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AUTONOMY-ORIENTED SOCIAL NETWORKS MODELING: DISCOVERING THE DYNAMICS OF EMERGENT STRUCTURE AND PERFORMANCE

SHIWU ZHANG

Department of Precision Machinery and Precision Instrumentation
University of Science and Technology of China, P.R. China
swzhang@ustc.edu.cn

JIMING LIU*

Department of Computer Science, Hong Kong Baptist University
Kowloon Tong, Hong Kong
jiming@comp.hkbu.edu.hk

A social network is composed of social individuals and their relationships. In many real-world applications, such a network will evolve dynamically over time and events. A social network can be naturally viewed as a multiagent system if considering locally-interacting social individuals as autonomous agents. In this paper, we present an Autonomy-Oriented Computing (AOC) based model of a social network, and study the dynamics of the network based on this model. In the AOC model, the profile of agents, service-based interactions, and the evolution of the network are defined, and the autonomy of the agents is emphasized. The model can reveal dynamic relationships among global performance, local interaction (partner selection) strategies, and network topology. The experimental results show that the agent network forms a community with a high clustering coefficient, and the performance of the network is dynamically changing along with the formation of the network and the local interaction strategies of the agents. In this paper, the performance and topology of the agent network are analyzed, and the factors that affect the performance and evolution of the agent network are examined.

Keywords: Autonomy-Oriented Computing (AOC); dynamics of social networks; service transactions; network topology; network performance.

1. Introduction

In social systems, individuals interact with each other and form different social networks. In a social network, a node denotes an individual in various granularities, such as a person, a class, a company, or a community. Accordingly a link represents a specific relationship between two individuals. The individuals are autonomous and self-organizing, that is, their behaviors are determined by their knowledge,

*Author for correspondence

characteristics, relations, and local information, and are not directed by any global factors. The individuals and relationships are evolving dynamically over time, as a result of their local interactions.

Autonomy-Oriented Computation (AOC) is a new computing paradigm, which explicitly utilizes the notion of autonomy, i.e. one of the natural characteristics of entities in a complex system, in the development of efficient methods to solve computationally challenging problems (e.g. to solve large-scale, distributed constraint or optimization problems) and to understand complex behaviors (e.g. to reveal the underlying mechanisms of a complex system).[17,18] There have been successful AOC applications in characterizing Web user surfing behaviors[16] and modeling HIV-Immune interaction dynamics.[35] In AOC, the autonomy of individuals is emphasized. By autonomy, we mean the ability of agents to manage their behaviors according to the local environment and their profiles. AOC is also appealing in characterizing the dynamics of social networks by taking into account the autonomy of individuals. In an AOC-based social network model, the social agents can only interact with each other according to their local information, and decide their behaviors independently without the direct influence from any global information.

In our work, we consider social networks as being both dynamic and adaptive. Generally speaking, there are two types of dynamics in a social network: The first is concerned with the dynamic changes in topological structures and the second is related to the dynamics of agent behaviors as well as the resulting network performance based on the various behavioral strategies of social agents. In a social network, there is a dynamic interplay between (1) changes in the memberships and relationships (as well as the topological structures) of social agents and (2) local interactions among the agents. As a result, the performance of the network as a whole will also evolve over time.

In any social network, the local interactions among social agents aim to satisfy certain demands or needs of agents. Thus, the events happening between two agents can be viewed as those taking place in a service transaction process; agents cooperate to complete a certain service request from other agents, gain some benefits for doing this, and then establish new relations as a result of the interactions. For instance, asking and answering a question is an information exchange service, whereas buying and selling commodities can be viewed as a business transaction service. A service-oriented agent network represents a typical social network, and hence, is well suited to in-depth studies on the dynamics of network topology, local interaction (partner selection) strategies, and network performance.

The aims of our present work are two-fold: (1) we will study the dynamics of social networks. The dynamics not only involve the topological changes of a social network and the activities happening in the network, but also address the changes in the individuals' behaviors/profiles and the network performance; (2) we will develop an AOC-based multiagent system to model the above-mentioned dynamic social networks. In the AOC model, the behaviors of agents are autonomy-oriented, and their interactions are defined as a service-transaction process. The AOC-based model and some preliminary empirical studies have been previously reported.[36,37]

The remainder of the paper is organized as follows. Section 2 surveys related work on social networks. Section 3 introduces the AOC-based model of a social network. Section 4 provides an illustrative example of the proposed model. Section 5 presents the local interaction strategies of social agents that determine the structure and dynamics of a network. Section 6 describes several measurements as used to evaluate the dynamics of a social network. Section 7 discusses a set of simulation-based experiments that are designed to examine the network dynamics based on the AOC model. Section 8 focuses on the dynamics of a network with respect to various local interaction strategies. Section 9 concludes the paper by summarizing the important features of the AOC-based model.

2. Related Work

Research on social networks has been carried out for over sixty years, and has become more active today, due to their ubiquity and practical impacts in the networked world. Early research focused primarily on analyzing the relative positions of individuals in a network and their corresponding roles and functions. Later research was focused on the characterization of network topology and evolution. Having discovered some important topological characteristics in social networks, recent studies started to examine the activities happening in a certain network, search strategies in social networks, and dynamic social network models, among other topics. Nevertheless, previous studies are generally lacking in addressing: (1) the roles and impacts of the autonomy of individuals in a social network, and (2) both the topological and performance dynamics of a social network.

2.1. *Centrality metrics*

Early studies on social networks have focused on the analyses of the role of an individual and how the position of the individual influences its function. Many analyses are based on the centrality metrics of individuals, such as connection degree which calculates the number of an individual's partners, closeness which calculates the average distance with which the individual contacts other individuals of the network, and between-ness which denotes the times that the shortest path between any pair of individuals in the network passes the individual.[5,12]

Centrality metrics measure the static characteristics of an individual, and denote the degree in which the individual accesses information, broadcasts, and controls information flow, respectively. Studies on centrality metrics help realize and predict the ability of social individuals. For instance, after 911 Terrorist Attack, Krebs analyzed the centrality metrics of terrorist networks. He pointed out that the head of a terrorist network has the highest connection degree, closeness, and between-ness.[14] Recently, Newman presented a formulation of between-ness that is based on a random-walk strategy, which can be more efficiently computed than calculating the times of an individual being passed by shortest paths.[22] In the above work, most analyses on centrality metrics are based on the static scenarios of social networks, and the evolution of centrality metrics is not considered. If the dynamics of centrality metrics are further explored, it will be possible to predict and reveal the covert network.

2.2. *Network topology*

Besides using centrality metrics as a microscopic characterization of a social network, studies have also addressed the macroscopic characterization problems by examining network topologies. In recent years, many social and natural networks have been verified to exhibit the small-world, high-clustering, and scale-free topologies. By small-world it is meant the average length of the shortest path between any arbitrary pair of individuals is small. Clustering characterizes a clustering property by calculating the average proportion that the neighbors of an individual are also neighbors to each other. Scale-free means that the distribution of connection degree follows a power-law distribution.

Small-world phenomenon has been first studied by Milgram in a mail-delivery experiment[19] and he coined the term of "six degree of separation" to refer to the average number of connections that can be made between any two persons. Later, Newman *et al.* pointed out that the average shortest path in a small-world network would increase very slowly along with the growth of network size.[25] Watts *et al.* have shown that besides the small average value of the shortest path lengths, many social networks have high clustering coefficients.[28] They also provided a rewired link model based on a regular network to construct a small-world network with a high clustering coefficient. Barabasi *et al.* have studied the distribution of connection degree of individuals in many social and natural networks, and have pointed out that the distribution of connection degree follows a power-law. He termed the networks as scale-free networks.[2,3] However, the scale-free phenomenon cannot be observed in Watts' rewiring model. Barabasi *et al.* introduced a growth and preferential attachment factor into the evolution of a network, and obtained a power distribution of connection degree. The resulting network has a low clustering coefficient which cannot account for the cluster phenomena in many social networks. Barabasi *et al.* observed that a scale-free network can resist randomly removing individuals, and it is easy to collapse while continuing to remove the highest connective individuals.[1]

In order to reveal the origin of the typical topologies in natural or social systems, Ebel *et al.* have developed a simple model that introduces transitive linking into an acquaintance network. They observed a power distribution of connection degree, a high clustering coefficient, and a small diameter simultaneously in the evolved network.[9,11]

In the above models, social individuals are often simplified into nodes with simple rules, which means the autonomous characteristics of the individuals are omitted. In fact, in the long-time evolution of a social network, the behaviors of individuals are managed by the individuals themselves. Local interaction strategies of the individuals may change and further affect the formation of the network.

2.3. *Activities in social networks*

After the topological characteristics of social networks are discovered, many models accounting for the characteristics have appeared. With these models, the activities happening in the networks can also be studied.

Kuperman *et al.* have studied an epidemiological model, called SIR (susceptible, infected, refractory), on networks ranging from regular networks to random networks, and analyzed the synchronization phenomena with respect to the disorder degrees of the networks.[15] Satorras *et al.* have examined computer virus on the Internet and identified the spreading characteristics of virus on scale-free networks. They have shown that the epidemic threshold on scale-free networks is absent, which means an epidemic is prevalent whether the spreading rate is small or not.[26] The same characteristic is found in the spreading of computer virus via email networks.[23] Dezso *et al.* have found that curing infected individuals according to their connective degrees can halt the virus effectively.[10] Epidemic diffusion in a finite sized scale-free and a weighted scale-free network has also been explored.[27,30]

The above studies were all based on SIR models. However, a percolation model on epidemic spreading was also developed. In the percolation model, the occupied probabilities of nodes and bonds were represented by susceptibility and transmissibility, respectively. Various spreading characteristics have been explored based on percolation theory.[20,21,24]

Besides the epidemic spreading on social networks, information flow in networks is also worth studying. With such studies, we can analyze the efficiency of information spreading on social networks. Zanette presented a rumor spreading model on a small-world network. He found a phase transition in rumor spreading according to the randomness level of the network.[34] However, information spreading is different from epidemic spreading in that information spreading is highly selective, and there is a decay in the transmission probability for organization distance. Huberman *et al.* studied information flow in email networks and indicated that information spreading is limited by the decay in transmission probability.[13,29]

Generally speaking, the networks used to study epidemic or information spreading can be classified into three categories according to their constructing models: Watts' rewiring model and its variants; Barabasi's growth and preferential attachment model and its variants; the networks constructed from real data. In these models, the topology of the networks is static while studying the activities on the networks, which is not realistic. The activities are simplified into spreading behaviors based on the probabilities, which also omits the autonomy of individuals and the influence of local interaction strategies given the topology of networks.

2.4. *Modeling a social network*

From the above introduction, we note that it is most important to construct a realistic network model in the studies of social networks. This is one of the major objectives of our project.

In a social network, individuals often interact according to the cumulative knowledge about their local environment, such as the trust and reputation of their neighbors. Carter *et al.* studied the relationship among trust and reputation, and constructed a value-based agent model in which agent roles and activities are decided by various values of agents.[8]

Cano *et al.* emphasized social exchanges in social networks and presented a framework of constructing a socio-cognitive grid in which social exchanges through mediators are the building blocks of social networks.[6] Yolum *et al.* presented a multiagent model based on a referral network. They regarded referral as the basic behavior when searching information in a social network. In the network, the agent model and interaction process are elaborately defined. The performance of the evolved network, the efficiency in mining and searching communities, are also examined.[31–33]

Recently, Carly proposed the concepts of dynamic social networks. She used a meta-matrix to describe relations among individuals and pointed out that the relations in dynamic social networks should be treated as probabilistic.[7] She also developed an agent model, named DIFS (Dynamic Information Flow Simulation), to analyze the structure, function, and activities of an intelligent organization.[4] In the model, the dynamics mainly concerned the activities, especially the information flow in the social networks.

To summarize, in the past several years, many researchers have analyzed the topologies of static social networks, discovered various topological characteristics, and tried to reveal the determining factors of those characteristics. With various models for discovering topological characteristics, many activities, such as disease diffusion and information spreading on social networks, have been examined. The methods of partitioning social networks have also been developed. However, social individuals have so far been considered as nodes with simple update mechanisms. That is, the most significant characteristic of social individuals, autonomy, has not been addressed.

Although later the developed multiagent models of social networks have started to emphasize the behaviors of individuals, social exchanges, referral networks, or DIFS have captured only partial aspect of social behaviors. In our work, we will present a more realistic, representative model of social networks, called *service-based agent networks*. In this model, all interactions are modeled as service-transaction processes with certain constraints. The *autonomy* of agents is explicitly incorporated. That is, the behaviors of the agents can only be determined by themselves, according to their local information with no direct influence of any global information.

The objective of our work is to develop an Autonomy-Oriented Computing (AOC) based model to study the dynamics of social networks, in which interactions among agents are modeled as service-transaction processes. The agents are autonomy-oriented, which means the agents determine their behaviors only according to their local information and their own profiles. With such a model, we can obtain a better understanding of: (1) how a social network evolves and (2) how a better network performance can be achieved based on certain local interaction strategies. That is, we will study the dynamics of network formation, agent profile, and network performance. The proposed AOC-based network model will also enable future studies on the development of various activities and efficient interactions or search strategies for service-based agent networks.

3. Autonomy-Oriented Modeling of a Service-Based Agent Network

In order to reveal the dynamics of an agent network, the profile and behaviors of an agent should be modeled. Each agent has a certain ability in finishing tasks under some constraints. Besides this, there are also other parameters to characterize the profile of an agent. Firstly, the agent aims to earn more utility by dealing with the tasks. Cumulative utility is used to describe the utility that the agent has earned in its past service-based activities. Cooperative degree is a fixed value to characterize the intrinsic willingness that the agent accepts a cooperative service request. Partnership degree denotes how well the agent can cooperate with and finish a requested service with another agent. To summarize, ability, cumulative utility, cooperative degree, and partnership degree are defined to characterize the profile of a social agent.

In a social network, all activities can be modeled in terms of service-based interactions. A service consists of various tasks and constraints about the tasks. The interactions between an agent and its partners are described as service-transaction processes. A service transaction process consists of the following steps: service matching, service evaluation, service propagation, and the evolution of agent profiles, as described below.

First of all, after an invoked service request arrives at an agent, the agent will start a service matching process. In the matching process, the agent will decompose the service into two parts. The first part is the candidate service which is composed of the subtasks that can be finished by the agent while satisfying the associated constraints; the second part is the remaining part of the service, whose subtasks cannot be finished by the agent.

Next, the agent will perform a service evaluation process. Based on its profile and the reward from such a service, the agent will judge whether to accept the candidate service and propagate the remaining service to its neighbors. If the agent declines the service request, the partnership between the agent and its partner who sends the service request will be downgraded. If the agent accepts the service, it will select a cooperative partner from its current partners and send the remaining service to it.

Once the service has been completed, there will be a reward for all the agents who are involved in accomplishing the service. On the other hand, if the service request is refused, there will be no reward. When the service is finished, the agents involved in the service-transaction processes will also build or strengthen their partnership for future cooperation. Thus the profiles of the agents will be updated as a result of service-based interactions.

With the above-mentioned model, network performance can be defined as the proportion of the services that are finished. Network topology is characterized by (1) the number of partners each agent has and (2) the clustering coefficient of the network. Different local interaction strategies may lead to different network topology, network performance, and the profiles of agents.

In the following section, we will detail the formulations of an agent profile and service-based interactions.

3.1. *Agent profile formulation*

We assume that there are N agents in an agent network. The profile of agent i is described by A_i that is defined in Eq. (1). A_i is dynamically changing along with the interactions among agents.

$$A_i = [B_i, \eta_i, \beta_i, \Lambda_i] \tag{1}$$

where B_i, η_i, β_i, and Λ_i denote agent ability, cumulative utility, cooperative (willingness) degree, and the set of partnership degrees, respectively.

(1) Agent ability B_i characterizes the ability of a social agent in accomplishing various tasks under certain constraints. It is an important characteristic of social individuals, which determines the behaviors of an individual. Here, we use two vectors to describe the tasks and the constraints:

$$\begin{aligned} B_i \quad\quad\quad\; &= [\text{Contents}_i, \text{Constraints}_i] \\ \text{Contents}_i \quad &= [t_{i1}, \ldots, t_{ik}, \ldots, t_{iN_{it}}] \\ \text{Constraints}_i &= [r_{i1}, \ldots, r_{il}, \ldots, r_{iN_{ir}}] \end{aligned} \tag{2}$$

where Contents_i denotes the tasks agent i can finish, and Constraints_i denotes under what conditions or constraints agent i can finish Contents_i. t_{ik} is the kth task that agent i can accomplish. N_{it} and N_{ir} are the total number of tasks and constraints, respectively. r_{il} is the lth constraint when agent i accomplishes the tasks, which consists of quality, cost, sequence, workload, and/or other attributes with respect to the tasks that the agent is to finish. In our later illustrative example, we will define the constraints as quality q_{il} and cost c_{il}.

(2) Cumulative utility η_i describes the cumulative rewards that agent i has earned in the past service-based interactions. A high cumulative utility means the agent

has a strong ability or occupies a good position. Cumulative utility also affects the future behaviors of agent i.

(3) Cooperative degree β_i describes the willingness with which an agent cooperates with its partners. It is an intrinsic characteristic. In our model, it comes with an agent and does not change in the interactions. If an agent has a low cooperative degree, it will decline other partners' cooperation requests or require a relatively high utility.

(4) Partnership degree Λ_i represents a set of partnership degrees between agent i and its partners. Specifically, the partnership degree between agents i and j is denoted by λ_{ij}. If two partners cooperate well, their partnership degree will become strong. Furthermore, a strong partnership between two partners will facilitate their future cooperation. In our model, the service that has been accomplished between two partners with a high partnership degree will cost less. And the partnership degree will decrease if the agent refuses the cooperation request.

3.2. *Service representation*

Service S_m is defined in Eq. 3. The service also consists of two parts: Contents and Constraints. Contents denotes the tasks in the service, while Constraints is the constraints on the tasks.

$$\begin{aligned} S_m &= [\text{Contents}_m, \text{Constraints}_m] \\ \text{Contents}_m &= [t'_{m1}, \ldots, t'_{mk}, \ldots, t'_{mN'_{mt}}] \\ \text{Constraints}_m &= [r'_{m1}, \ldots, r'_{ml}, \ldots, r'_{mN'_{mr}}] \end{aligned} \tag{3}$$

where t'_{mk} is the kth task in service m. N'_{mt} and N'_{mr} are the number of tasks in the service content and the number of corresponding constraints, respectively. r'_{ml} is the lth constraint in service S_m. In a service-based agent network, service constraints should include the reward and the requirement of a service. In our following illustrative example, we will define r'_{ml} as the price P_m of the service and the quality q'_{mk} of the tasks.

3.3. *A service transaction*

The interactions among social agents can be modeled as service-transaction processes. The agents can only interact with their direct partners based on their local information and profiles. Figure 1 provides an example of a service transaction.[36] As illustrated in the figure, a service request, S, is first invoked. Next, the service will be delivered to an agent of the network, which is referred to as a scheduler (i.e. A_1 in Fig. 1). The agents will communicate to evaluate the service [Fig. 1(b)] and get a solution [i.e. agents A_1, A_3, A_6, and A_7 are involved in Fig. 1(c)]. The agents will accomplish or decline to provide the service, and the agent network will then evolve [Fig. 1(d)].

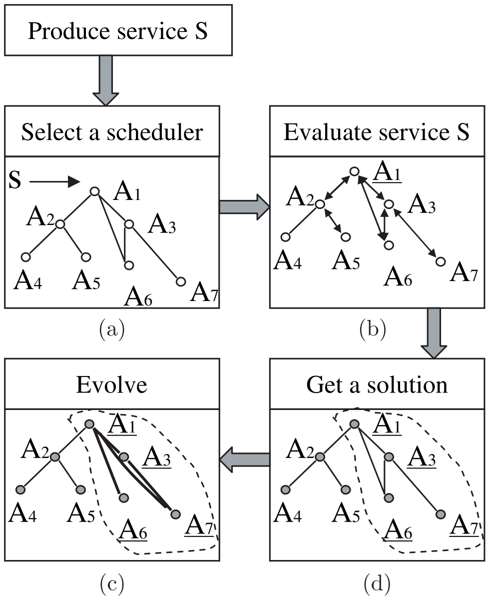


Fig. 1. A service-transaction process.

What follows provides the formulation of service-transaction processes.

(1) *Service matching.* A service can be invoked from an agent inside or outside of the network. After a service is invoked, it will be delivered to an agent called as a scheduler. The scheduler will begin a service transaction. If a service request or a cooperation request from agent j arrives at agent i, agent i will match the service with its ability model. $\overline{S}_{A_i}$ denotes the service that is delivered to agent i. Agent i will calculate the tasks in $\overline{S}_{A_i}$ that it can finish under the constraints, which constitute S_{A_i}. S'_{A_i} denotes the remaining service that cannot be accomplished by agent i under the constraints. The matching process will be different according to various constraints in different applications. Equation (4) defines the relationship of $\overline{S}_{A_i}$, S_{A_i}, and S'_{A_i}, in which $\oplus$ denotes a service composition operation:

$$\overline{S}_{A_i} = S_{A_i} \oplus S'_{A_i} \ \forall r'_l \text{ is satisfied.} \tag{4}$$

(2) *Service evaluation.* After the service matching, agent i will evaluate the service part that it can accomplish and decide whether to accept the service request:

$$E_i = f_i(S_{A_i}, B_i, \eta_i, \beta_i) \tag{5}$$

where E_i is the evaluation of S_{A_i}. If E_i is enough to satisfy the agent's demand, the agent will accept the service. Otherwise, the agent will decline the service request. The demand of the agent is calculated based on the profile of the agent.

If agent i declines the service request, the partnership degree λ_{ij} between agents i and j will decrease according to Eq. (6):

$$\lambda_{ij}(t+1) = \lambda_{ij}(t) \cdot \xi \tag{6}$$

where ξ is a penalty coefficient in $[0, 1]$.

(3) *Service propagation.* After agent i decides to accept the service request, it may select a partner to cooperatively finish the remaining service S'_{A_i} if it cannot finish all the service by itself. Intuitively, an agent inclines to select a cooperative partner with a high cooperative degree and a high partnership degree between them, since the notion of cooperative degree indicates the willingness to cooperate, and that of partnership degree implies the evaluation of the past cooperation:

$$\text{Select } h, \quad \text{where } \beta_h \cdot \lambda_{ih} \text{ is max in agent } N_i \tag{7}$$

where N_i denotes all the partners of agent i, except agents that have been searched in the service propagation. If agent h declines the request, agent i will deliver the service to another partner g with a high $\beta_g \cdot \lambda_{ig}$. If all partners of agent i decline the cooperation request, agent i will return service S'_{A_i} to agent j, the upper-level cooperative partner. Agent j will then select a new cooperative partner in its partners to accomplish the service.

As to be discussed below, agents can also choose their cooperative partners based on other information.

In this paper, we call the strategy that is used by an agent to select its cooperative partner a *local interaction strategy* or a selection strategy. As will be shown later, selection strategies can affect the dynamics of network topology as well as network performance.

(4) *Agent profile update.* After the whole service is accomplished, the agents that have participated in the service transaction will get rewards according to the previous evaluation. The agents that are involved in the service accomplishment will establish (if none) or strengthen their partnership for future cooperation. In doing so, the agents with a high cumulative utility will consume some utility in establishing a new partnership. That is, agent i will add a cooperative partner, h, to its partner group, and agent i will convert part of its utility to the partnership degree with its new partner, which is defined by the following equation:

$$\begin{aligned} \lambda_{ih} &= \eta_i \cdot \phi \\ \eta_i(t+1) &= \eta_i(t) - \lambda_{ih} \end{aligned} \tag{8}$$

where ϕ is a constant in $[0, 1]$. Note that during the evolution of agent partnerships, all updates depend on service-based interactions among agents. There is no direct influence of any global information or remote partners. That is, all interactions are local and autonomy-oriented.

The partnership degree evolves over time. However, some partnerships will become extremely weak, refusing cooperative service requests among agents. If a partnership is too weak, it will break. Hence, in our model, if partnership degree λ_{ij} is lower than a threshold κ, the partnership between agents i and j will break.

4. An Illustrative Example

In this section, we will describe an illustrative example to show how to conduct an experiment with the AOC-based model. Here, the constraints in agent ability is defined as Quality and Cost. Quality denotes the quality in which an agent accomplishes a certain task, and Cost denotes the cost in accomplishing the task. Thus, Contents$_i$ of agent i can be represented as: Contents$_i$ $= [t_{i1}, t_{i2}, \ldots, t_{iNc_i}]$, and Constraints can be represented as:

$$\begin{aligned} \text{Quality}_i &= [q_{i1}, q_{i2}, \ldots, q_{iN_i}] \\ \text{Cost}_i &= [c_{i1}, c_{i2}, \ldots, c_{iN_i}] \end{aligned} \tag{9}$$

where Contents$_m$ describes the tasks that are included in service S_m. Contents$_m$ $= [ts'_{m1}, ts'_{m2}, \ldots, ts_{mN'_m}]$, and Constraints describes quality Qs_{mk} for various tasks and reward p_m for the service from the requesting agent, respectively.

$$QS_m = [qs_{m1}, qs_{m2}, \ldots, qs_{iN_m}] \tag{10}$$

where quality qs_{mk} means that the agent has to finish task t_{mk} with a quality higher than qs_{mk}.

4.1. *Rules in service matching and evaluation*

In the service matching and service evaluation processes, an agent will first calculate the part of service that it can accomplish under certain constraints, then estimate the utility it may earn if accomplishing the service tasks. The agent will consider whether or not to accept the service according to the evaluation result.

In this section, we will define detailed rules in service matching and evaluation. Here, we assume that agent i is dealing with service m, and the service is delivered from agent n, there will be $S_m = \overline{S}_{A_i}$.

- **Rule 1:** *Agent calculating cost for completing partial service.*

(1) Get the list of the tasks that agent i can finish.

For j=1:N'_m
  IF ts_{mj} is in Contents$_i$
    IF $q_{ij}|B_i > qs_{mj}|S_m$
      Add ts_{mj} into the contents of S_{A_i}
    Endif
  Endif
Endfor

(2) Estimate cost C_{im} if agent i finishes the contents of service S_{A_i}, according to the ability of agent i:

$$C_{im} = \Sigma_{t_{ij} \in S_{A_i}} (qs_{mj}/q_{ij}) \cdot c_{ij}. \tag{11}$$

- **Rule 2:** *Agent calculating service utility.* Agent i will calculate the expected utility Pt_m if it accomplishes the service S_{A_i}, according to Eq. (12):

$$Pt_m = (C_{im} \cdot ln(e + \eta_i/\beta_i)) \cdot \delta \tag{12}$$

where δ is a constant in $[0, 1]$, which describes the greedy degree of the agents in the network. If the current cumulative utility η_i is very high, agent i will have a high expectation for rewards in dealing with the service. However, if agent i's cooperative degree β_i is very low, agent i will also be very greedy and ask for more rewards. The price of the remaining service S'_{A_i}, p'_{im}, will be determined as follows:

$$p'_{im} = p_{im} - C_m - Pt_m. \tag{13}$$

- **Rule 3:** *Agent deciding whether or not to accept the service.* In a service transaction, there will be an extra cost of cooperation among agents. The cost will be low when the partnership degree between an agent and its cooperative partner is high. Inversely, the cost will be high, when the partnership degree is low. The cost of the cooperation is defined as follows:

$$CA_{in} = (\epsilon - \lambda_{in}(t))./(\epsilon \cdot 10) \tag{14}$$

where CA_{in} denotes the cost of the cooperation between agents i and n. ϵ denotes a cost factor within $[2, 3]$.

Although the price of a service may be higher than the sum of the cost for accomplishing the service and the rewards that agent i has expected, agent i may still not accept the service. On the other hand, if agent i accepts the service, it has to find a cooperative partner to accomplish the remaining service S'_{A_i}. If the remaining price for service S'_{A_i} is too low, the partners will decline the agent's cooperation request. Otherwise, service propagation will hurt its partnerships. Therefore, a rational agent decides whether or not to accept the service request based on its estimate on the quality and the price of the remaining service S'_{A_i}:

$$Pa = \Sigma_{j \in S'_{A_i}} (qs'_j/qs_j) \cdot p_m - C_m - Pt_m - CA_{in}. \tag{15}$$

If $Pa > 0$, agent i will accept the service request and propagate S'_{A_i} to its partners. Otherwise, it will decline the service cooperation.

The above-mentioned rules will be incorporated into the agent service-transaction processes as described in the preceding section and summarized below:

Initialization
For i=1:step

1: Receive a service request and select a scheduler
2: Service matching and evaluation
3: If accept service **Then** propagate service; **Else** go to 7
4: Increase partnership degree
5: If accomplish the whole service **Then** go to 8
6: If find a next partner **Then** go to 2
7: Decline the service request
8: Update the profiles of agents
Endfor

5. Local Interaction Strategies

In the early discussion, we have mentioned that the way in which an agent selects its cooperative partners will affect the evolution of network topology as well as network performance. Recall that agent i selects a cooperative partner according to Eq. (7); that is, the agent selects a cooperative partner based on the multiplication of its cooperative degree and the partnership degree. However, it can readily note that the agent may select a cooperative partner based on other criteria or strategies.

In this section, we will introduce some of the local interaction strategies.

- **Strategy S1:** agent i selects a cooperative partner, maximizing the multiplication of its cooperative degree and partnership degree:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \beta_h \cdot \lambda_{ih} \text{ is max.} \tag{16}$$

- **Strategy S2:** agent i selects a cooperative partner, maximizing the multiplication of its cumulative utility and partnership degree:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \eta_h \cdot \lambda_{ih} \text{ is max.} \tag{17}$$

- **Strategy S3:** agent i selects a cooperative partner with the highest partnership degree:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \lambda_{ih} \text{ is max.} \tag{18}$$

- **Strategy S4:** agent i selects a cooperative partner that has the highest cooperative degree:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \beta_h \text{ is max.} \tag{19}$$

- **Strategy S5:** agent i selects a cooperative partner that has the highest cumulative utility:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \eta_h \text{ is max.} \tag{20}$$

- **Strategy S6:** agent i selects a cooperative partner, maximizing the multiplication of its cumulative utility and cooperative degree:

$$\text{Select } h \text{ in } \mathrm{N_i}, \quad \text{where } \beta_h \cdot \eta_h \text{ is max.} \tag{21}$$

- **Strategy S7:** agent i selects a cooperative partner that has the highest degree of connectivity (meaning that the selected partner has the maximum number of partners):

$$\text{Select } h \text{ in } N_i, \quad \text{where } N_h \text{ is max.} \tag{22}$$

With the above definitions of local selection/interaction strategies, we can now further study the dynamics of the agent-based social network, in its topological structure and performance.

6. Measurements

As noted earlier, once a network of autonomous social agents has processed a certain number of service requests, the relationships and behaviors of the network will start to evolve. In our present work, we are interested in dynamic changes in both the topological structure and the performance of a network. In what follows, we will first introduce some of the measurements that we will use.

6.1. *Network topology*

Network topology refers to the macroscopic characteristic of a social network, which can be studied through several measurements, such as the number of partners, clustering coefficient, the distribution of agent connection degree, and the so-called "diameter of the network".

The number of partners may reflect the performance of the network because all partners are developed for the purpose of cooperation in accomplishing service tasks. If the number of partners is high, the probability that the agents find good cooperative partners will also be high.

Clustering coefficient, γ, is another important factor that characterizes the clustering degree of the network. Clustering coefficient can be defined as follows:

$$\begin{aligned} \gamma &= (\Sigma_i \gamma_i)/N \\ \gamma_i &= NP_i/NPM_i \end{aligned} \tag{23}$$

where N is the total number of agents in the network. γ_i denotes the clustering degree of agent i. NP_i and NPM_i denote the actual number and the maximum possible number of partner pairs among agent group N_i, respectively. Here N_i denotes the agent group that is composed of the partners of agent i. A high clustering coefficient is the typical characteristic of a small-world network, which reflects that some service agents cluster together and their cooperation cost will be relatively low. A random network has a very low clustering coefficient.

The distribution of connection degree is another important measurement. It has been shown that the distribution of connection degree in most social networks follows a power law or has a heavy tail, which reflects the scale emerging from the evolution of the networks.

The degree of network stability reflects the dynamics of the internal structure of a network, which is computed based on the proportion of the changed partnerships of the network agents. Specifically, the degree of network stability, τ, is defined as follows:

$$\tau = \Sigma_{i \in N}(N_{ia}/(N_{ia} + N_{ic})) \cdot N_{ip} \tag{24}$$

where N_{ic} denotes the number of changed partners within a certain interval, which is the sum of the number of removed partners and the number of added partners. N_{ia} denotes the number of partners that have not changed after the given interval. N_{ip} denotes the difference in the number of partners within the interval.

6.2. *Network performance*

The performance of a social network is defined as the proportion of the accomplished services after a period of evolution, which is defined as follows:

$$PF = N_a/N_s, \text{for time} N_t \tag{25}$$

where PF denotes the performance of an agent network, N_a denotes the number of services that are accomplished, N_s denotes the number of all service requests received, and N_t denotes a period of time. A high network performance means that the network has evolved to be able to handle various service requests. Furthermore, different local interaction strategies can lead to different network performances.

7. The Dynamics of an Agent-Based Social Network

In this section, we will first describe Experiment A, which is concerned with a random agent network. In this network, the agents are initialized with several uniform distributions. The partnerships among the agents are established arbitrarily. Service requests are generated from the outside of the agent network. At each step, one service request arrives at a randomly selected agent in the network, i.e. a scheduler. In Experiment A, we do not consider the workload of the agents. The agent network evolves and forms along with service transactions. The parameters as used in the experiment are listed in Table 1.

Table 1. The parameters as used in Experiment A.

Number of steps	50,000	N	800
Number of tasks	20	ϕ	0.1
Selection strategy	S1	ϵ	0.7
ξ	2	κ	0.2

7.1. *The dynamics of network topology*

Figure 2(a) presents the dynamics of network structure in Experiment A, which includes the dynamics of clustering coefficient, the number of partners, and the normalized degree of network stability.[36] From the figure, we can observe an over-shoot phenomenon in the dynamics of clustering coefficient. Clustering coefficient, γ, increases very fast at the first 3000 steps. The reason is that the initial network is randomly created and the clustering degree is very low. Agents will quickly cluster as a result of service-based interactions. However, at the same time, the partnerships among the agents that seldom cooperate will break, and accordingly, clustering coefficient, γ, will decrease after 3000 steps. In this process, network performance increases because the agents can find suitable cooperative partners to finish services. There is no over-shoot phenomenon in the dynamics of network performance nor in the number of partners. Eventually, clustering coefficient, γ, becomes stabilized around 0.17.

For the purpose of comparison, we have also implemented a random network in which all the partners among the agents are built arbitrarily. We can obtain the dynamics of clustering coefficient in the random network that has the same number of partners as that of the agent network at a certain step. The dynamics of clustering coefficient in the random network is shown in Fig. 2(a). In the figure, we can observe that clustering coefficient of the random network increases slowly along with the number of partners. However, it is much lower than that of the agent network involving service-based interactions.

In other words, we note that the evolved agent network has a higher clustering coefficient, which is in fact consistent with that of a real social network.

The dynamics of network stability, which is defined in Sec. 6.1, is also examined in our work. Figure 2(b) presents the normalized degree of stability with respect to Experiment A.

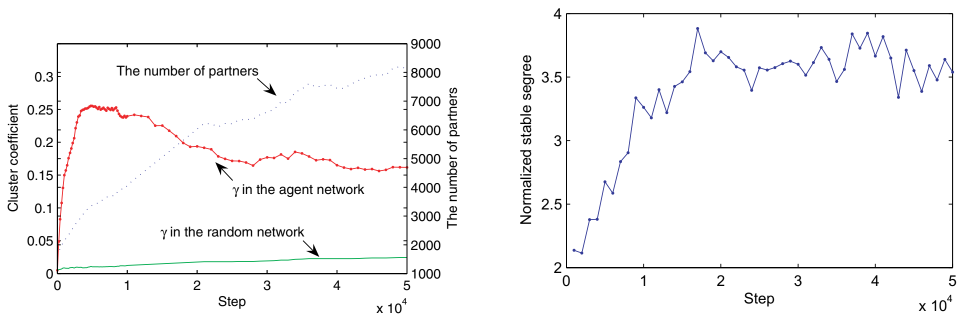
It can be observed that the normalized degree of stability in the network increases along with the number of partners [Fig. 2(a)] at the beginning, then it becomes stabilized after step 20,000. The result indicates that the microscopic topology of the social network becomes relatively stable after step 20,000.

7.2. *The dynamics of network performance*

Figure 3 displays the dynamics of network performance, the average number of partners and network efficiency in Experiment A.

In Fig. 3(a), the horizontal axis corresponds to the running step, whereas the vertical axis corresponds to network performance, i.e. the proportion of accomplished services for every 1000 steps and the average number of partners for each agent, respectively. In the first 20,000 steps, network performance increases quickly. After step 20,000, network performance fluctuates around 0.37.

From the above result, it can be concluded that the agent network can accomplish more services within a certain interval. This reflects the evolution of network



(a) Changes in clustering coefficient and the number of partners.

(b) The normalized degree of stability.

Fig. 2. The dynamics of network structure in Experiment A.

structure as well as the effects of the agent local interaction strategy: agents can readily select more suitable partners. The increase in accomplished services indicates that the agent network can self-organize to accomplish more services, which is an emergent property of the network resulting from the local interactions of the agents.

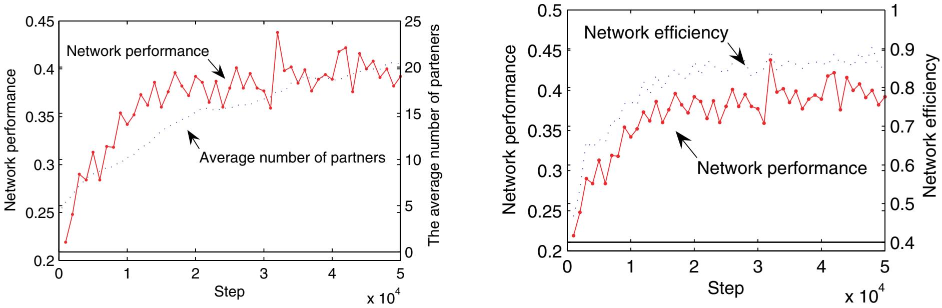
Also, it can be noted that the number of partners still increases after step 30,000, and network performance fluctuates. This phenomenon indicates that network performance cannot benefit from the increase in the number of partners after step 30,000.

Figure 3(b) displays the dynamics of network performance and network efficiency, respectively. Network efficiency is defined as the proportion of accomplished services in accepted services. From the figure, we note that the dynamics of network performance follows the dynamics of network efficiency. From Experiment A, we observe that the proportion of accepted services is always stabilized around 0.45 during the evolution. It can be concluded that the improvement of network performance is due to the increase in network efficiency. The network cannot accomplish most of the accepted services at the beginning. However, the network can accomplish almost 90 percent of the accepted services after 20,000 steps of evolution. That is, the network becomes more and more efficient.

7.3. *The dynamics of agent profiles*

Figure 4 presents the dynamics of agent profiles in Experiment A. Figure 4(a) displays the dynamics of the average cumulative utility and maximum cumulative utility. From the figure, we can see that the average cumulative utility of agents decreases rapidly in the initial 10,000 steps, then it becomes stabilized and increases slightly. The maximum cumulative utility keeps on increasing during the evolution, arriving at 12 after step 50,000.

The reason why the average cumulative utility of agents decreases at the initial stage is that the utility earned from the accomplished services is not sufficient



(a) Changes in network performance and the average number of partners for each agent.

(b) Changes in network performance and network efficiency.

Fig. 3. The dynamics of network performance in Experiment A.

for consumption on the partnership degree in establishing new partnerships. After 10,000 steps, the speed of increase in the number of partners slows down, and the improvement of network performance yields enough utility. Thus, the average cumulative utility of agents becomes stabilized.

Figure 4(b) shows the dynamics of average partnership degree and maximum partnership degree, respectively. The average partnership degree decreases drastically similar to that of the average cumulative utility. The maximum partnership degree increases first and then fluctuates around 1.7.

7.4. *The dynamics of service searching depth*

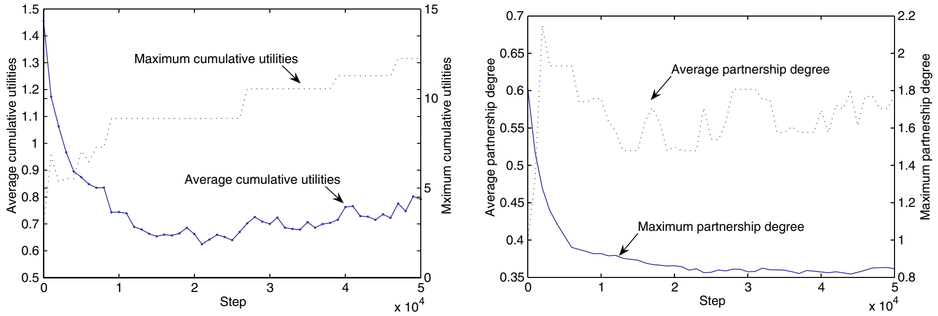
Here service searching depth is defined as the number of partners that have been searched before a service is finally accomplished, whereas service working depth is defined as the number of partners that are involved in accomplishing a service.

Figure 5 shows the average service working depth and average service searching depth of accomplished services for every 5000 steps.

As shown in Fig. 5(a), along with the evolution, the average service working depth increases slightly from 3.9 to 4.05, which means the network improves the degree of cooperation to increase network performance. However, service working depth decreases after step 30,000, which means the agents are not willing to consume more utility on cooperation. From Fig. 5(b), service searching depth increases from 10 to 16 during the evolution. The network is able to find more suitable agents to finish services. It is also the reason why network performance is improved.

7.5. *A snapshot*

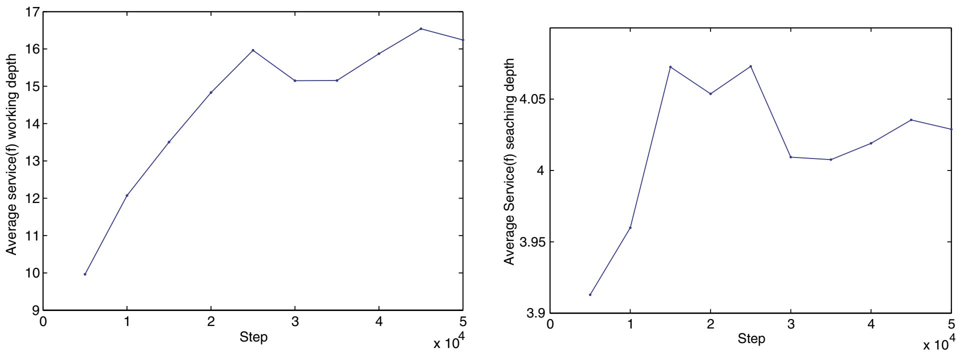
In this section, we will take a look at a snapshot at step 50,000 in Experiment A. Figure 6 shows the distribution of the number of partners at step 0 and step 50,000, respectively in Experiment A. It can be observed that the structure of the agent network has a heavy-tail distribution after many service-based interactions



(a) The dynamics of the average and maximum cumulative utilities.

(b) The dynamics of the average and maximum partnership degrees.

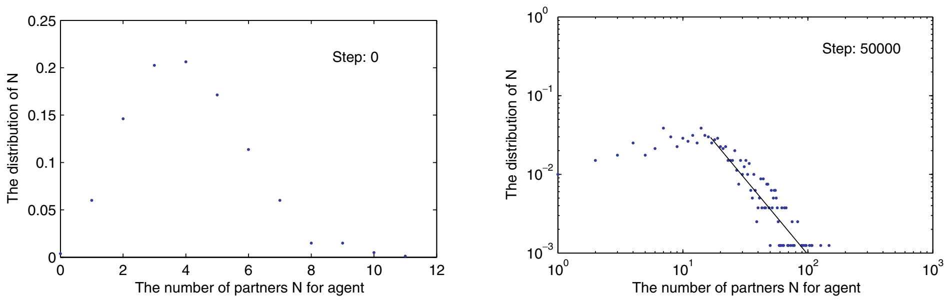
Fig. 4. The dynamics of agent profiles in Experiment A.



(a) The dynamics of service working depth.

(b) The dynamics of service searching depth.

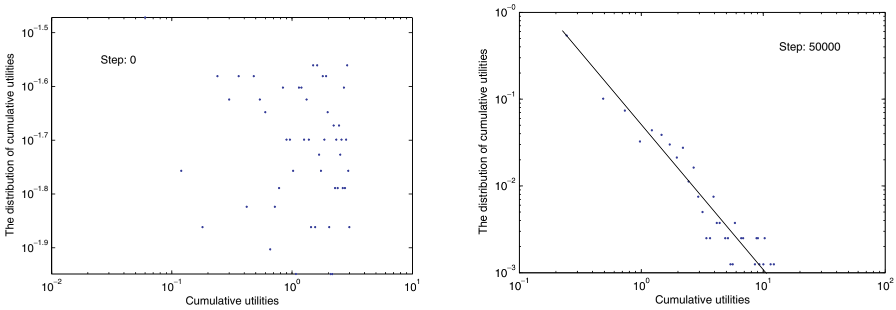
Fig. 5. The dynamics of service depth in Experiment A.



(a) The distribution of the number of partners at step 0.

(b) The distribution of the number of partners at step 50,000.

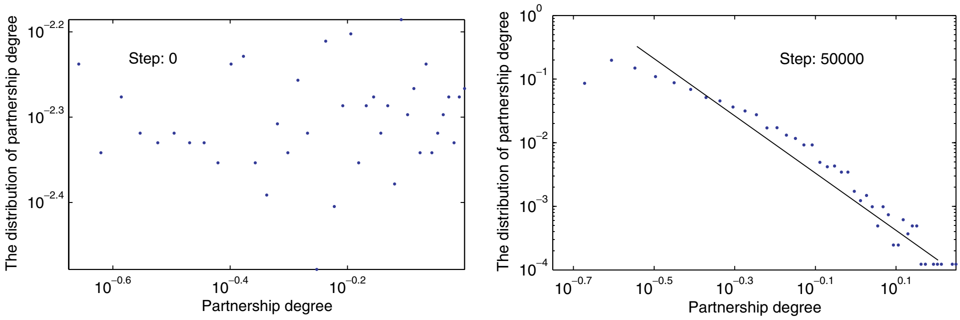
Fig. 6. The distribution of the number of partners for each agent in Experiment A.



(a) The distribution of cumulative utility at step 0.

(b) The distribution of cumulative utility at step 50,000.

Fig. 7. The distribution of cumulative utility in Experiment A.



(a) The distribution of partnership degree at step 0.

(b) The distribution of partnership degree at step 50,000.

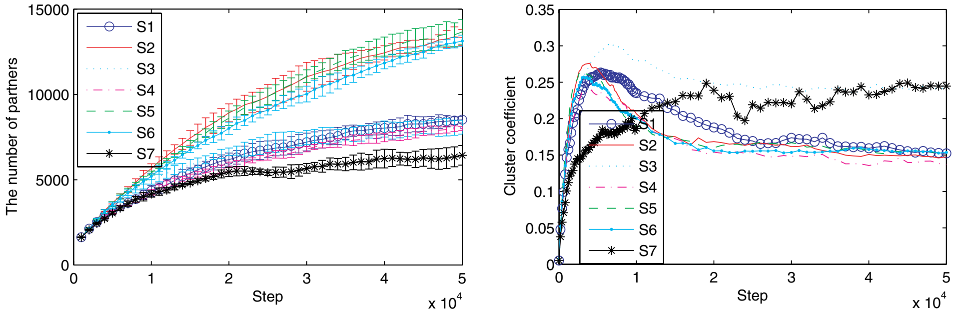
Fig. 8. The distribution of partnership degree in Experiment A.

(step 50,000), which is completely different from the distribution in the initial stage (step 0).

Figure 7 provides the distribution of cumulative utility at step 0 and step 50,000, respectively. The result indicates that the distribution of the agent cumulative utility follows a power law after a long period of evolution. Figure 8 gives the distribution of partnership degree at step 0 and step 50,000, respectively. The result also indicates that the distribution of partnership degree follows a power law from a random state after a long period of evolution. The result shows the emergences from the service-based interactions, the cumulative utility of the network congregates on a few agents, so does the partnership degree, which is also consistent with that of real social networks.

8. Global Network Dynamics with Respect to Local Interaction Strategies

In a social network, the local interaction strategy that an agent adopts is important, as it can directly affect the network formation as well as network performance.



(a) The number of partners with respect to selection strategies.

(b) The clustering coefficient with respect to selection strategies.

Fig. 9. The dynamics of network topology with respect to local interaction strategies.

In Experiment A, an agent selects cooperative partners according to selection strategy S1. In order to observe the effects of local interaction strategies, we have implemented Experiment B that applies selection strategies from S1 to S7. In Experiment B, the parameters are all the same as those in Experiment A, except for the local interaction strategies (selection strategies). Experiments on each selection strategy are conducted five times.

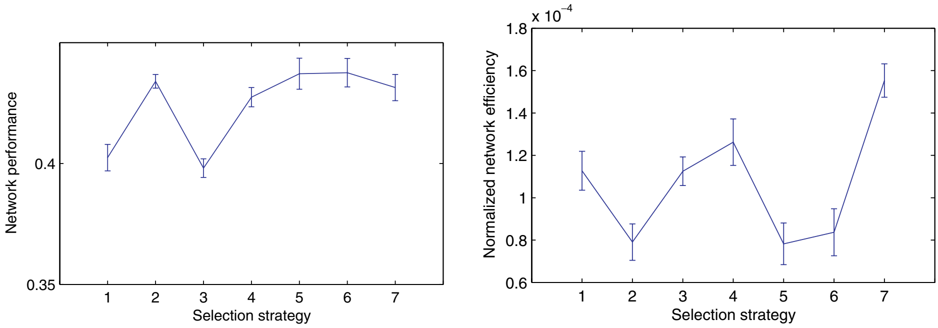
8.1. *Network topology*

Figure 9(a) presents the dynamics of the total number of partners in the networks with respect to selection strategies. The horizontal axis corresponds to selection strategies, whereas the vertical axis corresponds to the average value and the standard deviation of the number of partners under different selection strategies.

From the figure, it is clear that the dynamics of the number of partners falls into three categories. The first is that of the agent networks with selection strategies S2, S5, and S6, which have more partners during the evolution. The second is that of the agent networks with selection strategies S1, S3, and S4, which have fewer partners. The last is that of the network with selection strategy S7, which has the fewest partners. However, the network with selection strategy S7 still has a high performance. This indicates that selecting partners according to the number of partners is an efficient strategy because the network can accomplish more services with a relatively small number of partners. The result also indicates the effects of the local interaction strategies on the network topology.

Figure 9(b) displays the dynamics of clustering coefficient, γ, with respect to selection strategies. The horizontal axis corresponds to selection strategies, whereas the vertical axis corresponds to the clustering coefficient, γ, of the agent networks.

From the figure, there are over-shoot phenomena in the dynamics of γ from S1 to S6. However, the dynamics of γ in S7 is just like the dynamics of network



(a) Network performance with respect to selection strategies.

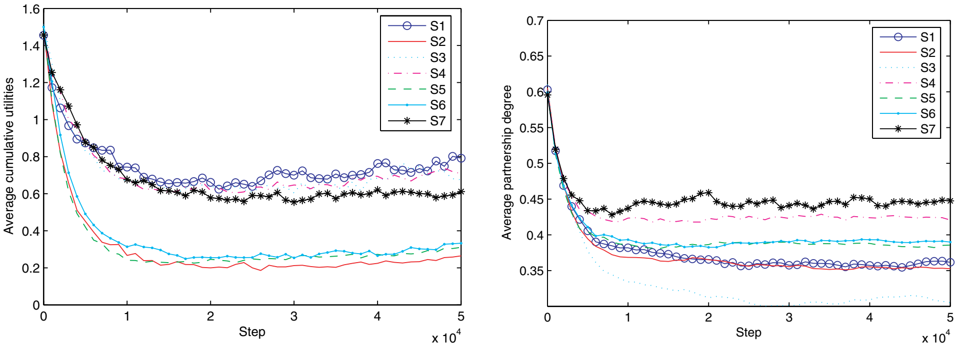
(b) Normalized network efficiency with respect to selection strategies.

Fig. 10. The dynamics of network performance and network efficiency with respect to local interaction strategies.

performance. The final clustering coefficients in networks with S3 and S7 are close, while the other five networks have lower clustering coefficients. That is, selecting cooperative partners according to the partnership degree or connection degree leads to a higher clustering network. The result clearly indicates the dynamic relationships between the topology of an agent network and the underlying local interaction strategies.

8.2. *Network performance*

Now let us compare network performance according to selection strategies. Figure 10(a) displays the average value and the standard deviation of network performance for five times with respect to different selection strategies. The vertical axis corresponds to network performance, whereas the horizontal axis corresponds to selection strategies that are defined in Sec. 5. In the figure, network performance is calculated from step 30,000 to step 50,000, so that the influence of the initial stage can be eliminated (note that network performance becomes relatively stable after steps 30,000). From the figure, we can see that the agent networks with selection strategies S2, S5, and S6 have better performances, while the networks with selection strategies S1, S3, and S4 have a lower performance. From Sec. 5, we note that selecting cooperative partners according to the cumulative utility of the partners is most reliable to achieve a better performance. However, selecting cooperative partners according to the partnership degree is not reliable. It can also be observed that selecting cooperative partners according to the number of partners can achieve a relatively high performance (selection strategy S7). This discovery has practical meanings: when an individual selects cooperative partners, it should select the partners that have a high utility earned in the past activities, while the partners that cooperate well in the past activities may not provide a satisfying cooperation.



(a) The average cumulative utility with respect to selection strategies.

(b) The average partnership degree with respect to selection strategies.

Fig. 11. Agent profile with respect to local interaction strategies.

Figure 10(b) provides the normalized network efficiency in Experiment B. The horizontal axis corresponds to selection strategies, whereas the vertical axis corresponds to the normalized network efficiency, which is defined as network efficiency divided by the number of partners from step 20,000 to step 50,000. From the figure, we can see that the network selection strategy 7 has the highest normalized efficiency, which means that the network can accomplish more accepted services with fewer partners. The network with selection strategies S2, S5, and S6 have a lower normalized efficiency, which is also different from the result of network performance.

8.3. *Agent profile update*

Figure 11(a) presents the dynamics of the average cumulative utility in Experiment B. From the figure, it is concluded that in all experiments, the average cumulative utility of the agents decreases rapidly in the initial stage, then it becomes stabilized at a low level. However, the curves are classified into three groups, according to the stable average cumulative utilities. The stable average cumulative utilities of networks with selection strategies S1, S3, and S4 are about 0.8, while those of networks with selection strategies S2, S5, and S6 are about 0.3. This result is consistent with the dynamics of the clustering coefficients under different selection strategies. It can also be concluded that an agent in the network with a higher performance is prone to get a lower cumulative utility.

Figure 11(b) gives the dynamics of average partnership degree in Experiment B. The result clearly indicates that the network with selection strategy S3, i.e. selecting a partner with the highest partnership degree, has the lowest average partnership degree. However, the network with selection strategy S7 has the highest average partnership degree and cumulative utility, which also reflects that selection strategy S7 is the best strategy that can benefit agent profile, network performance, as well as network efficiency, simultaneously.

9. Concluding Remarks

In the paper, we have presented an AOC-based model of social networks and conducted some in-depth studies on an illustrative example.

In the AOC-based model, agents are autonomous. They aim to accomplish services, which are either requested by their partners or generated from outside of an agent network, and find other partners to cooperatively accomplish the services. The service-based interactions among the agents lead to the dynamics of network formation and network performance. In the model, agent abilities and services are represented using sets of tasks and constraints, which are environment and application dependent. Other parameters are also defined to characterize various intrinsic or dynamic characteristics of the agents. With the model, we can observe and analyze the dynamics of network topology, network performance, and agents profiles.

We have demonstrated an example, in which agent abilities are defined in terms of the quality and cost in accomplishing a service. The agents determine their behaviors also according to the quality and cost of requested services. After a long period of interactions, the network forms a topological structure with a high clustering coefficient and a scale-free connectivity, and network performance is dynamically changing over time and with respect to local interaction strategies used. The relationships among network performance, network topology, agent profiles, and local interaction strategies have been experimentally examined. The result indicates that selecting cooperative partners with a high cumulative utility is efficient in an AOC-based service network. The overshoot phenomena in the dynamics of clustering coefficient are explained. We have also observed other interesting emergent behaviors in the networks.

The AOC-based model can be utilized to study various dynamics in different applications. The only thing that one needs to do is to formulate or acquire the constraints of services and agent abilities, and thereafter, the relationships among network topology and network performance can be discovered. With such a model, the activities happening in dynamic social networks can also be studied and analyzed.

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Shiwu Zhang received the B.S. degree in mechanical and electrical engineering from University of Science and Technology of China (USTC), and the Ph.D. in precision instrumentation and precision machinery from USTC, Hefei, China. He is currently a Lecturer in the Department of Precision Machinery and Precision Instrumentation, USTC. He has been a Post-Doctoral Research Fellow in the Department of Computer Science, Hong Kong Baptist University for a year.

His current research interests include web intelligence (WI), intelligent robots, and autonomy-oriented computing (AOC).

Jiming Liu is presently a Professor and the Head of Computer Science Department at Hong Kong Baptist University. He served as a Professor with tenure and the Director of the School of Computer Science at University of Windsor, Ontario, Canada in 2006–2007. Prof. Liu holds a B.Sc. in Physics from East China Normal University, an M.A. in educational technology from Concordia University, and an M.Eng. and a Ph.D. both in electrical engineering from McGill University. Prof. Liu has published over 200 research articles in refereed international journals and conferences and a number of books including authored research monographs, e.g. *Autonomy Oriented Computing: From Problem Solving to Complex Systems Modeling* (Kluwer Academic/Springer), *Spatial Reasoning and Planning: Geometry, Mechanism, and Motion* (Springer), *Multi-Agent Robotic Systems* (CRC Press), and *Autonomous Agents and Multi-Agent Systems: Explorations in Learning, Self-Organization and Adaptive Computation* (World Scientific). He has served as the editor-in-chief of *Web Intelligence and Agent Systems* (IOS Press), *Annual Review of Intelligent Informatics* (World Scientific), and *The IEEE Intelligent Informatics Bulletin* (IEEE Computer Society TCII) (2002–2006). He is an associate editor of *IEEE Transactions on Data and Knowledge Engineering* (IEEE Computer Society) as well as an editor for seven other international journals and book series.

Prof. Liu's present research interests include autonomy-oriented computing (AOC), self-organization, complex systems modeling, multi-agent systems, social networks, and web intelligence (WI).