A Penalty-Based Approach for QoS Dissatisfaction Using Fuzzy Rules

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Abstract. Quality of Service (QoS) guarantees are commonly defined in Service Level Agreements (SLAs) between provider and consumer of services. Such guarantees are often violated due to various reasons. QoS violation requires a service adaptation and penalties have to be associated when promises are not met. However, there is a lack of research in defining and assessing penalties according to the degree of violation. In this paper, we provide an approach based on fuzzy logic for modelling and measuring penalties with respect to the extent of QoS violation. Penalties are assigned by means of fuzzy rules.

Keywords: QoS, service level agreement, penalty, fuzzy logic.

1 Introduction

QoS guarantees defined in contracts may be violated due to various reasons. This situation needs to be handled through applying adaptation techniques not to bring dissatisfaction. The concept of penalty has been used in SLAs to compensate the conditions under which guarantee terms are not met [1]. Despite some research have been done on the description, negotiation and monitoring of SLAs, however there is not much work on the definition of penalty clauses. [4] studied on WS-Agreement specification to define penalties based on different types of violation. However, penalties are assigned to violation of a single property instead of assigning penalties to violation of overall QoS. Moreover, the approach introduces a method for measuring penalties which is for fixed predefined number of violations, instead of measuring the extent of violation and assigning penalties accordingly.

One main issue is how to determine the appropriate amount of penalties as compensations from providers to satisfy customers. As quality parameters can be satisfied partially, the assessment of penalties can be based on the degree of quality violation. Understanding the violation degree is a prerequisite for assessing penalties. However, measuring such violation is yet an open research challenge. In addition, the influencing factors in defining penalties need to be identified. A static amount of penalty (manual approaches) does not reflect the extent of violation at runtime. The amount and level of penalties are related to the degree of quality violation provided from the provider side. On the other side, the customers characteristics may also affect the amount of penalties. For

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example a penalty to satisfy a gold/loyal customer is different with the one for an occasional customer. To the best of our knowledge, there is no formal relation between the assigned penalty and its influencing factors. Moreover, the extent and type of penalties are not clearly expressed in related work. However, understanding such relation and providing a mapping between them are complicated issues. We argue what is missing is a suitable mechanism for modelling penalties that takes into account both provider and consumer sides. Apart from the degree of violation, we also consider the state of customer and service provider with respect to their past history (e.g. whether the service has been penalised previously) in determining the right amount of penalties. However, as the relation between a given penalty and its influencing factors is not linear, conventional mathematical techniques are not applicable for modelling penalties.

Recent approaches are dealing with the issue of partial satisfaction for quality commitments and different techniques were used such as applying soft constraint [6], fuzzy sets [3] and semantic policies [2]. Among them, [6] introduced the concept of penalties for unmet requirements. However, defining penalties and finding a relation between the assigned penalties and the violated guarantees are remained challenges in similar approaches. The goal of this paper is to apply an inference technique using fuzzy logic as a solution [5] to propose a penalty-based approach for compensating conditions in which quality guarantees are not respected. Fuzzy logic is well suited for describing QoS and measuring quality parameters [3]. We demonstrate a penalty inference model with a rule-based mechanism applying fuzzy set theory. Measuring an appropriate value for penalties with respect to the amount of violation is the main contribution of the paper.

In the following, we start by a motivating example in Section 2. In Section 3 we show the descriptions of penalties and in Section 4 we provide a rule-based system using fuzzy set theory for modelling and reasoning penalties. Section 5 shows some experiments in applying penalty for the problem of QoS dissatisfaction and we conclude the paper in Section 6.

2 Motivating Example

Let's assume that a user is wishing to use a food delivery service. Therefore, a contract is established between the user and the service provider. The contract defines non functional criteria such as delivery time, quality of the perceived service (the quality of food during the delivery service, for example the food is maintained at the ideal temperature), and availability of the delivery service. Therefore we define a list of parameters for our example as follows: time to delivery (t_d), quality of delivered food (q_d), availability of delivery service (a_d). These quality parameters together with a list of penalty terms are defined in a contract and illustrated in Table 1.

The delivery service will be penalized if it is not able to provide the quality ranges defined in the contract. An overall QoS violation will be calculated first and afterwards a penalty is assigned with respect to the extent of the violation.

Table 1. Motivating example

Quality Parameters	time to delivery quality of delivered food availability	between 10 to 15 min between 0.8 to 1 between 90 to 100% of the time
Penalties:	Minor or Null penalties Penalties on quality parameters Extra Service penalties Termination penalty	

We also take into account customer and provider perspectives by considering parameters from both parties. Parameters such as history of a delivery service and state of a customer can be involved. The history of a service shows whether the service is penalized previously. This can influence the amount of given penalties for future. The current state of a customer presents the importance of the customer for service provider. For example, minor violation of service delivery can cause a major penalty for provider in case the customer is gold (with good history). In contrast, a normal customer (with ordinary history) will not be given any extra service if the quality of delivered food is not good.

3 Definition of Penalties

In order to provide a formal model of penalties and build a reasoning mechanism to handle the penalties in the contract, in the following we try to summarize the different types of penalties that can be applied. We categorize the penalties into two main classes:

1. **Numerical penalties:** They are related to measurable qualities of service. In other words, we have to handle and work with variables of the service (e.g *the availability* > 0.9, the *responsetime* $< 0.2ms$).

2. **Behavioural penalties:** They are related to the behaviour of either the customer or the service provider. Consider the following case: a merchant wishes to obtain a service for online payment by bank card. The financial institution offered a 25% off if the settlement proceeds within two days of the request. Beyond these two days, the penalty is such as the trader does not have the discount and will therefore be required to pay all fees.

A penalty clause in an SLA may be of the following types:

- Penalty Null and denoted by P_0: no penalty is triggered because all agreed QoS are satisfied or minor violation has occurred.
- Penalty on the QoS: a penalty should be triggered on one of the QoS parameters Q_j in the contract if Q_i is not fulfilled.
- Penalty on the penalty: a new penalty P_j should be triggered if the previous one P_i is unfulfilled. Such penalty will be handled through the long term contract validation. The reasoning on the time aspect of the contract is out of the scope of the paper.

- Extra service penalty: if a QoS is not fulfilled by the service provider, to penalize him, an extra service might be offered to the customer.
- Cancellation penalty: this is a dead penalty for the service provider. A service substitution occurs.

4 Modelling Penalties

We present a fuzzy model to express penalties in a rule-base system. Our fuzzy penalty model is defined by the couple $FP =< \mathcal{S}, \mathcal{R} >$, where $\mathcal{S}$ is a fuzzy set on penalties and $\mathcal{R}$ is a set of inference rules.

4.1 Fuzzy Sets for Penalties

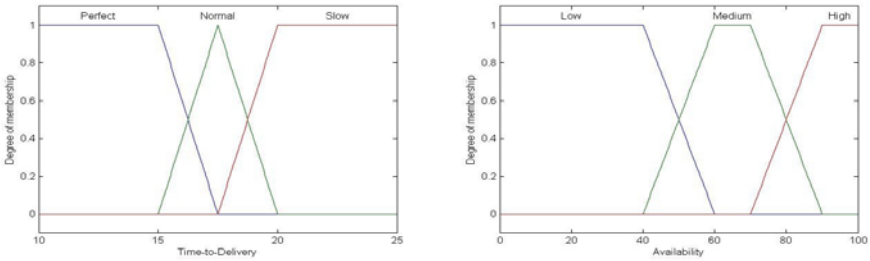
Our knowledge system includes linguistic variables defined by tuple $(\mathcal{Q}, \mathcal{C}, \mathcal{H}, \mathcal{P})$, where $\mathcal{Q}$ is a set of QoS parameters defined by fuzzy parameters as $\mathcal{Q} = \{t_d, q_d, a_d\}$ where t_d is the time to delivery, q_d is the quality of the delivered service and a_d is the availability of the delivery service. $\mathcal{C}$ is the current state of the customer, $\mathcal{H}$ is the history of the service to show whether the service is penalized previously and $\mathcal{P}$ is the set of penalties. We define these linguistic variables by fuzzy sets in the following.

The linguistic parameter of customer is defined by three fuzzy sets as in $\mathcal{C} = \{Normal, Silver, Gold\}$. We define two fuzzy sets to represent the state of service with respect to previous penalties as in $\mathcal{H} = \{Penalized, Not - penalized\}$. Finally penalties are described by five fuzzy sets to show the diverse range of penalties as in $\mathcal{P} = \{Null, Minor, Average, Major, Termination\}$, where *null* is no penalty, and *termination* is the situation in which the customer will terminate his contract with the delivery service. A fuzzy set represents the degree to which an element belongs to a set and it is characterized by membership function $\mu_{\tilde{A}}(x) : X \mapsto [0, 1]$. A fuzzy set $\tilde{A}$ in X is defined as a set of ordered pairs

$$\tilde{A} = \{(x, \mu_{\tilde{A}}(x)) \mid x \in X, \mu_{\tilde{A}}(x) \in [0, 1]\} \tag{1}$$

where $\mu_{\tilde{A}}(x)$ is the membership function of x in $\tilde{A}$. Therefore, a membership function shows the degree of affiliation of each parameter by mapping its values to a membership value between 0 and 1.

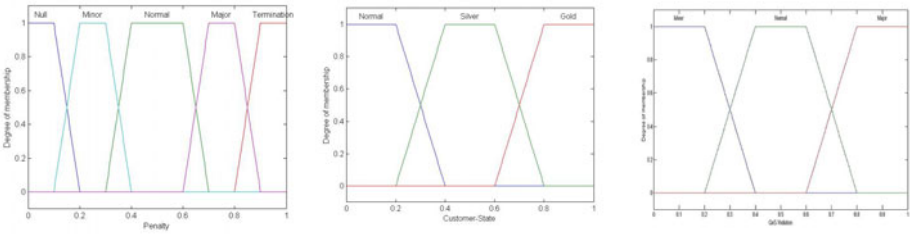
We associate membership functions to a given fuzzy set to define the appropriate membership value of linguistic variables. We start by providing membership functions for quality parameters from the motivating example. We take an approach that calculate an overall degree of violation with respect to the violation of each quality parameters. This way, we perform a trade-off mechanism and quality parameters are not treated independently. For each quality parameter a membership function is provided to show the degree of their satisfaction. We define three linguistic variables for each parameters such that t_d belongs to the set $\{Slow, Normal, Perfect\}$ and q_d is in the set $\{Unacceptable, Bad, Good\}$ and a_d is in the set $\{Low, Medium, High\}$. Figure 1 depicts the membership



(a) Time-to-Delivery membership function (b) Availability membership function

Fig. 1. Membership function for quality parameters

functions of time to delivery (a) and service availability (b). The functions are defined according to the contract and by an expert of the system. For example, the time to delivery between 10 to 15 min is *perfect*, between 15 to 20 min is *good* and more than 20 min is *slow*. Membership functions of penalty and customer state are shown in Figure 2 in (2a) and (2b) respectively.



(a) Penalty mf (b) Customer-state mf (c) QoS-violation mf

Fig. 2. Membership function for penalty ,state of the customer and QoS violation

4.2 Inference Rules on Penalties

The inference rules to trigger penalties are expressed as follows:

- $R_{\mathcal{Q}}$: QoS-based penalty rules. These are rules that reflect the violation of quality parameters. Penalties will be applied to a service if QoS guarantees stipulated in SLA are not fulfilled. It will be presented formally by $R_{\mathcal{Q}}$: $\mathcal{Q} \rightarrow \mathcal{P}$.

  For instance, in the SLA, the delivery service agreed with the customer: $10mns \leq delivery\ time \leq 15mns$ and *good* quality of delivered food. If the QoS delivery time is not fulfilled (partially), then penalty p_{e1} (e.g. 10% discount) will be applied. Depending on the severity of the violation a *harder* penalty might be applied. For example, if both QoS are not fulfilled then penalty p_{e2} (e.g. 20% discount) will be applied. The fuzzy inference system gives us such degrees for penalties. Both cases are presented respectively below by rules:

- R1 $(t_d = Slow) \wedge (q_d = Good) \rightarrow p_{e1}$
- R2 $(t_d = Slow) \wedge (q_d = Bad) \rightarrow p_{e2}$

– $R_{\mathcal{P}}$: penalty on penalty rules. These rules reflect whether the service was given a penalty. If a service was penalized previously and again does not fulfil a QoS, then a penalty will be *harder*. It will be presented formally by $R_{\mathcal{P}} : \mathcal{Q} \times \mathcal{P} \rightarrow \mathcal{P}$ such that $R_{\mathcal{P}}(q, p_1) = p_2 \Rightarrow p_1 \prec p_2$.
For instance, let us consider a service having a penalty p_{e1} w.r.t rule $R1$ and again provides a slow delivery time, then the penalty p_{e3} (e.g. 10% discount plus free delivery) will be applied. The rule can be presented as below:
  - R3 $(t_d = Slow) \wedge p_{e1} \rightarrow p_{e3}$

– $R_{\mathcal{C}}$: customer-related penalty rules. The rules defined here will be adapted according to a customer qualification. Such rules will be presented formally by $R_{\mathcal{C}} : \mathcal{Q} \times \mathcal{P} \times \mathcal{C} \rightarrow \mathcal{P}$.
For instance, if the provided QoS is not fulfilled knowing that a penalty is assigned to the service, and if a customer is gold (has a good history), then extra service penalty p_{e4} (giving some extra service to the gold customer e.g. one movie ticket) will be harder than the one applied for normal customer p_{e3}. The rules can be presented as below:
  - R4 $(t_d = Slow) \wedge p_{e1} \wedge (C = Normal) \rightarrow p_{e3}$
  - R5 $(t_d = Slow) \wedge p_{e1} \wedge (C = Gold) \rightarrow p_{e4}$

5 Experiments and Implementation

We have simulated our approach in a simulator based on fuzzy inference system. Initial membership functions were designed based on the contract in the motivating example and fuzzy rules are defined by the expert of the system. Figure 2c illustrates membership function for QoS violation (see [3] for further details). Having defined the QoS violation, we measure the extent of penalties taken into account the state of customers and previously applied penalties for the same service. For this, fuzzy rules are defined considering all three influencing factors. Figure 3 depicts fuzzy rules for penalty based on QoS violations, customer's state and service status with respect to previous penalties which are defined by the *service-state* parameter represented by fuzzy set $\{Penalized, Not-penalized\}$.

For example rule no. 8 shows that a major penalty will be given to a silver customer if major violation occurs from defined QoS, while rule no. 7 will give a normal penalty (has lesser effect than major penalties) to the normal customer when the same amount of violation happens. The role of service-state can be seen in the rule, e.g. by comparing the rule no. 5 with the rule no. 14. In general, a harder penalty will be given to the service which is already penalized from the provider side.

The inference system calculates the degree of penalty by applying all the rules in a parallel approach for given input values of influencing factors. For example assume a QoS violation of 0.7 which has a membership degree of 0.5 for both

5. If (QoS-Violation is Average) and (Customer-State is Silver) and (Service-State is Not-penalized) then (Penalty is Normal) (1)
6. If (QoS-Violation is Average) and (Customer-State is Gold) and (Service-State is Not-penalized) then (Penalty is Major) (1)
7. If (QoS-Violation is Major) and (Customer-State is Normal) and (Service-State is Not-penalized) then (Penalty is Normal) (1)
8. If (QoS-Violation is Major) and (Customer-State is Silver) and (Service-State is Not-penalized) then (Penalty is Major) (1)
9. If (QoS-Violation is Major) and (Customer-State is Gold) and (Service-State is Not-penalized) then (Penalty is Termination) (1)
10. If (QoS-Violation is Minor) and (Customer-State is Normal) and (Service-State is Penalized) then (Penalty is Minor) (1)
11. If (QoS-Violation is Minor) and (Customer-State is Silver) and (Service-State is Penalized) then (Penalty is Normal) (1)
12. If (QoS-Violation is Minor) and (Customer-State is Gold) and (Service-State is Penalized) then (Penalty is Major) (1)
13. If (QoS-Violation is Average) and (Customer-State is Normal) and (Service-State is Penalized) then (Penalty is Normal) (1)
14. If (QoS-Violation is Average) and (Customer-State is Silver) and (Service-State is Penalized) then (Penalty is Major) (1)
15. If (QoS-Violation is Average) and (Customer-State is Gold) and (Service-State is Penalized) then (Penalty is Termination) (1)
16. If (QoS-Violation is Major) and (Customer-State is Normal) and (Service-State is Penalized) then (Penalty is Major) (1)
17. If (QoS-Violation is Major) and (Customer-State is Silver) and (Service-State is Penalized) then (Penalty is Termination) (1)
18. If (QoS-Violation is Major) and (Customer-State is Gold) and (Service-State is Penalized) then (Penalty is Termination) (1)

Fig. 3. Fuzzy rules for penalty based on QoS violations, customer's state and previous penalties on the service

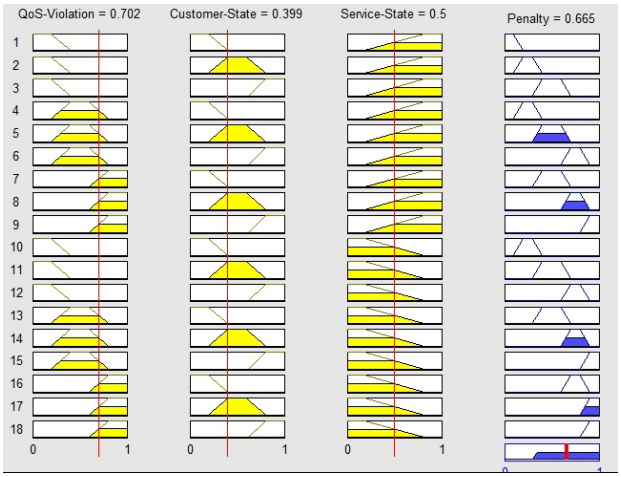


Fig. 4. A view of the inference system for applying penalties

normal and *major* fuzzy sets (according to their membership functions presented in the figure 2c). Such a violation, can trigger all the rules that include normal and major QoS violations. Note that the result of each rule depends on the membership degrees of other linguistic variable. For this example, rules with *minor* QoS-violation are not triggered at all. This situation is demonstrated in Figure 4. The result of each rule is integrated with an aggregation method to include the effect of all the rules. Figure 5 depicts a plot showing the penalties regarding QoS violation and customer's state. The figure represents possible values for penalties after defuzzification for all values of QoS violation and customer's state. For example, for the QoS violation of 0.7 and customer-state of 0.4 the penalty degree is 0.66 which is shown in the figure. The relation between QoS violation and customer's state can also be seen in the figure.

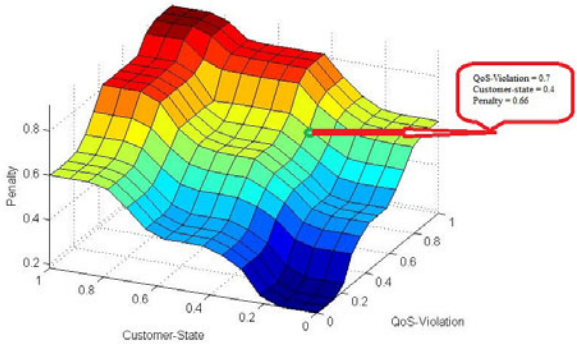


Fig. 5. The plot showing the penalties regarding QoS violation and customer's state

6 Conclusions and Future Work

Applying penalties is a complex research issue in service oriented computing which has not been paid enough attention in the literature. In this work, we elaborated the concept of penalty and propose a mechanism for modelling and measuring penalties. Penalties are modelled using a fuzzy approach and applying fuzzy set theory. The relation between penalties and their influencing factor are defined by fuzzy rules through an inference method. We have demonstrated the proposed penalty model through a motivating example and performed some initial result in measuring penalties.

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