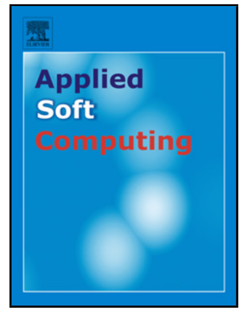

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Manufacturing Service Composition Model Based on Synergy Effect : A Social Network Analysis Approach

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Highlights

- The paper focuses on the social collaboration feature of manufacturing services, and we try to illustrate how social traits have impacts on the competitiveness of service in service social network (SSN). We believe it is important to consider collaboration capacity as a critical competitive factor in service composition when large number of online services orchestrated together. This paper attempt to integrate social network, service computing and synergy theory to address the new problem of service selection in SSN, and proposed a novel manufacturing service composition method based on weighted synergy network, where synergy effect is measured from the perspective of social relationships strength. The major contributions of the paper are:

- Define and extract five types of social relationships that have impacts on service performance in SSN, and develop calculation methods to measure each relationship strength.
- A service synergy effect model is proposed through the weighted aggregation of five types of social relationships strength, where the weight distribution of each relation factor is obtained by using information entropy and rough set.
- (3) Develop a new service selection optimization model based on synergy effect for building task driven dynamic alliance, and use a simulation experiment of service selection in intelligent automobile cloud manufacturing to verify its validity and advantages.

Abstract: Service social network is an umbrella term used to describe several interaction and collaboration phenomena that are shaping the future of how services are provided on the cloud manufacturing platform. Social relationship plays an important role when services are orchestrated with each other to build manufacturing business process, a role which has not been adequately investigated in previous research. The existing manufacturing service composition methods consider functional qualifications and Quality of Service (QoS) as major competitiveness factors. It is difficult to adopt them to situations where synergy effect is required and social relationships have significant impact on ensuring effective resources, information and knowledge hand-off in the complex task process. Focusing on the social collaboration feature of manufacturing services, a service composition method based on synergy effect is proposed. According to the data of service interaction and cooperation on the cloud platform, we extract and describe service social network and five kinds of relationships, namely interactive transaction, co-community, physical distance, resource-related, social similarity relationship. Based on the calculation of these relationships strength, the service synergy network is derived through the weighted aggregation. A service selection model that maximizes the overall synergy effect based on collaboration requirement is presented. The validity and advantages of our model and algorithm is validated through simulation experiment of intelligent automobile cloud manufacturing. The results show that our approach is not only efficient, but also finds better service scheme in line with the actual manufacturing scenario.

Keywords: Service composition, Service social network, Social relationship, Synergy effect.

1. Introduction

In Internet era, customer requirements reveals new characteristics, such as diversification, personalization and complex products. For example smart connected products such as smart watch, wearable devices, air conditioning equipment connect to internet are composed of physical, smart, connectivity components (Porter and Heppelmann, 2014). Additionally, these products are generally provided as services which requires large scale collaboration among geographically distributed developers, support personal and infrastructure. Enterprises with limited resources and capacity cannot independently construct the complete manufacturing value chain and transform raw materials into end products (Azevedo et al., 2017). Thus, it is necessary to collaborate with others for complementary resources to build business process to seize these emerging market opportunities. As services become the predominant vehicle of resource provisioning in industries, the selection of the most suitable services and their composition to support business work-flow based on dynamic alliances becomes extremely important. A muti-subject, cross-organization and cross-region collaborative design and manufacturing process needs to be automatically composed and a dynamic task-driven temporary cooperation alliance needs to be created with online services.

Current research has explored various criteria and models for service composition in the context of

Service Oriented Architecture (SOA) (Jula et al. 2014). They primarily use functional characteristics and Quality of Service (QoS) attributes as service selection criteria (Zhang et al. 2016; Lu and Xu 2017). These approaches generally consider each service as independent which needs to complete the sub-task assigned to it satisfactorily. However, in cloud environment large number of services that provide same or similar functions and has similar QoS attributes may be available which makes service selection more difficult. Additionally, there exist some dependent relationship constraints among complex sequential sub-tasks, such as resource logistics, and information and knowledge delivery (Castro et al. 2013), which bring out the synergy requirements for better service performance. In practice, service groups corresponding to the complex task should consider collaboration factors, and must not only have the requisite qualifications and satisfied QoS, but also own high-level synergy effect in order to ensure resources, information effective hand-off and smooth flow of sub-tasks. Moreover, high level collaboration will reduce the time and cost of coordination and promote the manufacturing efficiency and reliability (Liu et al. 2016). Meanwhile, it may result in sharing more resources, information and knowledge with associated service units, which can improve the service's own QoS (Zhu et al. 2016). Non-collaboration phenomenon, such as different platforms, longer distance and few interactive transactions can increase logistics and communication time cost, resulting in loss of productivity. Service conflicts may even appear when they compete and occupy the same resources at the same time, and non-compatibility may lower service QoS, increase the connection disorder due to policy restrictions and interface mismatch (Huang et al. 2016), and bring out a significant negative impact on the tasks execution. The recent approaches for service selection ignores these collaboration and conflict factors, which may result in sub optimal operation process, even task interruption or failure. Hence, to effectively build a task based dynamic alliance, synergy effect should be measured in detail and considered as a key competitiveness factors in manufacturing service composition.

Synergy is the creation of a whole that is greater than the simple sum of its parts. The synergy effect, first proposed in the 1960s by Ansoff (Ansoff and Brandenburg 1967), can be formed through cooperation with enterprises with complementary resources, which can realize 1+1>2. Subsequently, it is widely used in various fields (Health, Chemistry and Human management). Many scholars have proposed the definition and calculation model of synergy effect for building strategic alliances, developing collaboration networks, and organizing co-development projects and cross-functional teams (Feng et al. 2010; Schall 2016). (Lopes and Almeida 2014) identified three kinds of synergies: project scope synergy, fiscal synergy and information synergy. (Schaeffer and Cruz-Reyes 2016) identified interests, technology and resource synergy in R&D project portfolio selection. (Kumar et al. 2013) put forward a compatibility model to capture the degree of collaboration between different workers. (Rusek et al. 2016) defined collaboration relation as compatibility of municipal services based on similarity. (Gutiérrez et al. 2016) regarded the collaboration efficiency as the number of positive social relationships among members. Although the above research does not provide detailed measurement of synergy effect, it helps to enlighten our study.

Wisdom manufacturing (Yao et al., 2015) can provide comprehensive one-stop services for different users on demands, by integrating muti-level, muti-granularity manufacturing resources on cloud platform. These services having new characteristics of adaption, collaboration and socialization, can interact online and transfer resources offline between each other (Golightly et al. 2016). They will automatically cooperate and build a variety of social relationships based on task and social factors, forming dynamic service social network (SSN) that evolve over time. Various types of social relationships such as Interactive transaction, Co-community, Physical distance, Resource-related and Social similarity, which will certainly improve task performance and reduce time, cost when service orchestrated together, can affect production efficiency and the satisfaction degree of members involved. Social relationships offer an good opportunities to advance our understanding of service collaboration in terms of resource, information and knowledge. The wide application of industry internet and social network has generated big data of service interaction as a basis for computing social relationship, and also provided the possibility for quantifying the service synergy capacity from the perspective of relationship strength in SSN. Then, synergy effect as the important part of service competitiveness and their impacts on service selection are discussed in this paper are essential but not adequately investigated in previous research.

In manufacturing service socialized environment, complex tasks require multiple service units with different functions collaborate and interact with each other to complete complex tasks. Services with similar functions compete to play its role in certain tasks. Performance of composed services depends not only on individual service capabilities but also on collaborative capability of services. When large number of online services orchestrated together, it is important to consider collaboration capacity as a critical competitive factor. This paper attempt to integrate social network, service computing and synergy theory to address the new problem of service selection in SSN, and proposed a manufacturing service composition method based on weighted synergy network, where synergy effect is measured from the perspective of social relationships strength. The major and original contributions of the paper are: (1) Define and extract five types of social relationships that have impacts on service performance in SSN, and develop calculation methods to measure each relationship strength. (2) A service synergy effect model is proposed through the weighted aggregation of five types of social relationships strength, where the weight distribution of each relation factor is obtained by using information entropy and rough set. (3) Develop a new service selection optimization model based on synergy effect for building task driven dynamic alliance, and use a simulation experiment of service selection in intelligent automobile cloud manufacturing to verify its validity and advantages. The proposed approach considering collaboration relationship factor can generate more efficient solutions and obtain the optimal service scheme in line with the actual situation.

The rest of the paper is organized as follows. Section 2 discuses related literature on service selection and social networks. Section 3 presents a socialized service selection framework, extracts service social network and defines five social relationships. Section 4 present the service synergy network model. Section 5 constructs the service composition model considering synergy effect and applies an improved GSA algorithm for solving the problem. Section 6 describes the simulation experiment and results. Finally, conclusions and direction for future work are presented in Section 7.

2. Related Literature

2.1 Manufacturing service selection

The primary focus of manufacturing service selection has been to select services that have the highest degree of match with the functional requirements of the task through use of a syntactic or semantic search algorithm (Le and Quintanilla et al. 2016; Tao et al. 2017). A number of local optimal (Xu. 2015) and global optimal (Liu and Zhang 2016;Chen et al. 2015) models based on QoS for service selection have been proposed. Some researchers also considered transaction features (Wu and Zhu 2013), trust and other non-functional attributes of the service (Cao et al. 2015). They used QoS and trust in multi-attribute decision models and artificial intelligence and goal programming techniques to solve the optimization problem (Mehdi et al. 2015, Cremene et al. 2015). Current research regards each service as an independent and isolated entity having no interactions with other services or consumers and considers QoS as a fixed value, ignoring the impact of service correlation on QoS. (Jin et al. 2015) proposed three types of relationships between component services: composable, business entity and statistical relationships to develop a service-correlation-aware QoS model. Semantic relationships between services which are relatively easier to extract has been the focus for discovering and composing services (Guo. 2011).

Although the above research began to consider the correlation among component services, it is still limited to the semantic description and its influence on QoS, ignoring the social behavior characteristics of services, especially social relationships and their collaboration factors.

In recent years, social network theory has made significant progress and attracted the attention of many researchers. Social network methods are naturally infiltrated to service science because of the social nature of business services. (Benatallah et al. 2003) defined the service community as a collection of Web services with common functionality and distinct non-functional properties. (Yahyaoui et al. 2013) emphasized that Web services should not be treated as isolated components, since similar Web services compete against each other and different Web services collaborate with each other during composition and may replace other services when failure occurs. Understanding and capturing the way services collaborate, the factors which influence and enhance co-work in the future via SSN, and various types of social relationships between services is needed. Business entity relationships and compatible and conflict relationships were further studied (Tao et al. 2012). (Atzori et al. 2014) developed SIoT system architecture by integrating social network and IoT services together, and studied various relationship types (parental, co-location, co-work, ownership, social object relationship). However, their analysis was limited to IoT services in limited geographic situations and did not include business-level services. (Chen et al. 2013; Chen et al. 2015) constructed the global social service network (SSN) and provided generic quality criteria for social links which included dependency satisfaction rate, QoS preference, sociability preference and preferential service connectivity to improve the quality of service management. Although researchers focus on a service's sociability for improving the quality of service discovery, a model for supporting a service's social synergy is still not available. Most social relationships mentioned above are built based on only network theory and have no business-level meanings in the manufacturing process. Thus, a service's social behavior and its ability to enhance service collaboration has not been investigated in depth.

2.2 Manufacturing service social relationship

Service ecosystems based on cloud manufacturing are evolving by combining off-line resources and on-line services in a way that has enterprise-wide and societal dimensions. Major vendors of services are constructing social service ecosystems and are using social network platforms such as Facebook, Twitter and Flick to advertise and offer their resources and services (Hashmi et al. 2016). Services show high sociability and autonomously carry out social behaviors such as setting up several kinds of relationships, communicating with other services. A service's sociability is the intent to or actual action of interacting well with other nodes (Atzori et al. 2012). A SSN is constructed to mirror services' social reality, depicting a mutual belief and willingness to support the services' future social collaboration. Various types of relationships which have clear business meanings such as contact, friendship, follower, co-community and common interest can improve synergy effect and performance in social networks (Huang et al. 2014; Ha et al. 2015). Service nodes can take part in different communities and provide its resources and capacities to others (Manupati et al. 2015). The social capital of services will increase with the number of communities they participate in, leading to a higher probability of acquiring more network resources and further collaboration chances. This co-community relationship also enhances the service platform synergy effect, which has been widely studied in the E-commerce domain (Lim et al. 2015). In addition, a location factor has been found to impact the strength of social relationships among mobile nodes in the Internet of Things (An et al. 2013). Far distance can increase move time and cost, hinder service interaction. However, all relationships are used to analyze the network structure and trust management. How and which social relationships influence the service collaboration and enhance synergy benefit has not been investigated.

Moreover, service relationship also exists in a physical environment and has been a focus of attention in supply chain studies. Superior collaborative productivity originates from the creation and sharing of valuable resources that are complementary, rare, hard to imitate, and irreplaceable (Lillis et al. 2015). A resource related relationship can provide economies of scale and scope. Alliances enable sharing of complementary resources (Beesabathina et al. 2015) and combining of heterogeneous resources leads to a surplus over the value that each ally could create independently. Companies tend to build service chains with compatible resources that they can leverage and integrate to create a synergy surplus (Adegbesan 2009). Physical distance that produce more obstacles and increased cost is an important relationhip factor in enterprise communities (O'Leary and Cummings 2007). (Handley and Benton 2013) recognized location-specific factors: geographic distance, geographic dispersion and cultural distance, which generate high levels of information load, complexity and uncertainty. Geographically distant services suffer from lower familiarity and larger delays, with higher logistic and transportation costs (Aguezzoul 2014). Moreover, Identity-based attachment and Bond-based theory can to some extent explain why the strong to strong collaboration phenomenon always appears in different domains, and why entities prefer to form a common group with similar entities (Fiedler and Sarstedt 2014). (Connelly et al. 2013) asserted that the greater the similarity between firms, the greater the chances that they will establish collaboration based on the homogeneous behavior theory. Service similarity can enhance inter-alliance joint learning, trust and interaction, and is considered a primary factor to improve the success rate and collaboration efficiency (Meo et al. 2011). In addition, services can set up sporadic or continuous transaction relationships autonomously during their operation. Past transaction experience, long-term orientation and interdependence can produce trust-based synergies and reduce opportunism (Kumar et al. 2014). Learning the service's past social interactions, usage patterns or service habits will help discover and build alliances with enterprises with which they had a prior transaction history and collaboration relationship (Ahuja and Zaheer 2012). Furthermore, from a muti-relational perspective, resource sharing and complementary, transaction experience, distance, trait similarities are key factors contributing to the synergy effect (Touboulic et al. 2015). These research studies indicate that different social relationships can capture the way services collaborate for common benefit and can serve as an important additional basis for service evaluation and selection. However, these factors could not be analyzed and quantified precisely in the offline environment. The relationship factors described above haven't been classified clearly, nor have they been integrated with online social relationships to measure the synergy level.

Scrutinizing how connected services are related to each other in the online environment, researchers have identified various social relationships among entities. They found heterogeneous nature of these links, and developed nonlinear models to study the relationship synergy effect (Choi and Yeniyurt 2015). A service may exhibit multifaceted behavior and possess different positions, when one specific types of relationships provide less valuable information. One relationship serving as catalyst or constraint may affect other relationships among services. Most relationship data cannot be sensed and computed accurately in real time, leading to poor service network to enable effective service composition. (Maamar et al. 2011) identified a social relationship based framework of interconnected nodes of people, devices, and services, however, the muti-relational perspective that exists among services is seldom studied.

From a service collaboration perspective, synergy effect is measured by two elements: compatibility and resource sharing. Service in the same community will reduce interaction cost and time, improving collaboration QoS. Using the IoT and big data technologies in these domains, service relationships derived from both online and physical environments can be integrated to achieve synergy. Based on the deductive analysis, five types of significant relationships that are more valuable to reinforce synergy effect, have been identified and abstracted, namely interactive transaction, co-community, physical distance, resource-related and social similarity relationship. Despite this, service social network is still at an exploratory stage. Related issues such as how to define and extract service social relationships, classification and calculation of social relationships and aggregation rules for synergy effects have not been addressed. A muti-dimensional service synergy network should be constructed to emphasize how service collaboration through social relationships affects dynamic service performance.

3. Manufacturing service selection based on social relationship analysis

With online services becoming more intelligent, socialized and personalized, the convergence of social networks and Internet of Services (IoS) will be of great significance to promote service cloud applications in manufacturing industries. Social relationships between services must be considered as an important factor for the development of long-term synergy effects. Service selection needs to focus on collaboration factors that were previously neglected in complex task context. In this section, we first extract service social network and five types of social relationships which have a positive influence on service synergy. Then, a social service selection process based on weighted synergy network is presented.

3.1 Service social network

Based on the service interaction behavior sensed by IoT, five types of relationships such as interactive transaction, co-community, physical distance, resource related and social similarity relationships are extracted and defined. Representing services as nodes and social relationships as edges, service social network can be formed and represented as an indirect network graph $G_{SN} = (V, A, E, \xi)$ as shown in Fig.1. $V = (v_1, v_2, \cdots, v_n)$ represents set of service nodes, A is QoS set of service nodes, $E = (E_1, E_2, \cdots, E_m)$ is the set of edges i.e., social relationships, $\xi = (\xi_1, \xi_2, \cdots, \xi_m)$ represents the edges strength. The diverse social relationships and network structure described above can be identified and visualized by deeply mining the large-scale data from the cloud platform. To further understand the meaning and functions of these relationships, we analyze the original sources of these relationship definitions as follows:

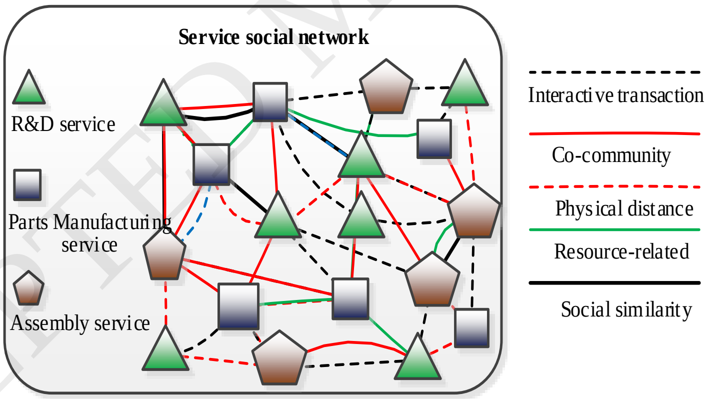


Figure 1. Service social network

Interactive transaction relationship (*SR_{IT}*) describes the collaboration history that two services have part in common complex tasks. If services *i* and *j* both participate in the same task T_k, i.e., usually *i* and $j \rightarrow T_k$, there exist a $SR_{IT}(i,j)$. (Guo et al. 2010) proposed statistical cooperate correlation referring to the relationship that two or more services are often banded to execute a task. (Chen et al. 2013) put forward sociability preference degree to define and compute the cooperation relation in the same work-flow. SR_{IT} is used to reveal service habits that show with whom the service has collaborated previously and with whom it prefers to work in the future. Since the amount of interactive transaction varies in different periods, we assume the transactions in the recent period have larger impacts. Hence, the total transaction volume in all periods and current collaboration activity are used to quantify the relationship strength.

Co-community relationship (SR_{COC}) is constructed when services come into contact and interact with each other in the same community. If services i and j belong to the same platform k, i.e., usually i and $j \in$ platform k, then $SR_{COC}(i,j)$ represent a co-community relationship. (Mezni H et al. 2017) emphasized the importance of co-platform relation to lower communication cost in muti-cloud environment. Services in the common platform will have stronger mutual trust, lower interaction and coordination cost. Larger the number of co-communities in which both service providers participate closer their connections will be and the higher the service synergy level. Hence, the proportion of the co-community in all the communities the service participated in is used to evaluate the relationship strength.

Physical distance relationship (SR_{Dis}) describes the distance factors and service location associated with delays, logistic cost and transportation time, and plays a role in determining the willingness of firms to engage in service alliance (Aguezzoul. 2014). $L(i)$ and $L(j)$ represents the location of service i and j, there exist $SR_{Dis}(L(i),L(j))$. When $L(i)=L(j)$, it means a co-location relationship. (An et al. 2013) gave the definition and calculation of distance factor through the similarity function of position information. Distance is a complex concept containing geographical, cultural and social elements. However, its concrete value may have no meaningful in business level, it is possible to map different distance intervals to travel time which will simplify the calculation and meet the requirement of manufacturing context.

Resource-related relationship (SR_{RR}) reflects the level of resource sharing and resource complementarity among different service units or providers. If services i and j both use the same resource R_k, i.e., usually i and $j \star R_k$, and the resource R_s is owned by i and R_t is owned by j are complementary, there exist $SR_{RR}(i,j)$. (Freitag et al. 2015) considered that the surplus depends on the level of the sharing and complementarity between both services' resources. (Lopes and Almeida. 2015) considered positive and negative resource synergy as the crucial factors in many portfolio situations. Each service shares several types of resource and different volumes per type. Hence, the sharing amount is based on resource volume per type multiplied by type number. The complementarity level equal to the number of different resources owned and is used to measure the relationship.

Social similarity relationship (SR_{Sim}) describes the similarity level of service nodes in individual profile, social attributes and operation environments. Social similarity can enhance mutual trust and promote service longtime collaboration (Chung S et al. 2015). (Rusek R et al. 2016) proposed that service similarity can be calculated by the distance between values of their attributes such as affiliation, delivery, nature, presence, scope and stakeholder. (Pan Y et al. 2017) constructed a new multidimensional service similarity model by aggregating collaborative, preference and trajectory similarity in online to offline (O2O) service context. In SSN, $SR_{Sim}(i,j)$ depends on the service's popularity, ownership, reputation and co-partners. Hence, a similarity model aggregating four attributes can be built to analyze the relationship strength.

3.2. The service selection based on synergy network

Due to the constraints of task relationships, collaboration factor should be considered in service composition process. Based on the above ideas, this paper proposes a manufacturing service selection process based on synergy network, as shown in Fig. 2. We illustrate the process using a fictitious example of automobile manufacturing. The manufacturing task has been decomposed into 3 sub-tasks (R&D T_1, Parts Manufacturing T_2 and vehicle assembly T_3). We need to select one service for each sub-task and make sure these services have the best synergy effect. The selection process consists of the following steps:

Step1: Automatically perceive real-time user requirements. Select candidate services using existing methods, and obtain candidate service sets (CS_1, CS_2, CS_3) for each task. (S_{11}, S_{12}) for task T_1, $(S_{21},S_{22},S_{23},S_{24})$ for task T_2, (S_{31},S_{32},S_{33}) for task T_3.

Step2: Calculate five service social relationships based on social network analysis, and compute synergy effect and create service weighted synergy network *WSN*, according to the task constraints.

Step3: Based on the *WSN* created in Step2, evaluate the synergy effect of service composition. Then, select the optimal combination of service instances that results in the highest synergy effect.

Step4: Execute and monitor in real-time using the system platform which allows users to evaluate service performance and provide feedback.

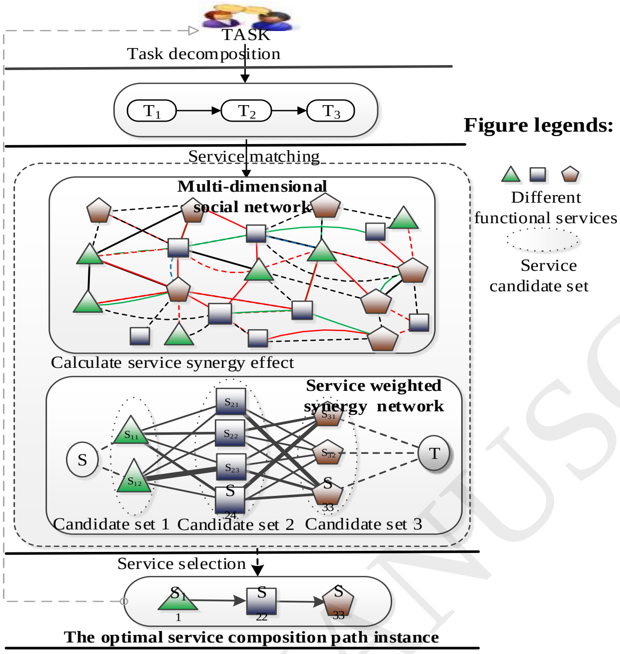


Figure 2. Social service selection process based on synergy network

4. Social synergy network model

Service synergy quality is a task-level interaction and social relationship effectiveness construct, which is defined as the extent to which the services collaboratively exploit shared capacity while minimizing cost and time through cooperation during the task process. The service synergy effect depends on social relationships between services and can be aggregated from the five relationship factors (*RFs*) described above. Computing the synergy effects to create WSN is the key task of the social service selection process described above. There is a need for an efficient and effective way of measuring the synergy effect. The process of calculating and creation of *WSN* consists of the following three steps:

(1) *Calculate the relationship strength of each relationship factor (RF)*: Based on the characteristics of each relationship, the strength of each relationship factor (*RF*) is computed as described in Section 4.1.

(2) *Aggregate RF relationship strength:* Using the rough sets and information entropy method, we assign a weight to each *RF*. Based on the weights assigned to the relationship strength, synergy effect between service pairs is computed. Section 4.2 describes the aggregation method.

(3) *Create service weighted synergy network*: Connect all service nodes that have a strong synergy effect. We only consider direct synergy relationships when creating a weighted synergy network in Section 4.2.

4.1 Calculating the social relationship strength

Each relationship strength is computed using service characteristics and their interaction.

4.1.1 Interactive transaction relationship

In a SSN, service collaboration can happen in different time periods. The collaboration time CT_i and transaction amount TA_i may vary across unit period UP_i. Hence, interactive transaction strength $QS_{IT}(i, j)$ depends on the total transaction amount *TA* across all periods and collaboration activities CA in the most recent period. $QS_{IT}(i, j)$ can be computed as:

$$QS_{IT}(i,j) = w_1 TA + w_2 CA = w_1 \frac{\sum_{k=1}^{m} CT_{i,j}^{UP_k} \times M_{i,j}^{UP_k}}{\sum_{k=1}^{m} CT_{R,T}^{UP_k} \times M_{R,T}^{UP_k}} + w_2 \frac{CT_{i,j}^{UP_{now}}}{\sum_{k=1}^{m} CT_{i,j}^{UP_k}} \quad (1)$$

Where $CT_{i,j}^{UP_k}$ and $M_{i,j}^{UP_k}$ denote the collaboration time and transaction amount in *k*th period. $CT_{i,j}^{UP_{now}}$ is collaboration time between *i* and *j* in the most recent period.

4.1.2 Co-community relationship

Communities include various cloud platforms, alliances and online groups. Co-community relationship strength $QS_{COC}(i, j)$ depends on number of co-community in which both services participates. Given a service *i* and *j*, $QS_{COC}(i, j)$ can be calculated as follows:

$$QS_{COC}(i,j) = \frac{NR(i,j)}{NR_{All}} \quad (2)$$

Where NR_{All} is the total number of communities in which both services participate. $NR(i,j)$ denote the number of co-communities that are common between service *i* and *j*.

4.1.3 Distance relationship

The geographical distance $D(i, j)$ can be calculated from geographic maps and other factors. Considering the impact of distance on the production plane and task process, we transform $D(i, j)$ into four types of travel time to better represent the distance relationship. Based on the service rules and transportation model used by logistics companies, we define 4 levels of travel time (*AT*), AT_1 *on demand* (one week), AT_2 *short-term* (one month), AT_3 *medium-term* (two to six months) and AT_4 *strategic long-term* (more than six month). If the travel time between services *i* and *j* is $AT_k \in (AT_1, AT_2, AT_3, AT_4)$, the distance relationship strength $QS_{Dis}(i, j)$ can be mapped to a discrete value corresponding to AT_k. Hence, given a service *i* and *j*, $QS_{Dis}(i, j)$ can be computed based on the rules defined by domain experts as follows:

$$QS_{Dis}(i,j) = \begin{cases} 1, AT(i,j) = AT_1 \\ 0.6, AT(i,j) = AT_2 \\ 0.3, AT(i,j) = AT_3 \\ 0, AT(i,j) = AT_4 \end{cases} \quad (3)$$

Where $AT(i, j)$ is the travel time between service *i* and *j*, *1, 0.6, 0.3, 0* are the values of $QS_{Dis}(i, j)$ normally distributed between [0,1]. Higher $QS_{Dis}(i, j)$ denotes a better distance-based synergy effect based on shorter travel time and lower cost.

4.1.4 Resource-related relationship

Resource-related relationship strength dependents on the level of resource sharing (*RS*) and resource complementarity (*RC*). The type and amount of resource sharing determines the *RS* level. The *RC* is computed based on the focal firm's SIC code and that of its partners. Hence, $QS_{RR}(i, j)$ measuring the resource-related relationship strength can be modeled as follows:

$$QS_{RR}(i,j) = w_1 RS_{i,j} + w_2 RC_{i,j} \quad (4)$$

$$RS_{ij} = \frac{tp(i,j) \cdot am(i,j)}{\max\{tp(i,j) \cdot am(i,j)\}}, RC_{ij} = \frac{N_d(i,j)}{\max\{N_a(i,j)\}} \quad (5)$$

$tp(i,j)$ and $am(i,j)$ denote type and amount of resource shared per type, there are several types of manufacturing resource, such as machine, material, human, knowledge resources and so on. $N_{different}(i,j)$ represents the number of different resource types. $N_{all}(i,j)$ is the number of all resource types in *i* and *j*. w denotes the weight assigned to $RS_{i,j}$ and $RC_{i,j}$.

4.1.5 Social similarity relationship

Similarity relationship strength $QS_{Sim}(i,j)$ can be measured by the similarity level between service *i* and *j*, based on four social attributes (service popularity *SP*, ownership *O*, reputation *R* and the number of common partners *CP)*. Hence, service *i, j* can be characterized by multi-dimension vectors (SP_i,O_i,R_i,CP_i) and (SP_j,O_j,R_j,CP_j). Comparing the distance of service profile, $QS_{Sim}(i,j)$ can be computed as follows:

$$QS_{Sim}(i,j) = SIM(i,j) = \frac{1}{1+d(i,j)} \tag{6}$$

Where $d(i,j)=\sqrt{\sum_{i=1}^{4}(a_i-a_j)^2}$ represents Euclidean Distance between service *i* and *j*, which has *4* attributes (SP_i,O_i,R_i,CP_i). Higher $QS_{Sim}(i,j)$ indicates a higher service synergy effect.

4.2 Aggregating *RF* relationship strength and creating WSN

Synergy effect is calculated by aggregating five types of social relationship. The value of social relationship has various forms(such as numerical, Boolean or real) and of different importance. Judging the overall synergy effect can be abstracted as a classification problem which can be solved by Rough Set Theory(RST). In this paper, we define the knowledge representation system of *RFs* in a unified framework with RST $Z=(U,A,V,f)$, where U is set of synergy effect of various service relations. $A=C\cup D$ denotes attributes set, C and D denote condition attribute(feasible relations between services nodes) and decision attribute set (synergy effect of selected service relations) respectively. V represents the value range of these attributes, $f:U\to V$ denotes the comprehensive map function. Thus, the synergy effect calculation is transformed to the classification of value range of synergy effect. The equivalence relation is the core of RST, it describes the similarity of different synergy effect in U. For any attribute set $\forall B\subset A$, equivalence relation can be denoted as $IND(B)=\{(x,y)\in U\times U:\forall a\in B(f(x,a)=f(y,a))\}$. Through attribute reduction, it can delete redundancy attribute and reserve only important attributes.

Through this process, the knowledge representation system is built in a unified framework, and the *RFs* weight problem is transformed to the importance degree of condition attributes in rough set. Based on the original data, the relation instances can be firstly divided into several classes by fuzzy clustering method. After deleting an attribute or *RFs,* we re-classify the instances and obtain the new classification. The decision table is formed as list (Table A) in Appendix1. The change degree of the classification computed by information entropy can represents the importance of the attribute deleted. Through normalization, the weight distribution can be conducted, and the correlation of *RFs* measured by mutual information is also considered. Then, synergy effect defined as QS(i,j), can be quantified by the linear weighting of social relationship strength. It explicitly provides a measure tool of collaboration level between service i and j for various social links. Hence，QS(i,j) is aggregated by the equation as follows：

$$QS(i,j) = w_1QS_{IT} + w_2QS_{COC} + w_3QS_{Dis} + w_4QS_{RR} + w_5QS_{Sim} \tag{7}$$

w_1, w_2, w_3, w_4, w_5 represents the weight of the five *RFs*. It is assumed that service node *i* and *j* have no synergy if *QS(i,j)=0,* and have the highest synergy effect if *QS(i,j)=1*. Here, synergy relationship strength is normalized and distributed between [0,1]. The higher value means that the resource transfer, information interaction, knowledge sharing and hand off among services are better.

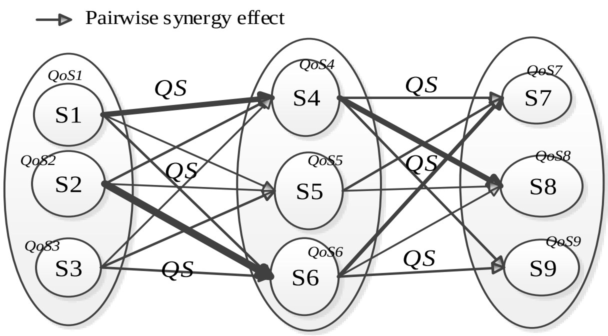


Figure 3. Service weighted synergy network *WSN*

Using equation (7), the pairwise synergy effect *QS(R,T)* can be computed. Then, we connect all service nodes whose pairwise synergy effect is greater than threshold value δ . The *WSN* which describes synergy relationships among service nodes can be constructed as shown in Figure 3. Taking the services as nodes and collaboration relations as the edges, service synergy network can be described as $G_{WSN} = (V, A, L, \varsigma)$ using the graph theory. $V = (v_1, v_2, \cdots, v_n)$ is service nodes set, A denotes the QoS set of all services, $L = (L_1, L_2, \cdots, L_m)$ is the edges set. $\varsigma = (\varsigma_1, \varsigma_2, \cdots, \varsigma_m)$ represents the strength of the pairwise synergy effect between nodes. The dynamic changes of QoS, service state and synergy effect will adjust the network structure of *WSN*, which has impact on service alliance formation to accomplish customized task.

5. Service Composition Model based on Synergy Effect

In a large Service Social Network (SSN), many services may satisfy the functional requirements of the task and these services may have similar QoS. Hence, we can take collaboration capacity as a additional competitiveness criteria in selecting services. As discussed above social relationships of services can create a synergy effect and are an important consideration in service combination. Based on service synergy network we develop a service selection model that support social collaboration between services.

5.1. Problem statement and variable definition

In wisdom manufacturing, the user needs *T=(Funset, QoS)* perceived in real-time can be decomposed into multiple sub-tasks $T=(T_1,T_2,\ldots,T_m)$ according to the process knowledge and resource conditions. Each sub-task is semantically matched to available services, *m* candidate service sets $CS=(CS_1,CS_2,\ldots,CS_m)$ are created for *m* sub-tasks, where each $CS_i=(S_1,S_2,S_3,\ldots,S_k)$. The weighted synergy network can be built as shown in Figure 6. Thus, service selection problem based on *WSN* can be stated as: select *m* desired services from the candidate sets to form a dynamic alliance whose overall synergy effect is highest. Table 1 summarizes the notations used in problem representation.

5.2. Service selection model

5.2.1. Computing the service synergy effect

The service synergy effect is the nonlinear sum of pairwise synergy edges. Aggregation rules and methods of traversing synergy edges are needed to compose social services, which is different from aggregation based on QoS. The service in the business process can relate to other nodes in various structures such as sequential, parallel, branch and loop. Table 2 shows the service aggregation rules for four types of manufacturing process structures commonly used .

5.2.2. Service selection model

Based on the analysis of *WSN* and the problem description, a new service selection model considers synergy effect is formed as follows：

$$MaxZ = \sum_{i=1}^{n} \sum_{\substack{j=1 \\ j \neq i}}^{n} qs_{ij} x_i x_j \tag{8}$$

$$s.t \sum_{i=1}^{n} x_i = q, i = 1,2,3\ldots,n, \quad x_i \in (0,1), i = 1,2,3\ldots,n, \quad \sum_{j=1}^{h} q_j = q \tag{9}$$

$$\sum_{i=1}^{n} x_i QoSC \geq \lambda_1, \quad \sum_{i=1}^{n} x_i QoST \geq \lambda_2, \quad \sum_{i=1}^{n} x_i QoSP \geq \lambda_3, \quad \sum_{i=1}^{n} x_i QoSR \geq \lambda_4 \tag{10}$$

$$\sum_{i=1}^{n} \sum_{j=1, i \neq j}^{n} x_i x_j qs_{ij} \geq \theta, \quad x_i = x_j = 1, qs_{ij} \geq \phi \tag{11}$$

Objective function (8) denotes the maximization of service synergy effect. Constraint (9) ensures that only one task can be done by a service, thus exactly q service nodes are assigned to q tasks in the service chain. Constraint (10) ensures that the service solution meet the QoS requirements. Constraint (11) require the service solution to meet the threshold value of synergy effect θ, and each pairwise synergy must be greater than ϕ. Based on the analysis of *WSN*, there exist several service paths that have higher synergy effect. We can transform social service selection problem into the shortest path problem, which can be solved by available algorithms, achieving the best service composition instance in *SSN*.

Selecting the best service from a list of alternative services for each task such that all user's QoS requirements are satisfied, is a non-trivial task as the number of possible combinations can be very huge. If there are N sub-tasks, each sub-task is corresponding to M candidate services, the number of service composition solution is $\Theta = M^N$. With the increasing number of candidate services and sub-tasks, the size of feasible solution space grows exponentially, resulting in the phenomenon of combination explosion. Previous research modeled service composition problem(SCP) in two ways: the combinatorial model defines the problem as a Muti-dimension Muti-choice Knapsack Problem (MMKP) and the graph model defines the problem as a Muti-constrained Optimal Path Problem (MCOP), which are both known to be NP-hard. Hence, SCP in SSN is also a NP-hard problem. The exact methods, such as enumeration method and the branch and bound algorithm, can solve efficiently small or medium sized SCP, but be out of the run-time requirements for large-scale service situation. However, intelligent algorithms such as GA, PSO, and bee algorithm, have been applied to accommodate the new situation and perform well for large-scale SCP. GSA as a new heuristic algorithm has good search ability and efficiency, which is suitable for solving the optimization problem of service composition. Hence, an improved GSA algorithm is developed to solve the problem, and its sensitivity is better for large-scale problem structure.

6. Experiment using a Case Study

With the development of cloud based manufacturing services, many companies such as Honda, GM, and Dongfeng Motor are moving towards services based manufacturing mode supported by cloud computing. Service composition to build dynamic task driven manufacturing value chain becomes very important. In this section, we firstly introduce a simple example to explain how synergy effect have impacts on the competitiveness of service in service selection intuitively, then an extend experiment is described in detail to prove the advantage of our model considering service collaboration factor.

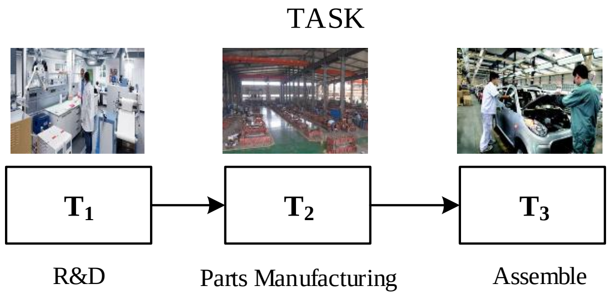


Figure 4. Intelligent vehicle manufacturing task order

6.1 Motivated example

Consider a vehicle manufacturing project T as a simple example, which has three sub-tasks R&D (T_1), Parts Manufacturing (T_2) and vehicle assembly (T_3) as shown in Figure 4. These sub-tasks are executed sequentially, where R&D unit transfers the design drawings, data and model parameters to Manufacturing unit, Manufacturing unit produces parts in accordance with the design requirements of R&D, and hands off different types of parts to Assembly unit. Manufacturer must select from service pool the most suitable services to compose this manufacturing process. Suppose that services S_1, S_2 matches the functional and QoS requirements of T_1, S_3, S_4 matches T_2 and S_5, S_6, S_7 matches T_3. Figure 2(a) shows service relationships and QoS assumed for each service. QoS-aware service selection method will find two optimal combinations $C_1=(S_1,S_4,S_6)$ and $C_2=(S_2,S_4,S_6)$, whose overall QoS are the same as 0.7+0.6+0.9=2.2.

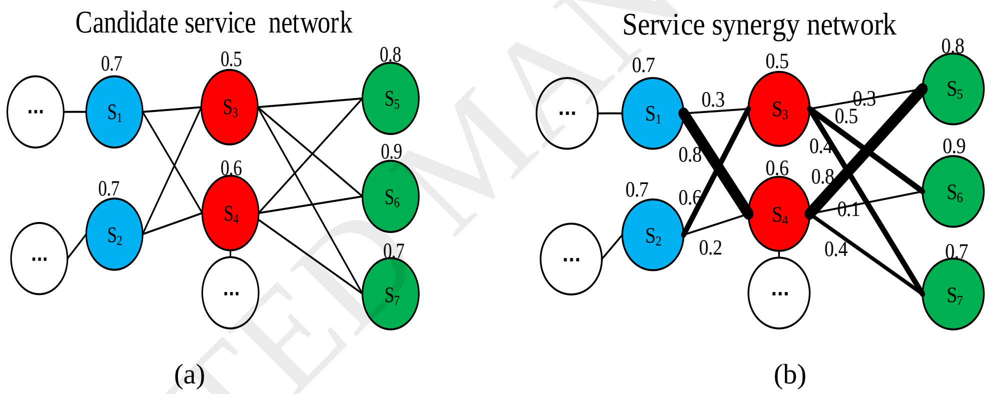


Figure 5. Candidate service network

Figure 5(b) shows the service synergy network with assumed synergy effect. The synergy effects between S_2 and S_4, S_4 and S_6 are 0.2, 0.1 respectively, which is low, since these services belong to different platforms and have few cooperation experience. Thus, the actual execution results of C_1, C_2 will not be satisfied. Considering the synergy effect a combination C_3= (S_1, S_4, S_5) may be better as it has QoS of (0.7+0.6+0.8=2.1) which is very close to the optimal value 2.2. In C_3, synergy effect between S_1 and S_4, S_4 and S_5 are 0.8, 0.8 respectively, which means they have more cooperation experiences, sharing resources, which can reduce interactive cost and enhance collaboration efficiency. When considering collaboration requirement, synergy effect of C_3 is 0.8+0.8=1.6, while the value of C_1, C_2 are 0.8+0.1=0.9, 0.2+0.1=0.3 respectively. Therefore, while service QoS of C_1, C_2 and C_3 are similar, considering synergy effect C_3 is the optimal solution. To build a superior task driven dynamic alliance, collaboration factor should be considered in the service selection.

6.2 Extend experiment

Due to the difficulty in getting real data, we create a fictitious case study of automotive manufacturing cloud and generate synthetic data set to illustrate the application of our approach. Figure 6 shows

Automotive cloud based manufacturing services assumed for our study. A manufacturing process is assumed to be composed of six sub-tasks (R&D, Technology Simulation, Raw Material Buying, Parts Manufacturing, Vehicle Assembly, Selling Services). Multiple services are available for each sub-task in the service cloud. Our proposed model is applied to compose services based on their function, QoS and synergy requirement. The design of the simulation experiment and the computations are detailed below.

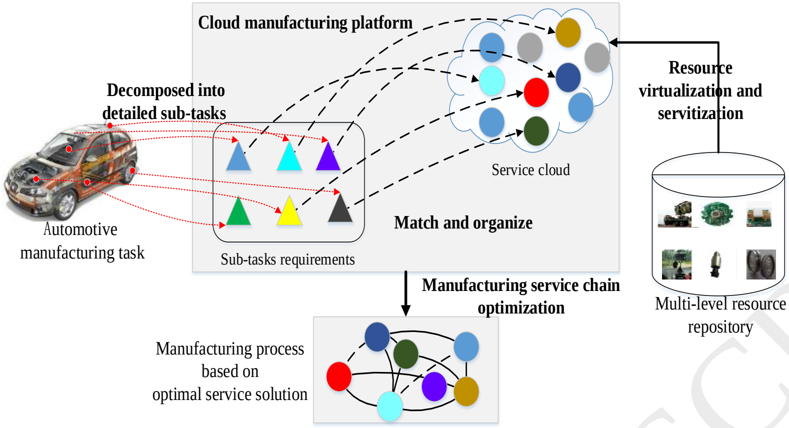


Figure 6. Automotive cloud based manufacturing services

6.2.1 Data Generation

Two personal computers are employed to simulate the experiment environment. One PC is used to run the service composition system and selection algorithm, while the other PC is used to operate manufacturing service repository. Each candidate service set contains 10 services which are functionally equivalent and have similar QoS. There are 30 service providers who own several services. Social attributes such as popularity, reputation and common partners, are considered. The values of each attribute for candidate services are randomly generated from [0, 10], [0, 1], [0, 10] respectively. The travel time related to geographic distance between service providers is selected from four levels (AT_1, AT_2, AT_3, AT_4). Each service is assumed to have 5 kinds of resources: physical equipment, materials, information, working knowledge, software and people, and they can share one or more types of resources with others, and the quantity of shared resources is [0,10] for each type of resource. Service collaboration times and transaction amounts generated during a unit period are distributed in the intervals [0, 20] and [0, 50] respectively.

6.2.2 Experiment Design:

Based on the data of QoS and social relationships, service weighted synergy network is first constructed. Then, four experiments were carried out to demonstrate that our model and algorithm performs better than others. Table 3 shows the experiments performed. The analysis and results are described in section 6.3.

6.2.3 Results of Experiment and analysis

(1) Synergy network analysis

Normalizing the relationship data to get consistent unit of measure and using the rough sets and the information entropy method, we obtain the comprehensive weight vector of five *RF*s (*IT*, *COC*, *Dis*, *RR* and *Sim*) as (0.38, 0.23, 0.05, 0.13, 0.21). SR_{IT} has the highest weight value, meaning it is an most important *RF*s since it shows that service transactions have a larger impact on synergy effect than others.. By computing the pairwise synergy effect by aggregating five relationship factors, *WSN* can be constructed as shown in Fig.7. The values of pairwise synergy effect are distributed between [0.2, 0.8] with an average value of 0.63. We divide this range into three level, high level [0.6, 0.8], middle level [0.4, 0.6] and low level [0.2, 0.4]. Most pairwise synergy effect is distributed in the interval [0.45, 0.62]. In different *WSN* and even in different periods, the synergy level may be various.

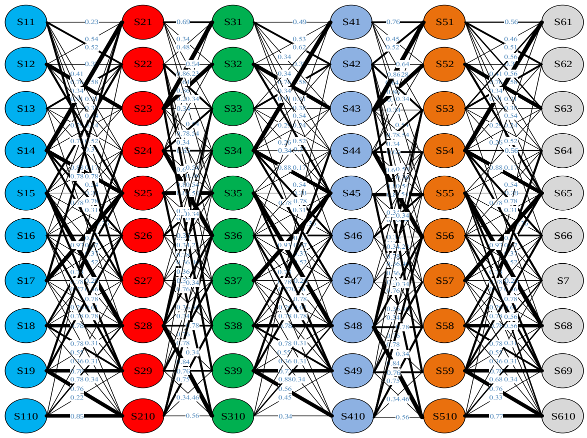


Figure 7. Service synergy weighted network of 60 nodes

In Experiment 1, the synergy effect values of all service compositions are obtained by the enumeration method as shown in Figure 8. It is easy to find that the solution values are distributed in the range [2.60, 3.58]. We can divide all values into three intervals I_1=[2.60, 2.95], I_2=[2.95, 3.28], I_3=[3.28, 3.58], which denotes low, middle and high synergy levels respectively. In our experiment, the synergy values are mostly in the range [3.05, 3.28], indicating they lie in a middle collaboration level. The optimal service scheme 1 (S_{12},S_{26},S_{38},S_{47},S_{55},S_{67}) (shown in Table 4) is obtained, it has the highest synergy effect of 3.58 but the computation time for the algorithm jumps to 3216.7ms. Hence, traditional solution method has difficulty in meeting the real-time requirement and solving the large-scale service problem.

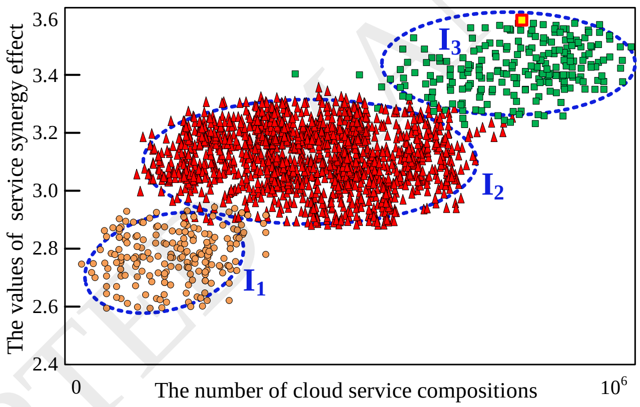


Figure 8. Synergy effect values of all service compositions

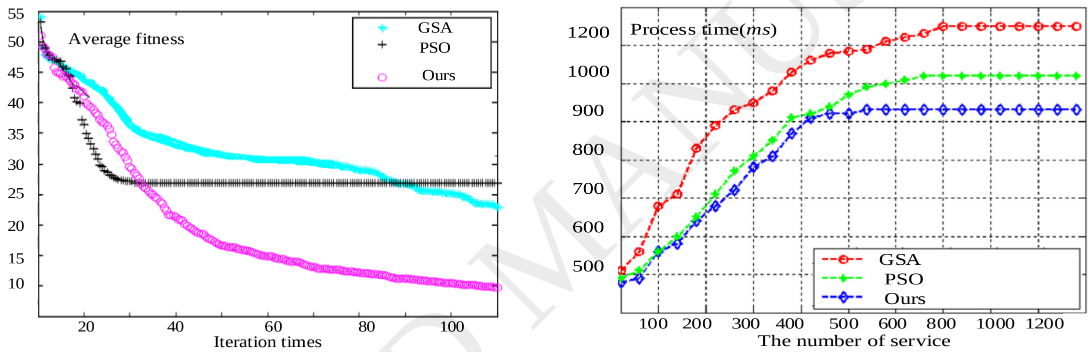
(2) Model comparison

We apply improved GSA algorithm to solve the proposed model. We set the population size $M = 400$, the maximum iteration times $MaxT = 100$, the inertia factor $\min w = 0.6$, $\max w = 1.1$, the learning factor $c_1 = c_2 = 0.8$ to conduct Experiment 2. After about 50 iterations, we get the optimal scheme 2 (S_{12},S_{25},S_{38},S_{47},S_{55},S_{63}), whose objective function value is 3.54. To further illustrate the validity and adaptability of our method, we compare the results with a QoS-aware model developed by (Karimi, Isazadeh and Rahmani. 2017). Scheme 3 (S_{13},S_{26},S_{37},S_{48},S_{57},S_{63}) is obtained based on QoS-aware model.

Based on the result shown in Table 4, we find that QoS of three schemes are close to each other. The possible reason is that the QoS of each service is similar in cloud, and it is not a key criterion in service selection any more. Our proposed method not only has a good overall QoS, but also has high level of synergy effect, which is very close to the optimal value obtained by linear programming. Moreover, the processing time of our algorithm is lower than LPM. Although scheme 3 has the highest overall QoS value, the synergy effect among services is the lowest at 2.68. Thus, using scheme 3 it is difficult to meet the collaboration requirements and task relations constraints. We further observe that S_{13} and S_{26} belong to different platforms, and the transaction level is low, leading to lower trust and higher communication cost. Moreover, physical distance between S_{37} and S_{48}, S_{48} and S_{57} are the highest, resulting in higher logistics cost and time. Many problems will arise in the implementation process of scheme 3, such as poor interaction and low logistics efficiency, even task failure. Hence, our model considering synergy effect is more suitable and can obtain the optimal service scheme .

(3) Algorithm comparison

To verify the effectiveness of our algorithm, we compare it with basic PSO and GSA in Experiment 3, where the number of sub-tasks is fixed at 6, the number of services for each sub-task is varied from 100 to 1000. Through 50-time tests, the fitness and search time of these algorithms are obtained as shown in Figure 9(a), (b). The mean fitness of PSO is higher than ours, and tends to be stable after 30 iterations, when its change is smooth and local optimum is raised. The fitness of GSA is the highest, although it has better global search but poor local search ability. The fitness of our algorithm decreases rapidly with the increase in number of iteration, and is at the lowest level. The processing time of all algorithms increases with the increase in number of candidate services. Hence, our algorithm has the least time and highest search efficient.



(a) (b)

Figure 9. Mean fitness and search time

The fitness is the difference degree between the current solution and optimal solution. When the number of services reach 500, the growth curve of our algorithm doesn't show exponential change. Because two-way learning mechanism and clustering strategy are applied to remove disadvantaged candidate services and reduce the search space of optimal solution. Additionally, group interaction strategy in PSO is used to improve the search speed of GSA.

As shown in Table 5, it is obvious that improved GSA algorithm performs better than GSA and PSO in max and mean results. Meanwhile, the SE value of improved GSA is less than other methods. It illustrates that the search results is more stable, and has better performance. With the increasing number of candidate services, the synergy value of all three algorithms increases. The possible reason is that services with better QoS are generated and selected in the manufacturing task, making the whole QoS of service composition scheme improved gradually.

To verify the scalability and stability of our algorithm in larger scale service situation, the Experiment 4 is performed. Five kinds of problem scale (number of tasks × number of available services) are set and represented as 6×15, 10×20, 20×30, 30×40, 40×50. The comparison of results of three algorithms are shown in Table 6, and confidence intervals (CI) on max fitness and time of our algorithm is superior to others. It was obvious that improved GSA algorithm performed better than basic GSA and PSO on search time and max fitness in different problem scale. The search time growth of all three algorithms tend to be flat, it further illustrates that improved GSA algorithm is suitable for large-scale manufacturing services.

7. Conclusions

This paper presents an approach for composing services that considers social relationships between services. Successful completion of complex tasks requires building dynamic alliances between manufacturing services as all the providers need to work as a team, where selected services corresponding to sub-tasks must make sure that resource hand off, information and knowledge delivery are smooth and efficient. Hence, not only the individual competitiveness but the synergy effect between candidate services should be considered as important criterion for service composition. In cloud platform where services have social relationships, which can create synergy effect, and social network analysis is critical for finding appropriate services for creating dynamic alliance. Since this area has not been thoroughly researched before, the approach presented in this paper improves the quality of service composition and significantly contribute to literature in this area. The major contributions of the proposed method are described below.

First, we provide new insight into IoS that integrates social network and synergy theory and adapts them to the new context. A new framework for service selection that considers the service synergy has been proposed. Based on the analysis of social interaction behavior, we defined five dimensions, namely, interactive transaction, co-community, physical distance, resource related, social similarity relationships and constructed multidimensional *SSN*, which can provide a basis for research in IoT, cloud manufacturing and service orchestration in the future. Second, present a service weight synergy network model to calculate the comprehensive synergy effect based on aggregation five relations strength: this model can serve as a basis for quantitative research on service assets. Third, a novel service composition model based on synergy effect that emphasizes collaboration factor is proposed. It overcomes the limitations of existing methods that only consider the functional and QoS attributes, and enhances the probability of successful collaboration among potential partners in SSN. Additionally, using an intelligent automobile manufacturing case experiment, the results reveal that our approach considering collaboration factor generate more efficient solution when organizing a business process with many services.

Due to the complexity and diversity of service social relationships, this paper only considered a few relationship types and *RFs*. Minor relationships are omitted yet they still have an important impact on service selection. For further research, it is imperative to further analyze the attributes of social relationships, so as to integrate new types of social relationships into the model. A service relationship has attributes like social capital that can measure service social value which can help in evaluating collaborative efficiency. More attention needs to be paid to this. The services synergy effect changes dynamically with time and location. An update mechanism is needed to create and describe the dynamics and uncertainty of synergy relationship. Moreover, different service application domains and task types may have different preferences and may tend to differently weigh diverse relationship elements. Sensitivity analysis and domain-dependence of social synergy should be done to consummate our model in various contexts, such as health-care, education and so on. The needs to be extended to consider domain-specific properties. In addition, the model needs to be tested on real systems.

Appendix 1: Method for computing Weights

Suppose the knowledge representation system of *RFs* as $Z = (U, A, V, f)$, where U is non-empty finite set. $A = C \cup D$ denotes attributes set, $C = (IT, COC, Dis, RR, Sim)$ and $D = (QS_1, QS_2, \cdots, QS_n)$ denote condition attribute and decision attribute set respectively. Then, the final *RF*s decision table can be constructed as shown in Table A. Based on the original data of each *RFs* of each instance, the relation instances are firstly divided into several classes by fuzzy clustering method. After deleting an attribute or *RFs,* we re-classify the instances and obtain the new classification. The change degree of the classification computed by information entropy represents the importance of the attribute deleted. Through normalization, the weight distribution of each *RF* can be conducted, and the correlation of *RFs* is computed by mutual information. The detailed computing process can be described as follow:

(1) Let $IS = (IS_1, \; IS_2, \cdots, IS_n)$ represents a set of relation instances, which has *m* *RF*s or attributes (*m*=*5*). We can create the attribute matrix by computing the *RF*s of the instances.

$$IS = \begin{vmatrix} s_{11} & s_{12} & \cdots & s_{1n} \\ s_{21} & s_{22} & \cdots & s_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ s_{m1} & s_{m2} & \cdots & s_{mn} \end{vmatrix} \qquad (1)$$

(2) The fuzzy similarity matrix $R = (r_{ij})_{n \times n}$ is created by computing the similarity between the instances using the equation $r_{ij} = \sum_{k=1}^{m} (x_{ik} \wedge x_{jk}) \Big/ \sum_{k=1}^{m} (x_{ik} \vee x_{jk})$.

(3) Using the equation $R^2 \rightarrow R^4 \rightarrow \cdots \rightarrow R^{2^k} = t(R)$, the fuzzy equivalent closure matrix is constructed. The cluster within each threshold λ can be described as C_i. There are *m* attributes to cluster the objects which results in *k* initial clusters $C = (C_1, C_2, \cdots, C_k)$. We then remove an attribute and re-cluster the object in *m-1* attributes. the new clustering result can be obatined as $C^{'} = (C^{'}_1, C^{'}_2, \cdots, C^{'}_k)$. The cluster within each threshold $\lambda^{'}$ can be described as $C^{'}_i$. Finally, all results of classification will be recorded.

(4) After removing one relation factors, the size of the mutual information $E(C_i; C^{'}_i)$ within the same threshold range can be calculated by $E(C^{'}, C) = H(C^{'}) - H(C^{'} | C) = H(C) - H(C | C^{'})$, and the amount of information contained in different attributes will be calculated by the following equation:

$$M_j = \frac{1}{r} \sum_{i=1}^{r} E(C_i; C^{'}_i), \; j = 1, 2, \cdots, m \qquad (2)$$

It shows that the information M_j of the deleted *RF* is less contained in the cluster. It means that the importance of the deleted *RF* is small.

(5) Finally, by comparing the amount of information M_j involved in various *RF*s, and the weight distribution of different *RF*s can be computed as follows:

$$w_k = \frac{M_k}{\sum_{i=1}^{m} M_k} \qquad (3)$$

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Table 1 Summary of notations

Symbol	Meaning
n	The number of candidate services
h	The number of desired candidate service sets
j	task node, $j = 1, 2, 3\ldots, m$
n_j	The number of candidate service sets CS_j, then $\sum_{j=1}^{h} n_j = n$
q	The total number of required services to form a dynamic alliance
q_j	The total number of services chosen from the candidate service set CS_j, $\sum_{j=1}^{h} q_j = q$
k	The number of the relationship factors (*RFs*) of synergy effect
N_j	The index set of candidate services in CS_j
QS_l	The relationship factors (*RFs*) of collaboration relationship, $l = 1, 2, 3\ldots, k$
$QS(i, j)$	The synergy effect between services *i* and *j*
w_l	The weight of each QS_l, then $\sum_{l=1}^{k} w_l = 1$
x	The decision variable $x_i = 1$, if candidate WS_i is selected, $x_i = 0$ otherwise

Table 2 Aggregation rules of service synergy effect

Synergy relationship	Service synergy effect $QS(R, T)$				
	QS_{Dis}	QS_{Sim}	QS_{RR}	QS_{IT}	QS_{COC}
Sequential	$\sum_{i,j=1,i\neq j}^{n} QS_{Dis}^{ij}$	$\prod_{i,j=1,i\neq j}^{n} QS_{Sim}^{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{RR}^{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{IT}^{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{COC}^{ij}$
Parallel	$\frac{2}{n}\sum_{i,j=1,i\neq j}^{n} QS_{Loc}^{ij}$	$\prod_{i,j=1,i\neq j}^{n} QS_{Sim}^{ij}$	$\frac{2}{n}\sum_{i,j=1,i\neq j}^{n} QS_{RR}^{ij}$	$\min\left(QS_{IT}^{ij}\right)$ $i, j \in [1, n], i \neq j$	$\frac{2}{n}\sum_{i,j=1,i\neq j}^{n} QS_{COC}^{ij}$
Branch	$\sum_{i,j=1,i\neq j}^{n} QS_{Dis}^{ij} \cdot p_{ij}$	$\sum_{i,j=1;i\neq j}^{k} QS_{Sim}^{ij} \times p_{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{RR}^{ij} \cdot p_{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{IT}^{ij} \cdot p_{ij}$	$\sum_{i,j=1,i\neq j}^{n} QS_{COC}^{ij} \cdot p_{ij}$
Loop	$L \times \sum_{i,j=1,i\neq j}^{n} QS_{Dis}^{ij}$	$\left(\prod_{i,j=1,i\neq j}^{n} QS_{Sim}^{ij}\right)^{L}$	$L \times \sum_{i,j=1,i\neq j}^{n} QS_{RR}^{ij}$	$L \times \sum_{i,j=1,i\neq j}^{n} QS_{IT}^{ij}$	$L \times \sum_{i,j=1,i\neq j}^{n} QS_{COC}^{ij}$

Table 3 Experiment descriptions

Experiment	Experiment objective	Model	Solution Algorithm	Result explanation
1	Obtain the optimal service composition	Our proposed model	Linear programming method (LPM)	Obtain optimal scheme (S_{12},S_{26},S_{38},S_{47},S_{55},S_{67})
2	Comparison with other Model	Our model QoS aware model	Improved GSA	Our model and algorithm performed better
3	Different Number of Available Services	Our model	Improved GSA, PSO, GSA	Our algorithm performed better than GSA, PSO
4	Different Number of Tasks	Our model	Improved GSA, PSO, GSA	Our algorithm perform better than GSA, PSO

Table 4 Comparison of result from different model

The scheme order number	Service composition instance	QoS	Synergy effect	Processing Time (ms)
1	(S_{12},S_{26},S_{38},S_{47},S_{55},S_{67})	4.34	3.58◎	3216.7
2	(S_{12},S_{25},S_{38},S_{46},S_{55},S_{63})	4.28	3.54◎	678.5
3	(S_{13},S_{26},S_{37},S_{48},S_{57},S_{63})	◎4.39	2.68	654.3

Table 5 Comparison of result of different algorithms

Number of services	Improved GSA		PSO		GSA	
	Max	Mean (SE*)	Max	Mean (SE*)	Max	Mean (SE*)
100	3.84	3.54 [0.543]	3.62	3.35 [0.635]	3.75	3.46 [0.641]
200	3.98	3.67 [0.642]	3.70	3.41 [0.724]	3.84	3.63 [0.638]
400	4.25	4.02 [0.638]	3.96	3.68 [0.718]	3.95	3.72 [0.694]
800	4.36	4.13 [0.657]	4.15	3.84 [0.736]	4.14	3.86 [0.732]
1000	4.44	4.24 [0.674]	4.26	3.93 [0.729]	4.23	4.02 [0.746]

SE*=standard errors

Table 6 Comparison of result of different problem scale

		Problem scale (task×service)				
		6×15	10×20	20×30	30×40	40×50
Improved GSA	Max fitness	8.75	10.36	11.56	12.43	15.63
	CI(95%)	[8.62, 8.78]	[10.24, 10.51]	[11.47, 11.74]	[12.39, 12.50]	[15.58, 15.76]
	Time	421	613	785	908	912
	CI(95%)	[415, 427]	[604, 618]	[8.62, 8.78]	[8.62, 8.78]	[8.62, 8.78]
PSO	Max fitness	9.21	11.38	12.69	14.57	18.14
	CI(95%)	[9.17, 9.28]	[11.32, 11.47]	[12.63, 12.78]	[14.48, 14.66]	[18.06, 18.23]
	Time	435	684	955	1003	1112
	CI(95%)	[428, 447]	[668, 702]	[942, 971]	[994, 1125]	[1097, 1146]
GSA	Max fitness	9.34	12.25	13.54	16.45	20.68
	CI(95%)	[9.25, 9.42]	[12.18, 12.37]	[13.48, 13.62]	[16.37, 16.53]	[20.61, 20.73]
	Time	511	852	1052	1102	1207
	CI(95%)	[503, 522]	[837, 869]	[1046, 1074]	[1087, 1125]	[1193, 1224]

CI=confidence interval

Table A *RF*s decision table

U	***C***					***D***
	IT(R,T)	*COC(R,T)*	*Dis(R,T)*	*RR(R,T)*	*Sim(R,T)*	*QS(R,T)*
IS_1	s_{11}	s_{12}	s_{13}	s_{14}	s_{15}	QS_1
IS_2	s_{21}	s_{22}	s_{23}	s_{24}	s_{25}	QS_2
....	....	....	....	....	....	....
IS_j	s_{j1}	s_{j2}	s_{j3}	s_{j4}	s_{j5}	QS_j
....	....	....	....	....	....	....
IS_n	s_{n1}	s_{n2}	s_{n3}	s_{n4}	s_{n5}	QS_n