MatchCom: Stable Matching-Based Software Services Composition in Cloud Computing Environments

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Abstract. User preferences on throughput, latency, cost, service location, etc. indicate specific requirements when choosing a web service from the cloud marketplace. Service providers can also adopt preferences to prioritize a set of end-users based on their Service Level Agreement and service usage history. An effective matching between preferences from both parties enables fair service marketing in the cloud marketplace. The existing approaches are insufficient in capturing both parties' preferences in the service composition process. To address this limitation, we propose `MatchCom`, a novel service composition approach driven by diverse preferences and formulate it as the stable marriage problem. Particularly, we present a novel fair preference ordering mechanism – in the context of a cloud marketplace, for enabling users to specify services provider ranking based on the capability they can provision, and for helping providers select the most suitable users to be served given users' profile. `MatchCom` extends the Gale-Shapely Algorithm with a service composer algorithm for optimising the stable service composition. We evaluate `MatchCom` on a service-oriented system with 10 abstract services, each of which has 100 candidate web services. We establish through the experimental results that `MatchCom` outperforms other baseline approaches and can maximize end-user satisfaction in the composition process.

Keywords: Service Composition · Quality of Services · Stable Matching

1 Introduction

The shift of industrial IT services to cloud-based service models has made service composition a key driving force for building on-demand service-oriented software

applications by composing multiple existing web services from the cloud marketplace [1]. However, the emergence of multiple functionally equivalent web services with different Quality of Service (QoS) values in the cloud marketplace can present challenges when selecting an optimal web service for composing software applications [2]. Further, it can be challenging when multiple users express different preferences and constraints to get the same service in the cloud marketplace. On the other hand, cloud service providers aim to maintain a positive service reputation while maximizing service revenue [2] [3]. To achieve this, it is important to prioritize users who have long-term business potential based on their Service Level Agreements (SLAs), service usage or other factors. In this context, preferences could be an effective mechanism for creating fair marketing in the cloud marketplace. Users express their preferences on service QoS constraints, service location, service cost, and reputation; and service providers rank the users based on their SLAs and service matches. However, existing research studies [4] [5] [6] have the limitation of supporting only end-user preferences, neglecting service provider's preferences when provisioning suitable web services.

To address these challenges, we present a novel Stable Matching Based Service Composition called `MatchCom` that explicitly captures the end user's and service provider's preferences and optimizes the preference stability-aware service composition. We employ Stable Marriage Problem [7] to model our service composition approach. Our key idea is to capture the end-user's preferences from their SLAs. Further, we use these preferences to rank all similar functionally equivalent web services that exhibit different QoS values. Similarly, the service provider ranks end users based on their SLA types. Then, we apply GSA-based `MatchCom` to find the stable service matches to form the composition solutions.

In a nutshell, the major contributions of this paper are ① we formulate the service composition as a stable marriage problem. ② we model a preference generation scheme for both end users and service providers in the global cloud marketplace. This scheme facilitates finding stable service matches driven by the service provider's and end-user's preferences over each other. ③ we tailor a Gale-Shapley Algorithm (GSA) and present a `serviceComposer` algorithm that tends to maximize the end-user's satisfaction in the composition process. ④ we evaluate `MatchCom` on a service composition system with up to 10 abstract services workflow, each of which has 80 to 100 candidate web services, under different QoS values derived from the real-world WS-DREAM dataset [9].

2 Stable Matching Based Service Composition

The stable marriage problem, introduced by Gale and Shapley in 1962 [7], involves matching two sets of agents, such as men and women. A crucial aspect of this problem is the ordering of preferences, where each man and woman rank each other in a strict order of preference and then a Gale and Shapley algorithm exploits these preferences to generate stable matches. We leverage this approach in our research with a particular focus on the diverse preferences-based service compositions in the global cloud marketplace; where QoS constraints, service budget, service region, and SLA types are considered the most preferred parameters for both entities to establish a strict order of preference over each other.

2.1 Preference Order Modelling

Here, we assume that there are x number of users $U_i, i = (1, 2, 3, ...x)$ and each user requests y number of tasks in the composite software application $U_{ij}, j = (1, 2, 3, ...y)$ with z dimension service constraints (e.g., QoS, Cost, service region/location S^{loc}) $U_{ijk}, k = (1, 2, 3, ...z)$ for choosing a web service in the composition. On the other side, based on functional (e.g., task) and QoS requirements, the service providers offer m set of web services $S_p, p = (1, 2, 3, ...m)$ in the global cloud marketplace and each set contains n candidate web services that are functionally equivalent to perform j^{th} task of user U_{ij}, $S_{pq}, q = (1, 2, 3, ...n)$ and each candidate web service has l dimension QoS values $S_{pqr}, r = (1, 2, 3, ...l)$ and SLAs type provisioned by cloud service providers as part of service delivery. Therefore, a matching model is defined $M(U, S)$, where each user U_i needs to rank all candidate web services in a set S_{pq} for a j^{th} task that satisfies the service location constraint $\mathbb{CL}$; otherwise, underlying candidate web service will be discarded from the ranking process using Eq. 1.

$$(S_{pq}) = \begin{cases} 1 \; if \; \mathbb{CL} = S^{loc}_{pq} \\ 0 \; if \; \text{otherwise} \end{cases} \tag{1}$$

Similarly, the service provider ranks all users U_i based on their SLAs type and service QoS values S_{pqr} legally provisioned in the SLA [2]. Therefore, the preference of j^{th} task of a user U_i over the q^{th} candidate web service S_{pq} is computed by aggregating the preference of each QoS constraint over QoS value exhibited by the candidate web service or vice-versa [4]. Further, we compute the best-case and worst-case values of each QoS objective (e.g., QoS constraint) imposed by a user or offered by the service providers as part of their service delivery. In the case of positive QoS (e.g., throughput) constraints criteria $\mathbb{CQ}^+$, the best case indicates the expected r^{th} QoS value of a web service must be larger than or equal to the required constraint value of k^{th} objective (constraint weight) of a user U_i, otherwise expected objective value consider as the worst-case value for the k^{th} constraint of a user U_i [6]. However, we calculate the exact values for the best-case and worst-case of each QoS objective required by the users over candidate web services. Further, the best-case and worst-case values are multiplied by +1 and -1, respectively, which shows how much the expected value is good or bad for each required objective of the user, as shown in Eq. 2.

$$\mathbb{CQ}^+(S_{pq}) = \begin{cases} \frac{U_{ijk}}{S_{pqr}} \times (-1) \; if S_{pqr} < U_{ijk} \\ \frac{S_{pqr}}{U_{ijk}} \times (+1) \; if S_{pqr} \geq U_{ijk} \end{cases} \tag{2}$$

$$\mathbb{CQ}^-(S_{pq}) = \begin{cases} \frac{S_{pqr}}{U_{ijk}} \times (-1) \; if S_{pqr} > U_{ijk} \\ \frac{U_{ijk}}{S_{pqr}} \times (+1) \; if S_{pqr} \leq U_{ijk} \end{cases} \tag{3}$$

where k indicates the z^{th} constraint weight for the j^{th} task of user U_i.

Similarly, for the negative QoS (e.g., response time) constraints criteria $\mathbb{CQ}^-$, best-case shows the expected objective value should be smaller than the required objective value of a user U_i, other than shows the worst-case value. These values are calculated using Eq. 3.

We generate i^{th} user preference $\mathbb{P}(U_{ij})$ for the j^{th} task over candidate web services by computing the net ranking value using Eq. 4.

$$\mathbb{P}(U_{ijk}) = \Sigma_{r=1}^{l}\mathbb{CQ}^{+}(S_{pqr}) + \Sigma_{r=1}^{l}\mathbb{CQ}^{-}(S_{pqr}) \tag{4}$$

$$\mathbb{P}_{sla}(U_i) = \begin{cases} w_s \; if \; U_i = (sla = Silver) \\ w_g \; if \; U_i = (sla = Gold) \\ w_p \; if \; U_i = (sla = Platinum) \end{cases} \tag{5}$$

$$\mathbb{P}(S_{pqr}) = [\Sigma_{k=1}^{z}\mathbb{CQ}^{+}(U_{ijk}) + \Sigma_{k=1}^{z}\mathbb{CQ}^{-}(U_{ijk})] \times \mathbb{P}_{sla}(U_i) \tag{6}$$

On the other hand, we consider diverse types of SLAs offered by cloud service providers as part of web service delivery in the cloud marketplace. Suppose end-users negotiated different types of SLAs such as silver, gold and platinum with the cloud service providers [11]. In this respect, the cloud service provider gives the highest priority to a user who has platinum SLA rather than gold and silver users SLA, as shown in Eq. 5. For the sake of simplicity, in this work, we give some weight to distinguish each SLA says silver ($w_s = 0.1$), gold ($w_g = 0.3$) and platinum ($w_p = 0.5$). The cloud service provider gives preference over the users U_i based on their SLA types and service QoS provision documented in their SLA. We compute the net ranking over each user service demand using Eq. 6.

2.2 Software Services Composition

After generating the preference matrices PU and PS using Eq. (4) and (6) respectively, Algorithm 1 shows the process of applying the Gale-Shapley Algorithm (GSA) to find the optimal stable match $M(j, q)$ between the j^{th} task of user u_i and q^{th} web service of set s_p. The preference matrices of all users PU and service provider's web services PS are provided as input to the algorithm and initialize all parameters that will be used in the next phase (Lines 5-17). From Lines 5-9, the user u_i selects the most preferred q^{th} web service from the candidate web services set s_p and form the matching $M(u_{ij}, s_{pq})$ if it is not matched with other tasks of user u_i in the PU list. From Lines 10-13, if a j^{th} task of user u_i has already had the match of n^{th} candidate web service in the PS list but j^{th} task prefers to q^{th} web service in the PS list over the current n^{th} web service match. Then, a new optimal match $M(u_{ij}, s_{pq})$ is formed and further, makes the n^{th} web service free in the PS list of candidate web services. However, the j^{th} task of user u_i rejects the q^{th} web service request in the matching process if it already had the higher preference ranking web service match than the preference ranking of q^{th} web service (Lines 14-16). From Lines 5-17, this process is repeated until the first task of all users u_i in PU list assigned the optimal web service from the PS list. After completing the first iteration, the q^{th} web service assigned to the first j^{th} task of all users U are stored in the array matrix C (line 19), and this step is repeated until all users' tasks assigned the set of optimal web services (Lines 4-19).

However, algorithm 1 produced the sets of concrete web services to form the composition solutions for all the users requesting services in the cloud marketplace. Further, C is provided as input to algorithm 2 for performing a next-level

Algorithm 1: matchGenerator(U, PU, PS)

```
1  Input: The set of users U and service provider's web services S. Users
     preferences PU (∀u_ij ∈ PU) and candidate web services PS (∀s_pq ∈ PS)
2  Output: array matrix C
3  Initialization: ∀u_ij ∈ PU and ∀s_pq ∈ PS to be free, M ← ∅
4  for ∀ u_ij ∈ U do
5      while s_pq ∈ PS is free and PS ≠ ∅ do
6          u_ij = j^th task of user u_i highest ranked on q^th web service of set s_p to
             whom q^th has not proposed yet
7          if u_ij is free then
8              assign q^th web service to j^th task of u_i
9              M ← M ∪ (u_ij, s_pq)
10         end
11         else if (u_ij prefers q^th web service over previous assigned n^th web
             service of set s_p) then
12             assign q^th web service to j^th task of u_i
13             M ← M(u_ij, s_pq)
14             assigned n^th web service to be free M ← M/(u_ij, s_pn)
15         end
16         else
17             j^th task of u_ij rejects q^th web service of set s_pq (and q^th remain
                 free)
18         end
19     end
20     C ← M
21 end
22 serviceComposer(C,U)
```

composition process that guarantees to satisfy all constraints imposed by end-users. In line 6, we calculate the aggregated QoS values and cost of all web services in C_i for the user u_i using QoS aggregation methods [11] and then check whether the global constraints are satisfied or not imposed by i^{th} user u_i (line 7). If true, then form the composite service for the user u_i (line 8), otherwise, user u_i rejects the composition plan and demands a new service composition plan, such user IDs are recorded in array u_d. This process is repeated until all web service sets in C are checked (4-11). In line 13, the current users set U is updated with users set u_d who demand the new service composition plans over the current infeasible plan. Further, algorithm 1 is invoked with updated user set U to find the optimal set of web services for the users u_d. The whole process is repeated until users set U to get empty and then return the optimal service compositions plans $u_i(cs)$ for all the users u_i.

3 Performance Evaluation

Our experiments aim to answer the research questions – **RQ1:** Is `MatchCom` approach more stable than the baseline approach?; **RQ2:** How `MatchCom` can outperform other baselines including evolutionary algorithm-based approaches?;

Algorithm 2: serviceComposer(C, U)

```
Input: C and U
Output: service composition matrix u_i(cs)
Initialization: u_i(cs) ← ∅, u_d ← ∅
while U ≠ ∅ do
    for ∀ u_i ∈ U do
        C_global ← checkQoS(u_i, C_i)
        if (C_global satisfy user u_i constraints) then
            u_i(cs) ← C_i
        else
            u_d ← C_i
        end
    end
    U ← u_d
    matchGenerator(U)
end
return u_i(cs)
```

RQ3: What is the running overhead of `MatchCom` compared to other approaches?

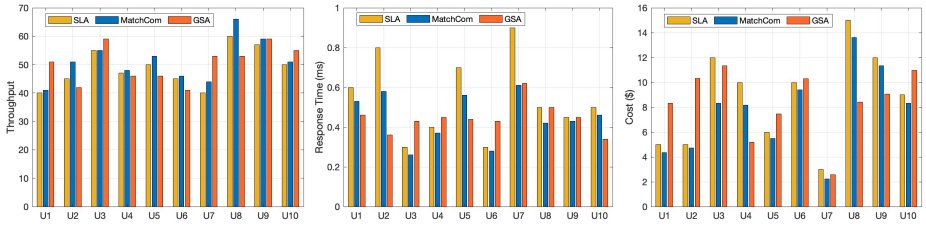
3.1 Experiment Setup

For experiment purposes, we employed a service composition system with 10 abstract services, which are sequentially connected to construct a service composition workflow [8]. Further, we deployed 100 candidate web services to perform each abstract service in the composition workflow. However, each candidate web service exhibits different QoS values, which are randomly picked from the real-world WSDream dataset [9]. Further, the service cost value and service region are generated randomly for each candidate web service participating in the composition. Apart from that, we randomly create end-user service requirements (number of tasks in the service, throughput, response time, service cost, and service region), which are generally documented in the end user's SLA.

3.2 Results and Discussion

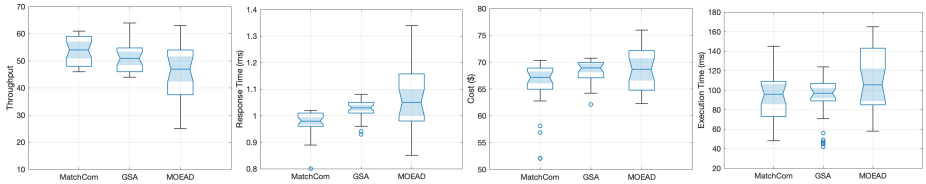
To answer the above RQs, we examine the performance of `MatchCom` against Baseline (GSA) [10] and MOEAD [11] based approaches.

RQ1: SLAs Stability of `MatchCom` against Baseline: To answer RQ1, we plot the service composition plans optimized by `MatchCom` and `GSA` approaches as shown in Fig. 1. In particular, we examine the end-users SLA constraints such as throughput, response time and cost on whether the composed service compositions are satisfied or not. As can be seen from Fig. 1a and 1b, SLA throughput and response time constraints are violated by the composition solutions generated by `GSA` approach for the end-users u_4, and u_6, whereas, `MatchCom` satisfies all users SLA constraints. Further, an interesting insight is shown from a cost



(a) Throughput **(b)** Response Time **(c)** Cost

Fig. 1: Users SLA constraints achieved by `MatchCom` and `GSA` approaches (users = 10, workflow: number of tasks = 10, number of candidate web service for each task = 100).



(a) Throughput **(b)** Response Time **(c)** Cost **(d)** Running Time

Fig. 2: Throughput, Response Time, Cost and Running Time yield by `MatchCom`, `GSA` and `MOEAD` approaches.

perspective as shown in Fig. 1c, GSA satisfies the QoS constraints for the end-user u_{10} but fails to meet the service budget requirement. However, `MatchCom` does not guarantee the higher values of QoS constraints satisfaction but satisfies all constraints under given budget requirements.

RQ2: Performance of `MatchCom`: To investigate RQ2, we assess the performance of `MatchCom` by comparing with baseline and evolutionary algorithm (MOEAD) based approaches. We run all approaches 30 times and record the best QoS value of throughput, response time and cost objectives from the optimal set of service composition solutions generated in each run. As shown in the boxplots of Fig. 2a and Fig. 2b, we see that `MatchCom` achieve much better QoS values for throughput and response time objectives with small variance than `GSA` and `MOEAD` approaches. Also, `GSA` obtains better QoS objectives values than `MOEAD`. Further, as we can see from Fig. 2c, overall `MatchCom` achieves better QoS values with less cost than `GSA` and `MOEAD`. Overall, `MatchCom` outperforms other approaches in achieving a better QoS value for each objective in the composition.

RQ3: Running Time of `MatchCom`: To understand RQ3, we plot the running time of all approaches as shown in Fig. 2d. As we can see `MOEAD` is the slowest due to exploiting a huge search space of X^N (X denotes an abstract service, and $N = 100$ is the number of candidate services to perform X abstract service). However, `GSA` and `MatchCom` take less execution time than `MOEAD` because they reduce the search space by discarding all candidate web services they are unable to satisfy the service region constraints mentioned in the end-user's preferences (constraints). But, `MatchCom` is slower than `GSA` because it favors maximising

the end-user satisfaction in the composition process whereas `GSA` does not care to satisfy all user's constraints, as we have shown in answering RQ1 and RQ2.

4 Conclusions

In this paper, we proposed a stable matching-based service composition approach called `MatchCom` leveraging stable marriage problem. We introduced a novel bilateral preference model that gives equal ownership to service providers and end users for fairly serving and consuming services in cloud marketplace. `MatchCom` service composer can generate fair preference ordering for both service providers and end users. The GSA produces stable service matches which the built-in service composer further uses to optimize the service composition solutions. Experimental results show that `MatchCom` is more effective than baseline approaches and favors to maximize the end-user's satisfaction in the composition.

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