Efficient Coalition Formation for Web Services

Michael Shell, *Member, IEEE,* John Doe, *Fellow, OSA,* and Jane Doe, *Life Fellow, IEEE*

Abstract—Web services are loosely-coupled business applications willing to cooperate in distributed settings within different groups called communities. Communities aim to provide better visibility, efficiency, market share and total payoff. There are a number of proposed mechanisms and models on aggregating web services and making them cooperate within their communities. However, forming optimal and stable communities as coalitions to maximize individual and group efficiency and income has not been addressed yet. In this paper, we propose an efficient coalition formation mechanism using cooperative game-theoretic techniques. We propose a mechanism for community membership requests and selections of web services in the scenarios where established communities already exist. Moreover, we analyze the scenarios where communities are not established yet and web services can form multiple communities. The ultimate objective is to develop a mechanism for web services to form stable groups allowing them to maximize their efficiency and generate near-optimal (welfare-maximizing) communities. The theoretical and simulation results show that our algorithms provide web services and community owners with applicable and near-optimal decision making mechanisms.

Index Terms—Web services; Cooperative game theory; Community of services;

1 Introduction

Over the past years, online services have become part of many scalable business applications. The increasing reliance on web-based applications has significantly influenced the way web services are engineered. Web services provide a set of stateless software functions accessible at a network address over the web. The recent developments are shifting web services from passive and individual components to autonomous and group-based components where interaction, composition, and cooperation are the key challenges [1], [2]. The main objective is to achieve a seamless integration of business processes, applications and web services. Delivering high quality services considering the dynamic and unpredictable nature of the Internet is still a very critical and challenging issue.

The need for highly available and responsive services has called for grouping and collaborative mechanisms of loosely-coupled web services, particularly in business settings. The idea of grouping web services within communities and the way those communities are engineered so that web services can better collaborate have been proposed and investigated in [3], [4], [5]. Communities are virtual groups of web services having similar functionalities, but probably different non-functional quality attributes, which form the QoS parameters. When communities are used, users send their requests to the masters of those communities, which are responsible of managing the communities, forwarding the requests to the suitable member web services and checking the credentials of those members. Communities aim to provide higher service availability and performance than what individual web services can provide. The high availability of services and the community resilience to failure are guaranteed since web services can cooperate and replace each other within the same community and since there is no single point of failure in the communities architecture.

Most of the recent work on communities of services are either user-centric and focus on user satisfaction [6] or system-centric and focus on the whole system throughput, performance and utilization. There are many contributions in distributed, grid, cluster and cloud services which are system-centric. However, in real world environments and applications, both users and service providers are self-interested agents, aiming to maximize their own profit. In those environments, both parties (users and services) will collaborate as long as they are getting more benefits and payoff.

In this direction, recently [7], [8] proposed mechanisms to help users and services maximize their gain. A two-player non-cooperative game between web services and community master was introduced in [8]. In this game-theoretic model, the strategies available to a web service when facing a new community are requesting to join the community, accepting the master's invitation to join the community, or refusing the invitation to join. The set of strategies for communities are inviting the web service or refusing the

- *M. Shell is with the Department of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, 30332. E-mail: see http://www.michaelshell.org/contact.html*
- *J. Doe and J. Doe are with Anonymous University.*

web service's join request. Based on their capacity, market share and reputation, the two players have different set of utilities over the strategy profiles of the game. The main limits of this game model are: 1) its consideration of only three quality parameters, while the other factors are simply ignored; and 2) the non-consideration of the web services already residing within the community. The game is only between the community master and the new web service, and the inputs from all the other members are simply ignored. The consideration of those inputs is a significant issue as existing web services can lose utility or payoff because of the new member, which can results in an unhealthy and unstable group. The problem comes from the fact that the existing members should collaborate with the new web services, so probably their performance as a group can suffer. Existing members may even deviate and try to join other communities if they are unsatisfied. Those considerations of forming stable and efficient coalitions are the main contributions of our paper.

In [7] a 3-way satisfaction approach for selecting web services has been proposed. In this approach, the authors proposed a web service selection process that the community masters can use. The approach considerers the efficiency of all the three involved parties, namely users, web services and communities. In this work, it is shown how the gains of these parties are coupled together using a linear optimization process. However, the optimization problem in this solution tends to optimize some parameters considering all web services regardless of their efficiency and contribution to the community's welfare. Moreover, there are no clear thresholds for accepting or rejecting new web services. The solution of the optimization problem could, for instance, suggest web services already residing within the community to increase or decrease their capacity to cover up the weakness of other parties in the system. However, a high performing web service could deviate anytime it finds itself unsatisfied within the community instead of adjusting its service parameters.

Contributions. In this paper, we use game theory to propose a cooperative game model for the aggregation of web services within communities. The solution concepts of our cooperative game seeks to find efficient ways of forming coalitions (teams) of web services so that they can maximize their gain and payoff, and distribute the gain in a fair way among all the web services. Achieving Fairness when the gain is distributed among the community members is the main factor to keep the coalition stable as no web service will expect to gain better by deviating for the community. In other words, the coalition is made efficient if all the members are satisfied. We first propose a representation function for communities of web services based on their QoS attributes. By using this function, we can evaluate the $worth$ of each community of web services. When facing new membership requests, a typical community master checks whether the new coalition having the old and new set of web services will keep the community stable or not. The community master will reject the membership requests if it finds out that the new coalition would be unstable, preventing any subset of web services from gaining significantly more by deviating from the community and joining other communities or forming new ones. The computation of solutions for cooperative game theory problems is combinatorial in nature and proven to be NP-complete [9], making this computation impractical in real world applications. However, using the concepts of coalition stability, we propose approximation algorithms running in polynomial time providing web services and community masters with applicable and near-optimal decision making mechanisms.

The rest of paper is organized as follows. Section 2 describes the architecture, considered parameters and some basic cooperative game theory concepts. Section 3 presents our solution model in three different scenarios. Section 5 describes our experiments and results. Finally, Section 7, concludes the paper and identifies future work.

2 PRELIMINARIES

In this section, we discuss the parameters and preliminary concepts that we use in the rest of the paper.

2.1 The Architecture

Our system consists of three main types of entities working together:

1) Web services are rational entities[1] providing services to end users. They aim to maximize their individual income by receiving enough requests from end users. In order to increase their revenue, web services seek for more tasks if they have the capacity and throughput to do so. Web services can join communities to have better efficiency by collaborating with others, to have access to higher market share, and to have opportunity of receiving a bigger task pool from end users. Throughout this paper, in our equations, we refer to web services as ws and to the set of web services hosted by a given community as C. To simply the notation, sometimes we simply write ws instead of $ws \in C$ to go through the elements ws of the set C.

2) Master Web Services or the community coordinators, are representatives of the communities of web services and responsible for their management. Communities receive requests from users and aim to host a healthy set of web services to perform the required

1. The term rational is used here in the sense that web services are utility maximizers

TABLE 1
List of web service QoS parameters.

Parameter	Definition
Availability	Probability of being available during a time frame
Reliability	Probability of successfully handling requests during a timeframe
Successability	Rate of successfully handled requests
Throughput	Average rate of handling requests
Latency	The average latency of services
Capacity	Amount of resources available
Cost	Mean service fee
Regulatory	Compliance with standards, law and rules
Security	Quality of confidentiality and non-repudiation

tasks. They seek to maximize user satisfaction by having tasks accomplished according to the desired QoS. In fact, higher user satisfaction will bring more user requests and increase the market share and revenue of the community.

3) Users generate requests and try to find the best available services. User satisfaction is abstracted as function of quantity and quality of tasks accomplished by a given service.

2.2 Web Service Parameters

Web services come with different quality of service parameters. These parameters with a short description are listed in Table 1.

We adopted a real world dataset [10] which has aggregated and normalized each of these parameters to a real value between 0 and 1. Since requests are not shared among web services and are distributed among all of them inside a community, each one of them comes with a given QoS denoted by (QoS_{ws}). We assume that (QoS_{ws}) is obtained by a certain aggregation function of the parameters considered in Table 1. We use this quality output later in evaluating the community *worth* or *payoff* function.

2.3 Web Service Communities

Figure 1 represents the architecture of web service communities. The communities are basicly an abstract model of web services, they aggrigate web services and communicate with other entities such as UDDI registeries and users, using identical protocols as web services. Web services join communities to increase their utility by having a larger market share and task pool. Community cordinators or master web services are responsible for community development, managing membership requests from web services and distributing user tasks among the community members. Communitiy coordinators try to attract quality web services and keep the community as stable and productive as possible to gain better reputation and user satisfaction which results in having a higher market share for the community. The way the web services reside inside communities and how communities of web services are engineered is described comprehensivly in [3].

2.4 Cooperative Game Concepts

Cooperative game is a branch of game theory that studies strategies of self-interested entities or agents in a setting where those agents can increase their payoff by binding agreements and cooperating in groups. We let N be a set of players. Any subset S of N can form a group called *coalition*. A *coalitional game* is a pair $G = (N, v)$ where v is called a *characteristic function*, which given a coalition, is a function $v : 2^N \to \mathbb{R}$ mapping the set of players of the coalition to a real number $v(S)$, the worth of S. This number usually represents the output or payoff or again the performance of these players working together as coalition. If a coalition S is formed, then it can divide its worth, $v(S)$ in any possible way among its members. The payoff vector $x \in \mathbb{R}^S$ is the amount of payoff being distributed among the members of the coalition S. The payoff vector satisfies two conditions:

- $x_i \geq 0$ for all $i \in N$, and
- $\sum_{i \in S} x_i \leq v(S)$

The second criteria is called the *feasibility* condition, according to which, the payoff for each agent cannot be more than the coalition total gain. A payoff vector is also *efficient* if the payoff obtained by a coalition is distributed amongst the coalition members: $\sum_{i \in S} x_i = v(S)$. This definition of the characteristic function works in *transferable utility* (TU) settings, where utility (i.e., payoff) is transferable from one player to another, or in other words, players have common currency and a unit of income is worth same for all players [11].

When dealing with cooperative games, two issues need to be addressed:

1. What coalitions to form?
2. How to reward each member when a task is completed?

The following definitions help address these two issues.

Definition 1 (Shapley value) Given a cooperative game (N, v), the *Shapley value* of player i is given by[12]:

$$\phi_i(N, v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (v(S \cup \{i\}) - v(S)) \tag{1}$$

Shapley value is a unique and fair solution concept for payoff distribution among the members of the coalition. It basically rewards members with the amount of marginal contribution they have to the coalition.

Definition 2 (Core) A payoff vector x is in the *core* of a coalitional game (N, v) if and only if:

$$\forall S \subseteq N, \sum_{x_i \in S} x_i \geq v(S) \tag{2}$$

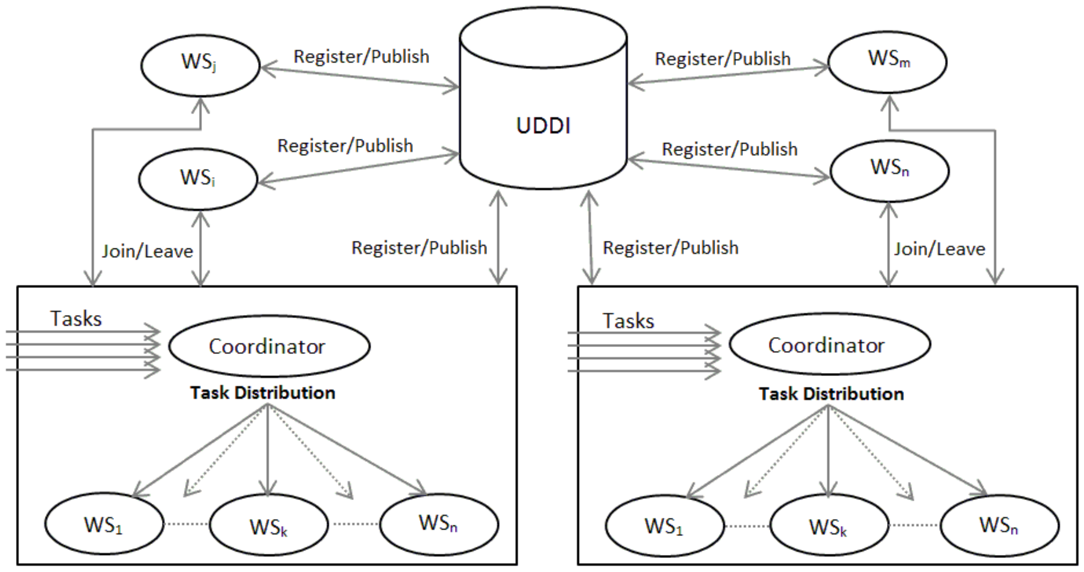


Fig. 1. Architecture of Web Service communities

The core is basically a set of payoff vectors where no subset of players S' could gain more than their current payoff by deviating and making their own coalition $\sum_{i \in S'} x_i \geq v(S')$. The sum of payoffs of the players in any sub-coalition S is at least as large as the amount that these players could earn by forming a coalition by their own. In a sense, it is analogue to Nash equilibrium, except that core is about deviations from groups of entities. The core is the strongest and most popular solution concept in cooperative game theory. However, its computation is a combinatorial problem and becomes intractable as the number of players increases. The core of some real-world problem games may be empty, which means having the characteristic function of the game (N, v), there might be no possible distribution of payoff assuring stability of subgroups.

Definition 3 (Convex cooperative games) A game (N, v) with characteristic function $v(S)$ is convex if:

$$v(S) + v(T) \leq v(S \cup T) + v(S \cap T), \forall S, T \subseteq N. \quad (3)$$

According to a classic result by Shapley [13], convex games always have a non-empty core. We will use a variation of convexity condition in our algorithm to check whether our coalitions are stable.

ϵ-core

When the *core* set of a game is empty, it means no coalition of players can gain anything by deviating. An outcome would be unstable if a coalition can benefit even by a small amount from deviating, which is a strong requirement. In fact, in some situations, deviations can be costly, or players may have loyalty to their coalitions, or even it can be computationally intractable to find those small benefits. It would only make sense for a coalition to deviate if the gain from a deviation exceeds the cost of performing the deviation. *ϵ-core* relaxes the notion of the core, and only requires that no coalition would benefit significantly, or within a constant amount(ϵ) by deviating (see Equation 2).

$$\forall S \subseteq N, \sum_{x_i \in S} x_i \geq v(S) - \epsilon \quad (4)$$

Coalition Structure Formation

Coalition structure formation is the problem of finding the best partition of web services into teams. In these settings, the performance of an individual service is less important than the *social welfare* of the whole system, which is the sum of the values of all teams. Having the game (N, v), a coalition structure (CS) is *socially optimal* if CS belongs to set $\arg\max_{CS} v(CS)$ where $v(CS)$ is the sum of the values of all coalitions inside CS. $v(CS) = \sum_{C \in CS} v(C)$.

3 Problem Formulation and Modeling

In this section, we present the web service and community coordinator's intractions, the task distribution process and revenue models in web service communities.

3.1 Task destribution

As mentioned in section 2.3, communities are robust service providers with well stablished market share and reputation. By maintaining their reputation and performance, they attract end users which choose them as service providers to perform their tasks. The community master is characterizd by a request rate (R_C) from users. Each web service comes with a given QoS (QoS_{ws}) from which the throughput Tr_{ws} is excluded. This exclusion allows us to build our analysis on the particular value of Tr_{ws}. Throughput is the average rate of tasks a web service can perform per time unit. Thus, web services perform tasks with an average output quality of QoS_{ws} and a throughput rate of Tr_{ws}.

The community master uses a slightly modified *weighted fair queuing* method to distribute task among its members. The goal is to allocate incoming tasks to web services with a rate matching throughput value of Tr_{ws}. In *weighted fair queuing* method *all* the input flow is multiplexed along different paths, however in our case if the input rate (R_C) of the community is more than summation of throughput values of web services, some of the input tasks will be queued and served with delay. Thus, the amount of tasks performed by community is $\sum_{ws \in C}(Tr_{ws})$ when $\sum_{ws} Tr_{ws} \leq R_C$. However, when the community has more web services having more total throughput value than community's request rate (R_C) the *weighted fair queuing* algorithm assigns a weighted task rate of $R_C \times \frac{Tr_{ws}}{\sum_{ws} Tr_{ws}}$ for each web service (ws) and the total rate of tasks being performed is R_C, the community's receiving request rate.

3.2 Community Revenue

The communities and web services earn revenue by performing tasks. The total gain is function of quality (QoS_{ws}) and quantity(Tr_{ws}) of tasks being performed. As mentioned in section 2.2 QoS_{ws} is obtained by a certain aggregation function of the parameters considered in Table 1. We have adopted a linear equal weigth average over all QoS parameteres listed in table 1 excluding the $Throuput$ and $Cost$ parameters. A community has the option to weigh specific QoS patameters more or less depending on the expectations of their clients.

The maximum potential output $(PO(C))$ of a community is aggregation of number of tasks, times their quality, for each web service participating as a member of the community:

$$PO(C) = \sum_{ws \in C} (T_{ws} \times QoS_{ws}) \qquad (5)$$

If the summation of throughput (Tr_{ws}) values of community members exceeds the input task rate of the community (R_C) the community cannot perform at its maximum potential. It means community has more web services than it needs for performing input task load. Therefore, in these cases, the actual output has to be normalized to the ammount of tasks being performed.

$$Out(C) = \begin{cases} PO(C) & \text{if } \sum_{ws} Th_{ws} \leq R_M \\ PO(C) \times \frac{R_M}{\sum_{ws} Th_{ws}} & \text{if } \sum_{ws} Th_{ws} > R_M \end{cases} \qquad (6)$$

TABLE 2
Three web services of example 1

WS	QoS_{ws}	Th_{ws}	$Th_{ws} \times QoS_{ws}$
1	0.8	4	3.2
1	0.8	5	4.0
1	0.8	3	2.4

Community	Worth	Community	Worth
$\{1\}$	3.2	$\{1,2\}$	7.2
$\{2\}$	4.0	$\{1,3\}$	6.8
$\{3\}$	2.4	$\{2,3\}$	6.4
$\{1,2,3\}$	8.0		
Community R_C: 12			

TABLE 3
Three web services of example 2

WS	QoS_{ws}	Th_{ws}	$Th_{ws} \times QoS_{ws}$
1	0.8	5	4.0
1	0.7	6	4.2
1	0.7	4	2.8

Community	Worth	Community	Worth
$\{1\}$	4.0	$\{1,2\}$	7.4
$\{2\}$	4.2	$\{1,3\}$	6.8
$\{3\}$	2.8	$\{2,3\}$	7.0
$\{1,2,3\}$	7.3		
Community R_C: 10			

The revenue function of the web service community, is a linear function of $Out(C)$ with a positive constant multiplier.

3.3 Case Study

In this section, we analyse a few numerical examples and discuss the motivation of web services and community intractions and the strategies they can adopt and the revenue they can earn adopting different strategies.

In the first example, we present a community with R_C value of 10, and three web services each having different QoS_{ws} and Th_{ws} values as listed in table 2.

4 WEB SERVICE COOPERATIVE GAMES

In this section, we present different web service community models and focus on the problem of how both web services and community masters as rational entities would adopt strategies to maximize their payoff.

4.1 Web Services and One Community

In this scenario, we assume the existence of a typical community managed by its master, and web services need to join it to be able to get requests from the master. The community master is characterized by a requests rate (R_M) from users. Each web service

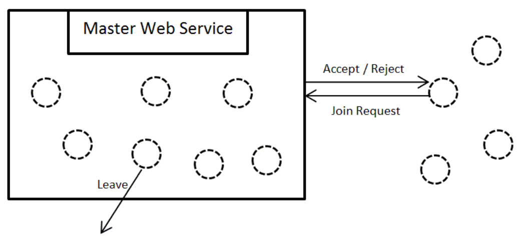


Fig. 2. Web Services and A Grand Community

comes with a given QoS (QoS_{ws}) from which the throughput T_{ws} is excluded. This exclusion allows us to build our analysis on the particular value of T_{ws}. Throughput is the average rate of tasks a web service can perform per time unit. Thus, web services perform tasks with an average output quality of QoS_{ws} and a throughput rate of T_{ws}. In this setting, we define the value of the coalition of the web services within a community as a function increasing in both T_{ws} and QoS_{ws} as follows:

$$output(C) = \sum_{ws \in C} (T_{ws} \times QoS_{ws})$$

$$v(C) = \begin{cases} output(C) & \text{if } \sum_{ws} T_{ws} \leq R_M \\ output(C) \times \frac{R_M}{\sum_{ws} T_{ws}} & \text{if } \sum_{ws} T_{ws} > R_M \end{cases} \tag{7}$$

The output of a coalition of web services is a function of the throughput and provided QoS. If the throughput rate is more than the master's input request rate, it means the web services inside the community are capable of serving more requests than the demand. Considering this factor, the valuation function is designed to balance the output performance so that it matches the exact throughput rate and QoS the web service can provide within the particular community.

In this first scenario, we only consider one grand coalition and analyze the system from the point of view of one single master web service and a collection of web services. The master web service decides which members can join the community and distributes the requests and income among its community members (see Figure 2).

The membership decision is made based on throughput and *QoS* of the considered web service. The goal is to have quality web services in the community so it stays stable and no other web services would have incentives to deviate and leave the coalition C. Therefore, a basic method would be to check the core of the coalition C considering all the current community members (all web services already residing within the community) and the new web service. This algorithm uses the *Shapley value* distribution method as described in Equation 1 to distribute the gain of $v(C)$ among all the members and then checks if the *Shapley value* payoff vector for this community having the characteristic function $v(C)$ is in the *core*. In the *Shapley value* payoff vector, the payoff for each web service ws_i is calculated based on its marginal contribution $v(C \cup i) - v(C)$ over all the possible different permutations in which the coalition can be formed, which makes the payoff distribution fair. Because of going through all the possible permutations of subsets of N, the nature of the *Shapley value* is combinatorial, which makes it impractical to use as the size of our coalitions grows. However, it is proven that in convex games, the *Shapley value* lies in the core [14], [11]. Thus, if the *Core* is non-empty, the payoff vector is a member of the *Core*. The following proposition is important to make our algorithm tractable.

Proposition 1: A game with a characteristic function v is convex if and only if for all S, T, and i where $S \subseteq T \subseteq N \backslash \{i\}, \forall i \in N$,

$$v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T) \tag{8}$$

Proof: We first prove the "only if" direction:

1. "only if" direction:

Assume:

$$v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T)$$
$$\rightarrow v(S \cup \{i\}) + v(T) \leq v(T \cup \{i\}) + v(S)$$

Considering $S \subseteq T$:

$$S \cup \{i\} = (S \cup \{i\}) \cup T$$
$$T = (S \cup \{i\}) \cap T$$

By setting $A = S \cup \{i\}$ and $B = T$ we have:

$$v(S \cup \{i\}) + v(T) \leq v(T \cup \{i\}) + v(S)$$
$$\rightarrow v(S \cup \{i\}) + v(T) \leq$$
$$v((S \cup \{i\}) \cup T) + v((S \cup \{i\}) \cap T)$$
$$\rightarrow v(A) + v(B) \leq v(A \cup B) + v(A \cap B)$$

Consequently, the game is convex.

2. "if" direction:

Assume the game is convex. Thus, for all $A, B \subset N$, we have:

$$v(A) - v(A \cap B) \leq v(A \cup B) - v(B)$$

By setting $S \cup \{i\} = A$ and $T = B$ where $S \subseteq T$:

$$v(S \cup \{i\}) - v((S \cup \{i\}) \cap T) \leq v(T \cup (S \cup \{i\})) - v(T)$$
$$\rightarrow v(S \cup \{i\}) - v(S) \leq v(T \cup \{i\}) - v(T)$$

□

Thus, in order to keep the characteristic function convex, new web services should have more marginal contribution as the coalition size grows.

Our algorithm works as follows. We have an established community with a master and some member web services already residing in the community. A web service would send a join request to the community. The ideal solution would be analyzing the *core* or *ϵ-core* stability of the group having this new member. As the normal core membership algorithm is computationally intractable, we exploit Proposition 1 and Equation 8 to check the convexity of our game having characteristic function where the new member is added. In the equation, we set C to be our community members (C) before having the new web service. We assign i to the new web service, and then verify the equation for S, setting $S = T/W1$ where $W1$ is the set of all possible subsets of the set N having the size 1. We can relax the equation a bit by adding a constant ϵ to the left side of the equation. We call this method *Depth-1 Convex-Checker* algorithm. If the equation is satisfied for all $W1$, we let the new web service join our community, since the web service will contribute positively enough to make our new community stable. Since only subsets of size 1 are checked, the following Proposition holds.

Proposition 2: The run time complexity of Depth-1 Convex-Checker algorithm is $O(n)$.

By this result, we obtain a significant reduction from $O(2^n)$, which is the complexity of checking all possible subsets of N. In our second method, we use the same algorithm, but this time we set $W2$ to be the set of all possible subsets of size two and one of the community C. We call this method *Depth-2 Convex-Checker* and its run time complexity is still linear:

Proposition 3: The run time complexity of Depth-2 Convex-Checker algorithm is $O(n^2)$.

It is possible to develop an anytime algorithm by continuing the verification of this condition against all subsets of size 3, 4, etc. until the algorithm gets interrupted.

4.2 Web Services and Many Communities

In this scenario, we consider multiple communities managed by multiple master web services, each of which is providing independent request pools (see Figure 3). Identical to the first scenario, master web services form coalitions with web services. We use coalition structure formation methods to partition web services into non-empty disjoint coalition structures. As mentioned in Section 2.4, the used algorithms [15], [14], [16] try to solve key fundamental problems of what coalitions to form, and how to divide the payoffs among the collaborators.

In coalition-formation games, formation of the coalitions is the most important aspect. The solutions focus on maximizing the social welfare. For any coalition structure π, let $v_{cs}(\pi)$ denote the total worth $\sum_{C \in \pi} v(C)$, which represents the *social welfare*. The solution concepts in this area deal with finding the maximum value for the social welfare over all the possible coalition structures π. There are $centralized$ algorithms for this end, but these approaches are generally NP-complete. The reason is that the number of all possible partitions of the set N grows exponentially with the number of players in N, and the centralized algorithms need to iterate through all

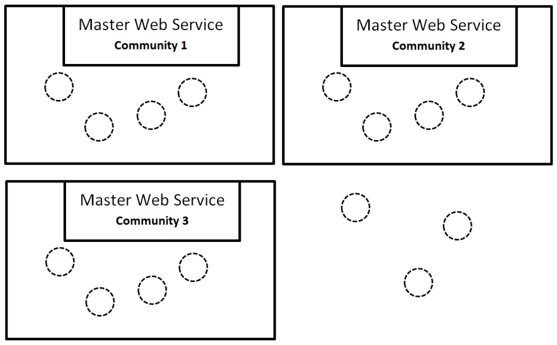


Fig. 3. Web Services and Many Communities

these partitions. In our model, we propose using a distributed algorithm where each community master and web service can be a decision maker and decide for its own good. The aim is to find less complex and distributed algorithms for forming web services coalitions[17], [18], [19]. The distributed merge-and-split algorithm in [17] suits our application very well. It keeps splitting and merging coalitions to partitions which are preferred by all the players inside those coalitions.

This merge-and-split algorithm is designed to be adaptable to different applications. One major ingredient to use such an algorithm is a preference relation or well-defined orders proper for comparing collections of different coalition partitions of the same set of players. Having two partition sets of players, namely $P = P_1, ..., P_k$ and $Q = Q_1, ...Q_l$, one example would be to use the social welfare comparison $\sum_{i=1}^{k} v(P_i) > \sum_{j=1}^{l} v(Q_j)$. For our scenario, we use *Pareto order* comparison, which is an individual-value order appropriate for our self-interest web services. In the Pareto order, an allocation or partition P is preferred over another Q if at least one player improves its payoff in the new allocation and all the other players still maintain their payoff ($p_i \geq q_i$ with at least one element $p_i > q_i$).

The valuation function $v(C)$ for this scenario is the same as *"Web Services and One Community"* scenario. However, in order to prevent master web services joining the same community, we set $v(C) = 0$ when C has either none, or more than one master web service as member.

In this scenario, as new web services are discovered and get ready to join communities, our algorithm keeps merging and splitting partitions based on the preference function. The decision to merge or split is based on the fact that all players must benefit. The new web services will merge with communities if all the players are able to improve their individual payoff, and some web services may split from old communities, if splitting does not decrease the payoff of any web service of the community. According to [20], this sequence of merging and splitting will con-

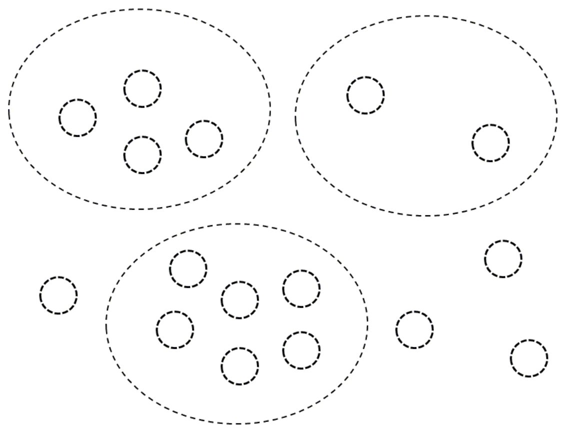


Fig. 4. Web Services collaborating independently

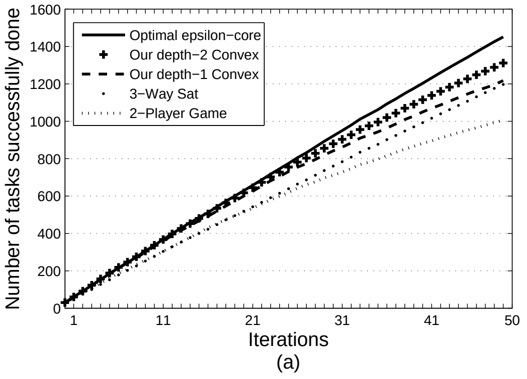
verge to a final partition, where web services cannot improve their payoff. More details of this algorithm and analysis of generic solutions on coalition formation games are described in [17].

4.3 Web Services Collaborating Independently

In this scenario, there is no pre-defined community and web services are interested in forming new ones to perform better and share benefits (see Figure 4). Consequently, there is no master web service providing requests for others, but each web service comes with its own request load called *market share*. Communities can be formed because by working together web services can expect to gain more than working individually. The worth or value of a coalition of web services is different in this setting. Let $metrics$ be the set of quality metrics, we average the values Q^m_{ws} for all quality metrics ($m \in metrics$) for each web service ws, multiply it by a weight reflecting the importance of each metric for each web service (w^m_{ws}) (Note that $\sum_m w^m_{ws} = 1$). For each web service, we multiply this weighted average by web service's market share (μ_{ws}) and the summation over all the web services of the community to be established would be the characteristic or valuation function. This function has the property to be increasing in the market share and QoS.

$$v(C) = \sum_{ws \in C} \left(\frac{\sum_{m \in metrics} Q^m_{ws} \times w^m_{ws}}{|metrics|} \right) \times \mu_{ws} \quad (9)$$

As there is no pre-defined master web services in this scenario, we assume that the members of each coalition either dynamically vote for one, or collaborate and distribute tasks in round robin or fair fashion. To form stable coalitions, we use the same merge-and-split algorithm we applied for the *"Web Services and Many Communities"* scenario.



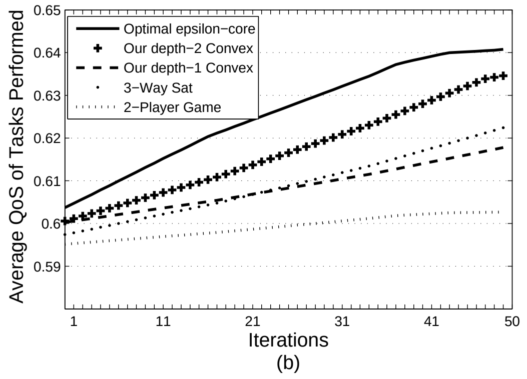


Fig. 5. Part (a): Cumulative number of requests successfully done. Part (b): Average QoS of requests performed.

5 Experimental Results and Analysis

In this section, we discuss the experiments we performed for our scenarios to validate the applicability and performance of our proposed methods in realistic environments. We created a pool of web services and populated most of their *QoS* parameters from a real world web service dataset [10]. We implemented the simulations using Java and executed the simulations on an Intel Xeon X3450 machine with 4GBs of memory. For other parameters missing from the dataset, we used normal random distribution with parameters estimated using the method of maximum likelihood.

One of the key criteria reflecting the performance of web service coalitions is the user satisfaction. User satisfaction can be measured in terms of quality and quantity of requests (or tasks) successfully answered by the communities. We initiate the communities with few web services, then let rejecting and accepting random web services go for a short number of iterations. After that, we start the request distribution for the communities and let them allocate requests among member web services. Thereafter, we measure the average output performance of tasks in communities following different methods.

Figure 5 depicts the results of optimal *ϵ-core*, *Depth-1 Convex-Checker*, *Depth-2 Convex-Checker*, *3-Way Satisfaction* [7], and *2 Player Non-Cooperative* [8] methods in

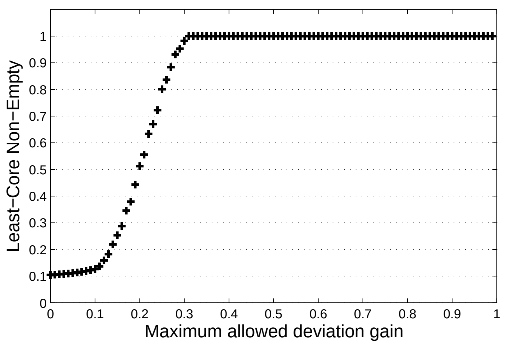


Fig. 6. Analysis of ϵ-*core* set non-emptiness, for different values of ϵ

one grand community with many web services scenario. For ϵ-*core*, we assign ϵ to 15% of total community worth, $\epsilon = 0.15 \times v(C)$, which allows subsets of the coalition to gain maximum 15% of $v(C)$. In the *optimal* ϵ-*core* method, we capped the coalition size to 25 web services, since the method is computationally intractable and anything more than that would make it impractical to run in our simulations. In the other methods, there were no cap on size of the community and we had communities of size 60 web services at some points. The results show that our *depth-2 convex checker* method is performing better compared to the other methods and its performance is close to optimal ϵ-*core* method. Our *depth-1 convex checker* and the *3-Way Satisfaction* method, are also performing well.

As mentioned in Section 2, the concept of *core*, assumes no coalition of players can gain anything by deviating, which is a fairly strong requirement, and that is why the notion of ϵ-*core* was introduced. Least-Core $e(G)$ of a game G, is the minimum amount of ϵ so that the core is not empty. We evaluated the non-emptiness of ϵ-*core* set using the valuation function and a set of web services. We picked random number of web services from the dataset and formed around 10,000 random coalitions consisting of 3 to 26 web services. We choose 26 as the maximum number of members in our coalition since it is computationally very complex for larger coalitions to verify whether ϵ-*core* set is empty or not. Also instead of considering ϵ amount of constant deviation in ϵ-*core* definition (Equation 4), we similarly defined *relative* ϵ-*core* concept where no coalition would benefit more than ϵ $\times$ *v(C)* by deviating. We set ϵ between 0 and 1 and verify the *relative* ϵ-*core* set non-emptiness. The results in Figure 6 illustrates that almost 10% of our random web service coalitions have non-empty *core* solution and ϵ-*core* solution is *always* non-empty when we let agents gain only 30% more of $v(C)$ by deviating.

One of the properties of coalition structure formation algorithms in our third scenario is that they partition web services with low throughput rate so that they usually join coalitions with less request rate.

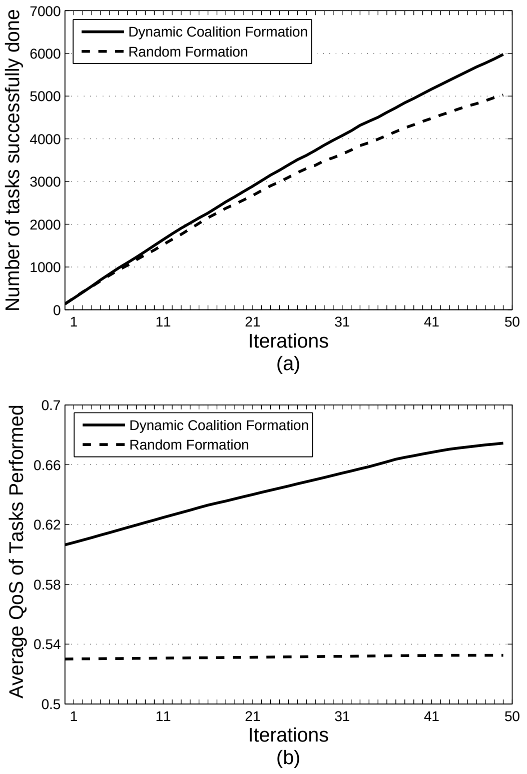


Fig. 7. Part (a): Cumulative number of tasks successfully done. Part (b): Average QoS of tasks performed.

Since the characteristic function $v(C)$ and the fair Shapely payoff vector is proportional to web services' contribution, the web services with small contribution will get paid much less in communities having web services with high throughput. On the other hand, according to the valuation function $v(C)$, web services with high throughput will not contribute well to communities with low amount of user requests (low market share). The strong web services are likely to deviate from weak coalitions, joining a stronger one, which makes the initial coalition unstable.

In Figure 7, we compare our *Web Services and many Communities* scenario with a method which ignores QoS parameters and forms coalitions by allowing web services to join only if they have enough requests for themselves. In other words, web services can join a community when the request rate is less than the throughput of all the member web services. We name this method *Random Formation* and use it as a benchmark for our QoS-aware coalition formation process. As the results illustrate, our method forms better coalitions of web services improving performance and satisfaction for both web services and coalitions.

6 Related Work

Game theory provides a rich set of frameworks and mathematical tools for rational agents seeking to maximise their profit and efficiency through choosing best available streteghies in multi-agent enviroments.

7 Conclusion

In this paper, we proposed a cooperative game theory-based model for the aggregation of web services within communities. The goal of our services is to maximize efficiency by collaborating and forming stable coalitions. Our method considers stability and fairness for all web services within a community and offers an applicable mechanism for membership requests and selection of web services. The ultimate goal is to increase revenue by improving user satisfaction, which comes from the ability to perform more tasks with high quality. Simulation results show that our, polynomial in complexity, approximation algorithms provide web services and community owners with applicable and near-optimal decision making mechanisms.

As future work, we would like to perform more analytical and theoretical analysis on the convexity condition and also minimal ϵ values in ϵ-*core* solution concepts based on the characteristic function in web service applications. From web service perspective, the work can be extended to consider web service compositions where a group of web services having different set of skills cooperate to perform composite tasks. Also bargaining theory from cooperating game theory concepts can be used to help web services resolve the instability and unfairness issues by side payments.

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