CHAPTER – 4

4 QOS DISCREPANCY IMPACT (QDI) AND COHESION BETWEEN SERVICES (CBS): QOS METRICS FOR ROBUST SERVICE COMPOSITION

4.1 OVERVIEW

Service composition in the service-oriented architecture is a significant activity. In regard to achieve the quality of service and secured operations from the web service compositions, they need to verify their impact towards fault proneness before deploying that service composition. Henceforth, here in this chapter, we devised the set of exploratory metrics, which enables to assess the services by multi-objective QoS factors. These designed explorative measures reconnoiter the higher and lower ranges of the SCFI, which is from the earlier compositions that notify as either fault inclined or hale. The experimental results explored from the empirical study indicating that the devised metrics are significant towards estimating the state of given service composition is fault tending or hale.

4.2 PROLOGUE

Service-Oriented Architecture (SOA) simplifies information technology-related operational tasks by consumption of ready-to-use services. Such SOA found to realize currently in e-commerce domains such as B2B, B2C, C2B, and C2C the web services are one that considered serving under this SOA.

Web services are software components with native functionality that can be operable through the web. Another important factor about this web services is that more than one service can compose as one component by coupled loosely. The standard WSDL is web service descriptive language that let the self-exploration of the web services towards their functionality and UDDI is the registry that allows the devised web services to register and available to required functionality [66].

The composition of web services is the loosely interconnected set of Web service operations that act as a single component, which offers solutions for different tasks of an action. Since the task of the composition is integrating different web services explored through different descriptors, it is the most fault-prone activity. The functionality of service composition includes the activities such as (i) Identify the tasks involved in a given business operation. (ii) Trace related web services to fulfill the need of each task. (iii) Couple these services by exploring the order of that services usage, which is based on the expected information flow. (iv) Resolve the given operation by ordering the responses of the web services that coupled loosely as one component.

To achieve the quality of service and secure transactions in web service composition and usage, the impact of the composition should estimate before deploying those loosely coupled web services as one component.

The Web service compositions used earlier that could find in repositories and the services involved in those compositions helps to assess the impact of these web services towards fault-proneness.

The current composition strategies [67], [48], [49], [68], [17], [18] are error-prone since these State-of-the-art techniques are not mature enough to guarantee the fault-free operations. However, finding these compositions as fault-prone after deployment is functionally costly and not significant towards end level solutions, also may lead to dangerous vulnerable. Hence the process of estimating the composition scope towards fault proneness is mandatory.

4.3 ASSOCIATED WORK

Service compositions with malfunctioned web services lead to form the highly fault-prone compositions. Henceforth the web service composition to serve as one component under SOA is complex and needs research domain attention to deliver effective strategies towards the QoS centric service.

The model devised in [19] defined set of QoS factors to predict available services. Many of existing quality-aware service selection strategies aimed to select the best service among multiple services available. The model devised in [18] considering the linear programming to find the linear combination of availability, successful execution rate, response time, execution cost and reputation, which is regarding find the optimal service composition towards given business operation. The model devised in [68] is considering the temporal validity of the service factors. The authors in [20] modeled a mixed integer linear program that examines both local and global constraints.

The model devised in [17] is selecting services as a complex multi-choice multi-dimension rucksack problem that tends to define different quality levels to the services, which further taken into account towards service selection. All these solutions are depended strongly on the positive scores given by users to each parameter. However, it is not scalable to establish them in prospective order.

Though the QoS strategies defined are used in service composition the factor fault-proneness of the service composition as usual. Regarding this, a model devised in [69] explored a mechanism for fault proliferation and resurgence in dynamically connected service compositions. Dynamically coupled architecture outcomes in further complexness in need of fault proliferation between service groups of a composition accomplished by not depending on other service groups.

In a gist, it can conclude that almost all the benchmarking service quality assessment models are attributed specific, user rating specific or both. Hence importance of attributes is divergent from one composition requirement to other, and contextual factors influence the user ratings, and another crucial factor is all these benchmark models are assessing services based on their performance, but in practice, the functionality of one service may influence by the performance of another service. Henceforth here in this chapter, we devised a statistical approach that estimates the impact scale of service composition towards fault proneness, which is based on a devised metric called composition support of service compositions and service descriptors.

In contrast to all the explored existing models, we devised a statistical assessment strategy in our previous work called Web Service Composition Impact Scale towards Fault Proneness.

4.4 QOS DISCREPANCY IMPACT (qdi) AND COHESION BETWEEN SERVICES (cbs): METRICS FOR SERVICE COMPOSITION

The Dataset opted is of 14 attributes (see Table 4.1) with values of type continue and categorical. The detailed exploration of these attributes given in our earlier article. The dataset opted is of the records, such that each record is of the 14 composition QOS representative attribute values. In regard to facilitate the attribute optimization process devised here in this chapter, the values of the attributes in the given dataset should be numeric and categorical. Henceforth, initially, we convert all continuous values to categorical.

Let us consider an application with set of m tasks and each task t can fulfill with any individual service among available services $S = \{st_1, st_2, ..., st_m \forall st_i = \{s_{i1}, s_{i2}, ...s_{ip}\}\}$

Table 4.1: Description of dataset attributes

Attribute ID	Attribute of Complete Record	Description	Value state of the Attribute
1	Connotation	Services of same provider used for optimality	Ratio against expected
2	Cyclic	Number of services required to be cyclic	Services involved in composition with cyclic behavior
3	Dependent	No of services dependent of others	The count of service in composition dependent of other services
4	Parallel	No of services executes parallel	Count of services in composition with parallel execution
5	Repetitive	No of services invoked repeatedly due to failure	Count of services invoked repeatedly due to response failure

6	Uptime	Average of the services as composition uptime	Average of percentage of services uptime involved in composition
7	Services count	No of services in composition	Total Number of services involved in composition
8	Diversity	No of services of divergent providers or environment	Services that are not of same provider or same environment
9	Roundtrip time	The completion time of the composition	Composition completion time
10	Cost	composition cost	Total cost of the services as composition cost
11	Reliability	response accuracy	Percentage of response accuracy
12	response time	Composition response Time	Average response time of the services involved in composition
13	versioning ratio	Composition versioning count	No of times composition changed due to change of services, removing existing or adding new services
14	Status	Indicates composition is fault inclined or hale	1 represents fault inclined, 0 represents hale

The services in the set $st_i = \{s_1, s_2, s_3, \ldots s_x\}$ are a x number of similar services to resolve the task t_i of given application. Hence the solution to the given application is the composition of the services such that only on service among the x similar services of each task should consider for composition. Thus, the objective of our proposal is which service should select from each set of x similar services.

The selected services toward service composition can influence the QoS. Hence, it is essential to pick optimal services. The meta-heuristic model proposed in this approach is based on the characteristics of services and their composition, which are described as follows:

- A service can rate best in its independent performance. But might fail to deliver some performance as a dependent service during composition.
- A service can rate divergently concerning its various QoS factors. As an example, a service s can be best concerning uptime, but the service might be moderate regarding cost, worst in the context of execution time.
- The importance of the QoS factors might vary from one composition requirement to other.

According to the characteristics of the services described, it is evident that the best ranked independent service is not always optimal towards the composition. But at the same moment verification of the composition with all possible services of the task is also not scalable and robust. The services under a composition that performed well under some prioritized QoS factors always need not be the best fit for service composition under other prioritized QoS factors. Regarding this, the said meta-heuristic model in its first stage, finds the fitness of the independent services, which is based on primary QoS factor opted. This process is labeled as local fitness evaluation of the services. Further services are ranked according to their fitness and will use in the same order to finalize a service towards composition.

4.4.1 Input Data format

Let a set of service level QoS metrics $M = \{m_1, m_2, m_3, m_4, ...m_{|M|}\}$ of each service in the given service set

$S = \{st_1 = \{s_{11}, s_{12}, ...s_{1i}\}, st_2 = \{s_{21}, s_{22}, ...s_{2j}\}, ...st_m = \{s_{m1}, s_{m2}, ...s_{mp}\}\}$.

Let $E = \{e_1, e_2, e_3, ..., e_n \forall [e_i : t_j \to t_{j+1}]\}$ be the set of n edges such that each edge connecting two tasks in composition sequence. Let $CT = \{[t_i, t_j, t_k, ...], [t_x, t_y, t_z, ...], ...\}$ be the set of task-sets such that the connections between tasks of each tasks-set influenced by any of the connection QoS constraint called dependent, parallel, rollback or togetherness. This can be defined as each tasks-set of CT is expecting cohesion between services. The term cohesion can determine under our proposed model as the services used for these tasks should be from the same provider or from the providers mutually agreed to support each other.

4.4.2 QoS Discrepancy Impact

If we consider a QoS metric m_{opt} as the prime metric for ranking the services, then the metrics of QoS of the services could categorize as positive and negative. The positive metrics are those which require higher values and the negative metrics are those which require optimal minimal values.

Henceforth the values of negative and positive metrics are normalized as if the metric m_k is positive then $\nu(m_k) = 1 - \frac{1}{m_k}$ or if negative then $\nu(m_k) = \frac{1}{m_k}$.

Next, for each service set, based on the normalized values of the related services from maximum to minimum the services are given a ranking so that different metrics are given a different ranking for each service. Further, the QoS discrepancy determines by applying this given ranking.

If we consider a rank set of service $[s_j \exists s_j \in st_i \wedge st_i \in S]$ is $rs(s_j) = [r(m_1), r(m_2), ...r(m_n)]$, then for the service we can measure the QoS Discrepancy Impact qdi as below,

$$\mu(s_j) = \left(\frac{\sum_{i=1}^{|M_{s_j}|} r(m_i \exists m_i \in M_{s_j})}{|M_{s_j}|} \right) \qquad \text{(Eq 4.1)}$$

In the above equation, $\mu(s_j)$ depicts the mean of the all the QoS metric ranks of the metrics M_{sj}.

$$\sigma(s_j) = \sqrt{\frac{\sum_{k=1}^{|M_{s_j}|} \left(\mu(s_j) - \{r(m_k) \exists m_k \in M_{s_j}\}\right)^2}{|M_{s_j}|}} \quad \text{(Eq 4.2)}$$

In the above equation $\sigma(s_j)$ is the standard deviation of the QoS metric ranks given to a service s_j.

$$g(s_j) = \frac{\sum_{k=1}^{|M_{s_j}|} \left(\mu(s_j) - \{r(m_k) \exists m_k \in M_{s_j}\}\right)^3 \Big/ |M_{s_j}|}{(\sigma(s_j))^3} \quad \text{(Eq 4.3)}$$

$$g(s_j) = \sqrt{g(s_j) * g(s_j)} \quad \text{(Eq 4.4)}$$

In the above equation $g(s_j)$ represents the skewness [70] related to the QoS metric ranks distributed for service s_j.

The value of skewness may be negative or positive, and close to 0 which denotes that all QoS metrics ranks are nearer, equal to 0 indicates all QoS metrics is having the same rank.

For only positive skewness values, we must determine the square-root of the square of the resultant skewness.

As per ANOVA [71],

- The skewness if is less it denotes that the ranking is uniformly distributed that could be, best, moderate, or worst ranks and not a combination of the three types of ranks.
- The distributed ranks mean denotes the centrality of the distributed ranks
- Standard deviation denotes the deviation of these ranks with respect to each other.
- The less variance between skewness, mean and standard deviation represents the ranks distribution with less skewness, less deviation and moderately average of near ranks.

So, the measurement of the fitness of the service s_j may be done as below,

$$\mu(g(s_j),\mu(s_j),\sigma(s_j)) = \frac{g(s_j)+\mu(s_j)+\sigma(s_j)}{3} \quad \text{(Eq 4.5)}$$

From this equation, the mean $\mu(g(s_j),\mu(s_j),\sigma(s_j))$ of the resulting skewness ($g(s_j)$), mean ($\mu(s_j)$) and standard deviation ($\sigma(s_j)$ of service s_j is measured as below,

$$\sigma^2(g(s_j),\mu(s_j),\sigma(s_j)) = \frac{\begin{bmatrix} (\mu(g(s_j),\mu(s_j),\sigma(s_j)) - g(s_j))^2 + \\ (\mu(g(s_j),\mu(s_j),\sigma(s_j)) - \mu(s_j))^2 + \\ (\mu(g(s_j),\mu(s_j),\sigma(s_j)) - \sigma(s_j))^2 \end{bmatrix}}{3} \quad \text{(Eq 4.6)}$$

$$qdi(s_j) = \frac{1}{\sigma^2(g(s_j),\mu(s_j),\sigma(s_j))+1} \quad \text{(Eq 4.7)}$$

From this equation,

- $qdi(s_j)$ denotes for a service s_j the inverse of the QoS discrepancy Impact.
- σ^2 or resultant variance for a value between 0 and 1 is normalized so that more variance results in more QoS discrepancy impact. Here the inverse results in lower qdi .
- For avoiding the error of divided by zero, we have added 1 to the variance.

4.4.3 Measuring Cohesion Between Services (cbs)

If we consider $C = \{c_1, c_2, c_3, \ldots\ldots, c_z\}$ as a set of all possible compositions that can arrange, For a composition c_i , the cohesion between services (cbs) represents the cohesion in the total number connections (connection created between services offered by the same provider or by the providers with the mutual and official relationship) against the number of total links that need cohesion (see section 4.4.1). So, the measurement of the cohesion between services $cbs(c_i)$ is as below,

$$cbs(c_i) = \left[\sqrt{\frac{(\mu(cbs(c_i), CBSR) - cbs(c_i))^2 + (\mu(cbs(c_i), CBSR) - CBSR)^2}{2}} + 1 \right]^{-1} \quad \text{(Eq 4.8)}$$

In the above equation,

- $CBSR$ denotes the Cohesion count of the number of edges in total between tasks having the cohesion required for the service composition of the target application.
- $cbs(c_i)$ denotes for composition c_i the cohesion between the services and its measurement is done with normalization of the standard deviation obtained from $cbs(c_i)$ and $CBSR$ to $0 \le cbs(c_i) \le 1$
- The resultant standard difference increased by 1 with which the error, divide by zero, is avoided.
- $\mu(cbs(c_i), CBSR)$ denotes the mean of the $cbs(c_i)$ and $CBSR$

4.4.4 Measuring qdi of the Composition

Next, for a composition c_i, the overall composition fitness measurement can be done as below,

First, for a services composition, the services are measured for the mean of fitness values as below,

$$\mu(c_i) = \frac{\sum_{j=1}^{|c_i|} \{qdi(s_j) \forall s_j \in c_i\}}{|c_i|} \qquad \text{(Eq 4.9)}$$

Where $\mu(c_i)$ denotes the mean of the inverse of QoS discrepancy Impact related to the services comprising a composition c_i

Next, for a service composition the services are measured for the standard deviation of the Inverse of the QoS discrepancy Impact as below,

$$\sigma(c_i) = \sqrt{\frac{\sum_{k=1}^{|c_i|} \left(\mu(c_i) - \{qdi(s_k) \exists s_k \in c_i\}\right)^2}{|c_i|}} \qquad \text{(Eq 4.10)}$$

Where $\sigma(c_i)$ denotes the standard deviation of the fitness distributed across the services comprising of a composition c_i

Then for a services composition, the services are measured for the skewness of the $\overline{qdi}$ (inverse of the qdi)

$$g(c_i) = \frac{\sum_{k=1}^{|c_i|} \left(\mu(c_i) - \{\overline{qdi}(s_k) \exists s_k \in c_i\} \right)^3 \Big/ |c_i|}{(\sigma(c_i))^3} \qquad \text{(Eq 4.11)}$$

$$g(c_i) = \sqrt{g(c_i) * g(c_i)} \qquad \text{(Eq 4.12)}$$

Where $g(c_i)$ denotes the skewness seen across the fitness distributed over services comprising a composition c_i

Next, in a service composition the services, variance of the mean, standard deviation, and skewness of the fitness values are measured as below,

$$\sigma^2(g(c_i), \mu(c_i), \sigma(c_i)) = \frac{\begin{bmatrix} (\mu(g(c_i), \mu(c_i), \sigma(c_i)) - g(c_j))^2 + \\ (\mu(g(c_i), \mu(c_i), \sigma(c_i)) - \mu(c_j))^2 + \\ (\mu(g(c_i), \mu(c_i), \sigma(c_i)) - \sigma(c_j))^2 \end{bmatrix}}{3} \qquad \text{(Eq 4.13)}$$

Where σ^2 denotes the variance between $g(c_i)$, $\mu(c_i)$ and $\sigma(c_i)$

Finally, the difference divides 1, resulting in the composition QoS Discrepancy Impact $qdi(c_i)$ (difference and qdi are proportionate), as below,

$$qdi(c_i) = \sigma^2(g(c_i), \mu(c_i), \sigma(c_i)) \qquad \text{(Eq 4.14)}$$

$$\overline{qdi}(c_i) = [qdi(c_i) + 1]^{-1} \qquad \text{(Eq 4.15)}$$

Where the ‘ $qdi(c_i)$ ’ is increased by 1 for avoiding the error of divide by zero.

4.4.5 Ordering resultant compositions by composition aptness value and connotation aptness value

The resultant compositions sequentially order by their values of an inverse of QoS Discrepancy Impact $\overline{qdi}$ in the order of max to min. Then the best compositions, i.e., "max best service compositions ($cbest$)" are selected. These $cbest$ compositions are ordered considering their cohesion in between the services cbs in the order of max to min. Finally, from the ordered $cbest$ compositions the "final best compositions" ($fbest$) are selected.

4.5 EXPERIMENTS AND RESULTS EXPLORATION

The model devised is analyzed for its performance with a dataset created to represent the tasks coupling requirements and the QoS factors different priority requirements. Table 4.2 explores the dataset applied in the performance assessment of the devised approach. The parameter of dependency scope of the services composition, requires the metric coupling between services (cbs) assessment. The significance of the different prioritization of the factors of QoS is highly relevant the service quality discrepancy impact (qdi) measurement. In service selection, the metrics, cbs, qdi are applied in sequentially arranging the services. The services of a diverse set lying in the range of 70 to 250 are used in the experiments. The expression language known as R is used in performing statistical analysis based on an explorative approach, the devised model performance analysis assessment is done using computational metrics known as time complexity, and time is taken for task completion. The devised models' scalability and robustness also estimate with the additional performance assessment metric, optimal service selection for composition. In this context, this model designed by us is contrasted with another two models called GRASP [51] and Greedy [48] which uses the strategies of assessment same as the model devised by us.

Table 4.2: The Data used for experiments

Number of tasks	450
Range of tasks to be scheduled	70-250
Range of dependency scope	5-75

The results of the experiment performed show the proposed model is efficient regarding scalability and robustness, according to the performance metrics, time complexity (see Figure 4.1), service composition completion time (see Figure 4.2), and the composed services task completion time (see Figure 4.3). The inferences from the Figure 4.1 show, in contrast to the GRASP and Greedy models our devised explorative statistical analysis model towards a ratio of 100 services the time factor involved is low and stable. As depicted in Figure 4.2, the designed model compared to the remaining models of benchmark shows optimal scheduling completion time in the range of tasks from 70 to 250. The estimation of the selection of an optimal service for the composition is done towards task completion time considering a ratio of 100 tasks composition. In Figure 4.3, the devised model for explorative statistical analysis is contrasted with GRASP and Greedy techniques for investigating scalable and robust factors.

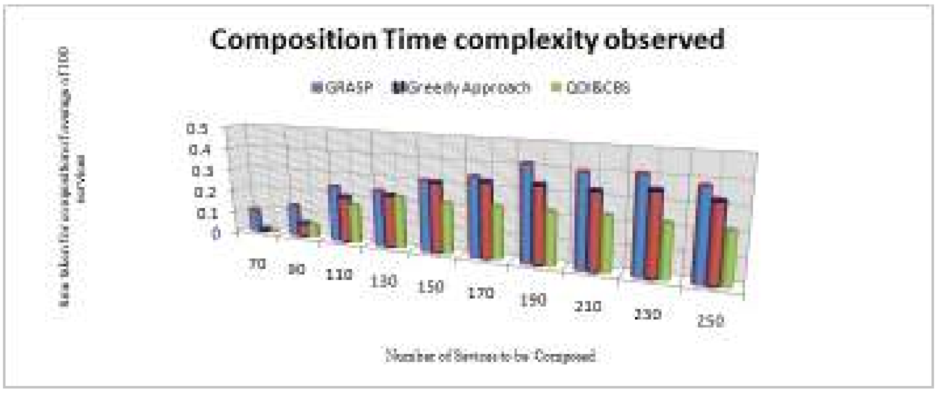

Figure 4.1: Time complexity observed to compose an average of 100 services

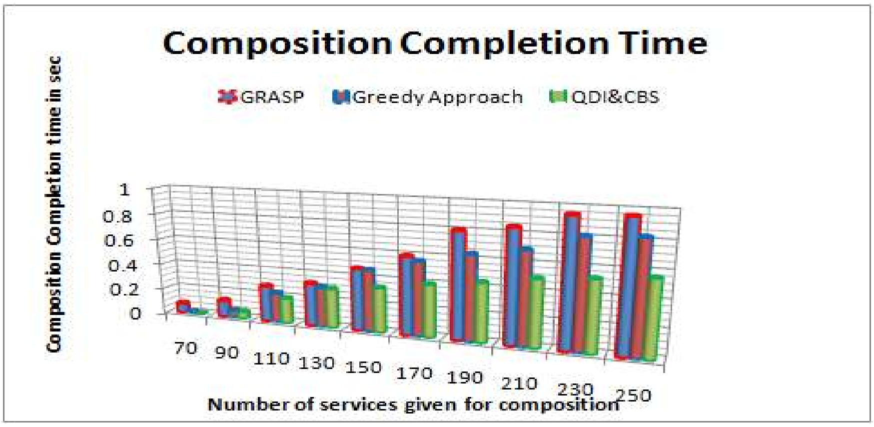

Figure 4.2: Composition completion time observed

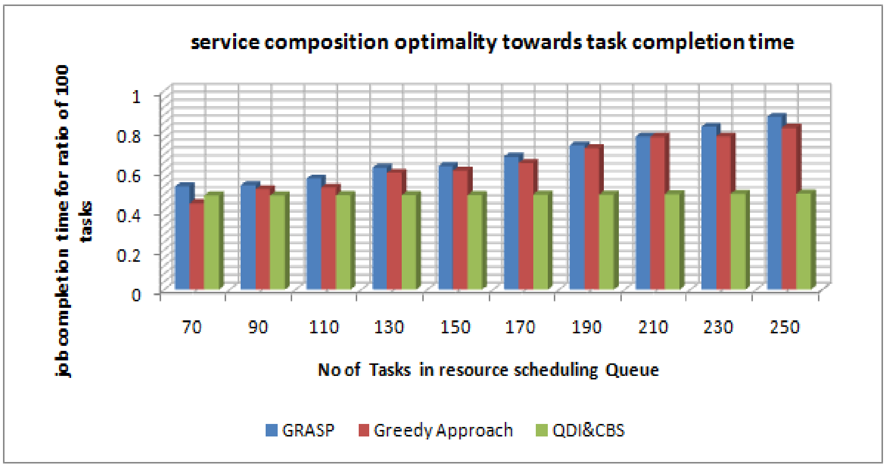

Figure 4.3: Optimal resource utilization Observed

We can infer a growth of 1.1% and 0.65% respectively in Average Scheduling time complexity respectively with GRASP and Greedy techniques, in contrast to our devised QDI&CBS. An increase of 2% and 1.2% in the Task Scheduling completion time respectively is seen with GRASP and Greedy techniques in comparison to QDI&CBS.

4.6 CHAPTER SUMMARY

We have devised in this chapter a meta-heuristic model for providing recommendations towards a QoS aware web service composition. In contrast to the remaining models of the benchmark, the model devised is not limited to a single or just two QoS factors specifically. Our approach devised help in selecting services based on a diverse range of QoS factors combination and combinations prioritization with the support of an important composition factor. The services of optimal requirements for a composition may select with the help of one of the devised metric, QoS Discrepancy Impact which overcomes the verification procedure for each available service towards the specified task applicability in a service composition. The services are assessed and ordered, and the applicability of a service is determined based on the metric value associated with a service. Also, the composition initiator involves those services only which have QoS Discrepancy Impact as per the given threshold values. This ability of the devised strategy considerably overcomes the difficulty associated with other prevailing models. The metric coupling between services is another metric which has the significant role in reducing the complexity of the computing involved in finishing the task. The result achieved is possible with the strategy developed by us which uses the global fitness scale, with which in a service composition a selected service is assessed for its task compatibility based on the best QoS Discrepancy Impact. In case a service fails to qualify the fitness requirements then the next service associated with the task having best QoS Discrepancy Impact is verified for the service composition. In majority of the tasks, the service having best QoS Discrepancy Impact meets the global fitness scale requirements. So, there is a very less requirement for verification of multiple services combinations in the service composition. The outcomes of the experiments are remarkable which show the significance of the devised approach. Also, the scope of future research in various directions is shown possible with the experimental outcomes of the designed procedures. A possible direction for future research is the estimation of the correlation between QoS factors for the assessment of QoS Discrepancy Impact and in a similar way assessment of the correlation between services for determining the Coupling between Services. Another possible research topic that could be our next possible direction of research is applying fuzzy logic in the assessment of the QoS Discrepancy Impact metric.