with the other nodes in its evolving area to search for the optimal local topology. Then, each node negotiates with the relevant node for local topology adjustment to make the whole network converge to the optimal topology model. We also evaluate the feasibility of our approach on two simulated examples which are ring topology and centralized topology.

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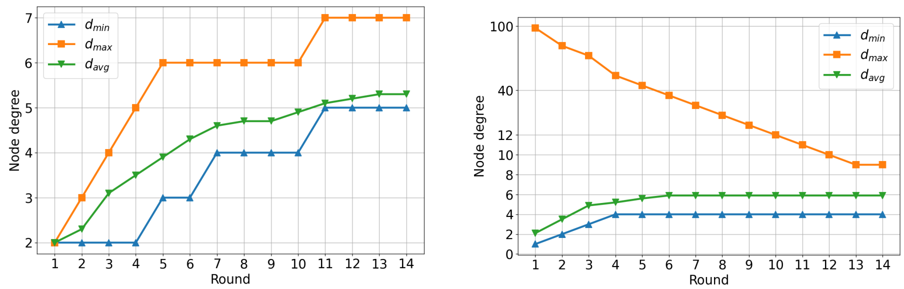

(a) Ring Topology (b) Centralized Topology

Fig. 1. The change of d_{min}, d_{max} and d_{avg} in different topologies.

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