Retailer Selection in Future Open Competitive Communications Environments[1]

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Abstract: The highly competitive communications markets of the future should encompass mechanisms for enabling users to find and associate with the most appropriate retailers, i.e., those offering at a certain time period, adequate quality services in a cost efficient manner. This paper presents such mechanisms. Our starting point is the definition of a business case, through which the role of the best candidate-retailer selection problem is explained. In the sequel, the problem is analysed and the identified sub-problems are concisely defined, mathematically formulated and solved. The identified components of the best candidate-retailer selection problem are targeted to the evaluation of the quality of a retailer offer and the reduction of the set of candidate retailers by exploiting *learning from experience* notions. At the final sections results are provided and concluding remarks are made.

Keywords: Retailer, Service architecture, TINA, 0-1 linear programming, Learning from experience

1. INTRODUCTION

The ongoing liberalisation and deregulation of telecommunications will introduce several actors in the respective market of the future [1,2,3,4]. In principle, the main role of all the players in such a competitive environment will be to constantly monitor the user demand, and in response to create, promote and provide the desired services and service features. The following are some key factors for success. First, the efficiency with which services will be developed. Second, the quality level, in relation with the corresponding cost, of new services. Third, the efficiency with which the services will be operated (controlled, maintained, administered, etc.).

The challenges outlined above have brought to the foreground several new important research areas. Some of them are the definition of new business models [3,4], the specification of service architectures (SAs) [5,6,7,8,9,10,11], the development of advanced service creation environments (SCEs) [12,13,14,15,16] and service features (e.g., the personal mobility concept [6,17,18,19]), and the exploitation of advanced software technologies, e.g. distributed object computing [20,21] and intelligent mobile agents [22,23,24,25]. The aim of this paper is, in accordance with the cost-effective QoS provision and the efficient service operation objectives, to propose enhancements to the sophistication of the functionality that can be offered by legacy service architectures.

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A typical view of the competitive telecommunications world of the future can be the one depicted in figure 1. Without being exhaustive four main different entities can be identified, namely, the *user*, *retailer*, (*3rd party*) *service* (or *content*) *provider*, and *connectivity provider*. The role of the (3rd party) service (content) provider is to develop and offer service (content). The role of the retailer is to provide the means (services) through which the users will be enabled to access the (services - content offered by the 3rd party) service (content) providers. Limited by techno-economic or administrative reasons each retailer offers services only inside a domain. Moreover, it can be envisaged that an arbitrary area will, in general, fall within the domain of several retailers (figure 2). Finally, the role of a connectivity provider is to offer the network connections necessary for supporting the services.

Such highly competitive and open environments should encompass mechanisms that will enable users to obtain services through the most appropriate retailers, i.e., those offering, at a given period of time, adequate quality services in a cost efficient manner. In this paper the relevant problem is called *best candidate retailer selection*. The aim of this paper is (primarily) to address this problem from a theoretical perspective and (secondarily) to show how the solution can be incorporated in legacy service architectures. Even though our reference service architecture will be the one specified by the Telecommunications Information Networking Architecture Consortium (TINA-C) [3,7,8,9,26,27,28] the presented practices can be applied to other models as well.

Our approach is the following. The starting point is the presentation of a target *business case*. In general, a business case can be seen as a scenario that should be supported in an open competitive communications environment. Its contribution will be to enable the clarification of the role of the best, candidate retailer selection problem, and to provide information on the manner in which the proposed solution can be integrated in legacy service architectures. In the sequel, the problem will be analysed and the identified sub-problems will be concisely defined, mathematically formulated, and solved.

In its more general version the best, candidate retailer selection problem can be described as follows. Given a user wishing to access a certain service, the user preferences, requirements and constraints regarding the features of the service, and the set of candidate retailers and their offers (e.g., cost at which each service feature - quality level combination is provided), find the retailer that offers the most satisfactory service configuration pattern (allocation of service features to quality levels) in the most cost-effective manner.

The problem above can be analysed as depicted in figure 3. In general, the core of the selection process requires a method for evaluating the quality of each retailer offer. This paper includes the mathematical description of a pertinent problem, its formulation as a 0-1 linear programming problem [29,30], and a brief outline of computationally efficient solution algorithms. Regarding the determination of the set of candidate retailers, two approaches can be envisaged. The first (and simpler) one engages all the possible candidate retailers in the negotiation. The second, which will be also considered in this paper, is motivated by the fact that, in certain cases, an extensive negotiation can entail a needless amount of computations and interactions (and consequently, an associated excessive resource consumption). In this perspective, the notion of *learning from experience* [31,32,33] will be exploited, so as to *confine* the set of candidate retailers. This aspect will be based on, so-called, retailer *rating* mechanisms, which take into account the quality of previous retailers' offers (*performance* criterion) and whether the expectations raised in the past (by previous offers) have been met (*reliability* criterion).

The rest of this paper is organised as follows. Section 2 describes the business case through which the role of the best candidate retailer selection problem, and the manner in which the proposed solution can be integrated in legacy service architectures, is explained. The description is done in terms of the involved business level entities and the computational level components. Section 3 presents the mathematical definition, formulation and solution to the problem of evaluating the quality of an offer that is made by a retailer. In essence, the section presents in finer detail a version of the logic of the (service architecture) computational components that play a role in the retailer selection problem. Section 4 introduces the learning mechanisms that confine the set of candidate retailers that should be involved in the selection procedure. These mechanisms are also potential ways of improving the competence of the (service architecture) computational components that play a role in the retailer selection problem. Section 5 provides a set of indicative results. Finally, section 6 includes future plans and some concluding remarks.

2. BUSINESS CASE DESCRIPTION

This section provides the description of the business case, through which the importance of the retailer selection may be understood. Sub-section 2.1 provides the description in terms of business level entities, while in sub-section 2.2 the description is refined by introducing the role of the computational level components.

2.1 Description in terms of business level entities

It is assumed that a user wishes to access a specific service. Moreover, it is assumed that the user can be served by (falls in the domain of) various *candidate retailers* (CRs), as depicted in figure 2. Enabling the service usage through the most appropriate retailer requires the realisation of the three general phases depicted in figure 4.

The first general phase involves service independent features like user authentication, authorisation, etc. It involves the user and an entity that will be called default retailer (DR). In essence, at the end of this phase the user is enabled to request services. This phase will not be further addressed in this paper.

The second general phase is the core of the retailer selection. It is assumed that a user wishes to access a given service through the most appropriate retailer. The entities involved in this phase are the user and the candidate retailers. In general, the set of candidate retailers can be determined by means of a brokerage (or simpler, a directory) service. Nevertheless, some retailers can be eliminated, as will be explained later in this paper (see section 4). In general, the basis for the best, candidate retailer selection is founded by the user preferences, requirements and constraints regarding the specific service, and the retailer policies (e.g., cost at which each service feature - quality level combination is provided).

In the third phase the result of the selection is available, and hence an association, and subsequently a service usage, may start between the user and the selected retailer.

2.2 Description in terms of computational level concepts

The TINA-compliant computational level model of the business case is depicted in figure 5. Of interest to our study is the TINA access session concept, which is the gateway to the usage of a specific service. In general, a session is defined as the temporary relationship among a group of objects that are assigned to collectively fulfil a task for a period of time. The access session is a service independent concept, and can be seen as the gateway to any specific service usage. It comprises activities that allow user authentication, user profile control (inspection), and service invocation.

The Initial Agent (IA) is the component that enables the initial access to a domain. The User Agent (UA) component represents the user beyond the terminal domain (e.g., in the default retailer domain). Its role is to intercept and process user requests. The UA has subordinate objects (SOs) that maintain user specific information. For brevity, these objects are not shown in full detail in figure 5. The UA and SO components maintain the user profile related information (e.g., preferences, requirements and constraints regarding certain services, potential service subscriptions, etc.). The User Application (UAP) models the entity (user interface) with which the user is confronted when in the access session mode. The Provider Agent (PA) represents the retailer in the user domain. The UA invokes the Service Factory (SF) for initiating a specific service usage.

The overall retailer selection task requires an entity that will act on behalf of the user. Its role will be to capture the user preferences, requirements and constraints regarding the requested service, to deliver them in a suitable form to the appropriate retailer entity, to acquire and evaluate the corresponding retailer offers, and ultimately, to select the most appropriate retailer. As a second step, the retailer selection task requires an entity that will act on behalf of each candidate retailer. Its role would be to collect the user preferences, requirements and constraints and to make a corresponding offer, taking also into account the underlying connectivity providers.

Based on the discussion above the following key extensions are made so as to cover the functionality that was identified above. First, the UA is extended, by being assigned with the role of selecting on behalf of the user the best retailer. Second, the *Retailer Agent* (RA), is introduced and assigned with the role of promoting the services offered by a candidate retailer. In other words, the UA possesses the user preferences, requirements and constraints from the profile, interacts with the RAs of the candidate retailers so as to obtain their offers, and selects the most appropriate retailer for the desired service. The RA promotes the offers of a candidate retailer, interacts with UAs, and the underlying connectivity provider mechanisms.

Figure 6 presents in more detail the interactions among the computational level components. The detailed description of these interactions is omitted for brevity.

3. EVALUATING THE QUALITY OF THE OFFER OF A RETAILER

In this section we describe in more detail a version of the logic that underlies the UA and RA interactions. As already presented the UA interacts with the RA of each candidate retailer $r \in R$, where R denotes the overall set of candidate retailers. The aims of the UA - RA interactions are the following. First, to supply to the RA the user preferences and constraints regarding the specific service. Second, to obtain the corresponding retailer offers. Third, to select the retailer that makes the best offer.

The tasks outlined require a method that will enable the assessment of the quality of the offer of each retailer. In this respect, sub-sections 3.1, 3.2 and 3.3 include the definition, formulation and solution, respectively, of a problem that can be used for evaluating the quality of the offer of a candidate retailer r. Based on this problem, subsection 3.4 describes the resulting retailer selection algorithm and, in finer detail, the functionality of the involved computational level components (namely, UA and RA).

3.1 Formal problem statement

Each UA acts on behalf of a user u, whose profile is known. User u wishes to use a given service s. A fundamental assumption at this point is that service s is composed of a set of distinct service features (e.g., see figure 7), which will be denoted as $SF(s)$. Furthermore, let us assume without loss of generality that these service features are offered (supported) by the candidate retailers. This assumption can readily be relaxed as will be explained in subsequent sections (e.g., see in section 5 the discussion referring to table 2). Among these service features, of interest to the user are those designated in the user profile and will be denoted as $SF(u,s)$ ($SF(u,s) \subseteq SF(s)$). Each service feature $i \in SF(s)$ has an associated set of possible quality levels, represented by the set $Q(i)$. The set of quality levels that are in line with the user profile is denoted by $Q(u,i)$ ($i \in SF(u,s)$). It holds that $Q(u,i) \subseteq Q(i)$. The user preferences and the retailer policies determine each of these quality level sets.

The user satisfaction level (measure) that results from the assignment of service feature-i at quality level-j is denoted as $b_{SQ}(i,j)$ ($i \in SF(u,s)$, $j \in Q(u,i)$), while the associated price (tariff) that will be imposed on the user by retailer r is denoted as $p_{SQ}(r,i,j)$ ($r \in R$, $i \in SF(u,s)$, $j \in Q(u,i)$).

The objective of our problem is to find a service configuration pattern, i.e., an assignment $A_{SQ}(r)$ of service features i ($i \in SF(u,s)$) to quality levels j ($j \in Q(u,i)$), that is optimal for retailer r. The assignment should maximise an objective function $f\big(r, A_{SQ}(r)\big)$ that models the quality of the retailer r offer. Among the terms of this function there is the overall user satisfaction level that results from the assignment, which is expressed by the function $b\big(A_{SQ}(r)\big)$, and the price (tariff) at which retailer r will provide the assignment, which is expressed by the function $p\big(r, A_{SQ}(r)\big)$.

The constraints of our problem are the following. First, each service feature-i ($i \in SF(u,s)$) should be assigned to only one quality level-j ($j \in Q(u,i)$). Second, a cost-related constraint can be imposed. As an example, a value $p_{\max}$ can be defined for representing the maximum price (tariff) that can be afforded by the user for the service usage. The $p_{\max}$ value can be seen as an expression of the user constraints. The corresponding mathematical description of the constraint is $p\big(r, A_{SQ}(r)\big) \le p_{\max}$. The third problem constraint refers to the user satisfaction level (measure), which should not be lower than a given value $B_{\min}$ (this may be seen as an expression of the user requirements). The corresponding mathematical description of the constraint is $b\big(A_{SQ}(r)\big) \ge B_{\min}$.

As an example the model of figure 7 can be considered. A given user wishes to access a service. The service consists of four service features, each offered at three quality levels. The user profile indicates that the user is interested in 3 out of 4 service features. Moreover, these service features may be offered to the user in only 2 of the 3 allowable quality levels. A benefit (measure of the user satisfaction) will be derived from the provision of a service feature at an associated (allowable) quality level.

Thus, we may observe the following: (i) $\{sf_1,...,sf_4\}$; (ii) $SF(u,s)=\{sf_2, sf_3, sf_4\}$; (iii) $Q(u,sf_2)=\{q_{22}, q_{23}\}$, etc.

The overall problem can be formally stated as follows.

Problem 1: [Evaluation of the Quality of the Retailer-r Offer]. Given:

(a) a user u who wants to use a service s,

(b) the profile of user-u,

(c) the set of service features $SF(u,s)$ of service s that are of interest (relevant) to user u (this set is formed by the service specification, the user profile and the retailer capabilities),

(d) the set of quality levels $Q(u,i)$ at which each service feature i ($i \in SF(u,s)$) can be offered, according to the service specification, the retailer capabilities and the preferences of user u,

(e) the user satisfaction level $b_{SQ}(i,j)$ (expressing the user preferences), which derives from the assignment of service feature i ($i \in SF(u,s)$) to quality level j ($j \in Q(u,i)$)

(f) the price $p_{SQ}(r,i,j)$ that retailer r associates with the assignment of service feature i ($i \in SF(u,s)$) to quality level j ($j \in Q(u,i)$),

(g) the upper bound on the overall price (tariff) $p_{\max}$ that the user can afford for the service usage (this value is an expression of the user constraints),

(h) the lower bound $B_{\min}$ on the user satisfaction level that has to be experienced during the service usage,

find the best service configuration pattern, i.e., assignment of service features to quality levels $A_{SQ}(r)$, that optimises an objective function $f\left(r, A_{SQ}(r)\right)$ that is related to the overall user satisfaction $b\left(A_{SQ}(r)\right)$ and price $p\left(r, A_{SQ}(r)\right)$ suggested by the assignment, under the constraints $p\left(r, A_{SQ}(r)\right) \le p_{\max}$, $b\left(A_{SQ}(r)\right) \ge B_{\min}$ and that each service feature is assigned to exactly one quality level.

3.2 Optimal formulation

In this sub-section the problem above is formulated as a 0-1 linear programming problem [29,30]. In order to describe the assignment $A_{SQ}(r)$ of service features to quality levels, the decision variables $x_{SQ}(i,j)$ ($i \in SF(u,s)$, $j \in Q(u,i)$), which take the value 1(0) depending on whether the service feature-i is (is not) assigned to quality level-j, are introduced. The problem of obtaining the most appropriate assignment $A_{SQ}(r)$ may be obtained by reduction to the following optimisation problem.

Problem 1: [Evaluation of the Quality of the Retailer-r Offer].

Maximise:

$$f\left(r, A_{SQ}(r)\right) = \sum_{i \in SF(u,s)} \sum_{j \in Q(u,i)} \left[c_B \cdot b_{SQ}(i,j) - c_P \cdot p_{SQ}(r,i,j)\right] \cdot x_{SQ}(i,j) \tag{1}$$

subject to

$$\sum_{j \in Q(u,i)} x_{SQ}(i,j) = 1 \qquad \forall i \in SF(u,s) \tag{2}$$

$$b\left(A_{SQ}(r)\right) = \sum_{i \in SF(u,s)} \sum_{j \in Q(u,i)} b_{SQ}(i,j) \cdot x_{SQ}(i,j) \ge B_{\min} \tag{3}$$

$$p\left(r, A_{SQ}(r)\right) = \sum_{i \in SF(u,s)} \sum_{j \in Q(u,i)} p_{SQ}(r,i,j) \cdot x_{SQ}(i,j) \le p_{\max} \tag{4}$$

$$A_{SQ}(r) = \left\{ x_{SQ}(i,j) \mid i \in SF(u,s),\ j \in Q(u,i) \right\} \tag{5}$$

Relation (1) expresses the objective of finding the best assignment of service features to quality levels that maximises the cost function, which is associated with the overall user satisfaction and the corresponding price. In other words, relation (1) expresses the quality of the retailer r offer (or equivalently, the objective function value that is scored by retailer r).

Weights c_B and c_P provide the relative value of the user satisfaction related part and the price related part. Constraints (2) guarantee that each service feature will be assigned to exactly one quality level. Constraint (3) guarantees that the level of user satisfaction will not be lower than a pre-defined value that is dictated by the user requirements. In the same manner, constraint (4) guarantees that total cost will not exceed a predefined value.

3.3 Computationally efficient solutions

In general, there are several approaches that may be followed for solving the problem that was presented above. The first one is to exhaustively search the solution space, provided that it is not prohibitively large. The complexity of the search in this case is $\prod_{i \in SF(u,s)} |Q(u,i)|$, i.e., a function of the service features that are relevant to the user and the quality levels at which these service features may be offered.

In case the solution space is large the design of computationally efficient algorithms that can provide good (near-optimal) solutions in reasonable time is required. Classical methods in this respect are simulated annealing [34,35], taboo search [36,37], genetic algorithms [38,39,40,41], greedy algorithms [30], etc. Hybrid or user defined heuristic techniques may also be devised.

3.4 Retailer selection algorithm – Role of computational components (UA and RA)

Based on the discussion so far this sub-section describes the algorithm, on which the UAs and the RAs base the accomplishment of their tasks. The algorithm should be seen as a more detailed description of the tasks in the retailer selection procedure, also taking into account the mathematical problem in subsections 3.1, 3.2 and 3.3.

Step 1. The UA component is acquainted with the preferences, requirements and constraints of user u regarding service s. These are expressed by the following data. First, the set of the service features $SF(u,s)$ that are of interest (relevant) to the user. Second, for each service feature i ($i \in SF(u,s)$) the corresponding set of allowable quality levels $Q(u,i)$. Third, the values $b_{SQ}(i,j)$ that describe the user satisfaction level stemming from the provision of service feature-i at quality level-j ($j \in Q(u,i)$). Fourth, the upper limit on the price $p_{\max}$ and the lower limit on the user satisfaction $B_{\min}$ that the user can afford, or wants to experience, respectively, during the service usage.

Step 2. The UA obtains the list of candidate retailers, R, and the references of the respective RAs.

Step 3. The UA component activates the appropriate negotiator entities (e.g., threads or mobile agents as specified in [4]). Each negotiator entity will undertake the interactions with a candidate retailer $r \in R$. The negotiator entities will be under the control of the UA.

Step 4. Each negotiator entity obtains the offer of a retailer $r \in R$ for the user preferences, requirements and constraints regarding service-s. These are expressed by the prices $p\left(r, A_{SQ}(r)\right)$ associated with the provision of service feature-i at quality level-j.

Step 5. Each negotiator entity evaluates the quality of the retailer offer by solving the appropriate instance of problem 1. The result (if feasible) is sent to the UA.

Step 6. The UA selects a retailer by comparing the objective function values that each retailer has scored.

Step 7. End.

4. DETERMINING (CONFINING) THE SET OF CANDIDATE RETAILERS

This section describes the method for confining the set of candidate retailers, so as to reduce the required interactions and the associated computations and resource consumption. In other words, this section provides enhancements to the UA intelligence, by incorporating learning-from-experience concepts. Learning refers to a component's ability to use the information it has obtained from the environment, in order to improve (modify) its decisions and behavior.

As already stated the reduction of the set of candidate retailers will be based on, so-called, retailer *rating* mechanisms. The rationale of these mechanisms is presented in subsection 4.1. Subsection 4.2 provides the mathematical framework that underlies the rating mechanisms. Subsection 4.3 presents the revised version of the UA and RA intelligence.

4.1 Retailer rating fundamentals

The UA can decide to confine the set of candidate retailers based on an estimation of the retailers' expected behaviour. In our approach this estimation comprises two factors. The first is a measure of the quality of the previous offers that have been made by the retailer, and is called performance criterion. The second is the reliability criterion. Its aim is to reflect whether the service finally provided to the user corresponded to the agreement reached during the negotiation phase. Our approach is further analyzed in the following paragraphs.

The performance criterion is motivated by the fact that there may be different levels of user satisfaction with respect to the various retailers' offers. In this respect, there may be retailers that, in principle, do not satisfy the user with their offer. Hence, recording the previous experience can easily assist the UA in deciding whether or not to negotiate with a specific retailer.

The reliability criterion covers cases in which the retailer does not honour the agreement (or in other words, does not meet up to the expectations) established in the negotiation phase. In this sense, the reliability criterion introduces the flavour of trust among the user and the retailer. Obviously, recording pertinent information may encourage or discourage a UA in negotiating with particular RAs. This part of our work is influenced by notions appearing in [42,43].

Naturally, the UA should apply the mechanisms for confining the set of candidate retailers, in cases it is highly likely that the information on which it will be based is accurate. More specifically, it can be envisaged that the retailers will be changing their policies, in order to adapt to the market demand. In this respect, UA updating mechanisms are required. To this end, several approaches can be found in the literature, e.g., the Boltzman exploration strategy. Moreover, according to a straightforward approach that is adopted in this paper, it can be envisaged that the UA will confine the set of candidate retailers, in case criteria, indicating that the essential (fundamental) information is not outdated, are satisfied.

4.2 Mathematical description of the retailers rating mechanisms

This subsection provides the formulas that realise the retailer rating mechanisms.

4.2.1 Formulations for the performance criterion of the retailer rating mechanisms

Each retailer r may be rated according to the performance criterion through the following formula:

$$RP_{post}(r) = RP_{pre}(r) + k_p \cdot \left(rp(r) - E\left[rp(r)\right]\right) \tag{6}$$

where $RP_{post}(r)$ and $RP_{pre}(r)$ are the retailer-r performance-based rating after and before the updating procedure, $rp(r)$ is a (reward) function that describes the quality of the retailer-r current offer (with respect to the other retailers), and $E\left[rp(r)\right]$ is the mean (expected) value of the $rp(r)$ value. In general, the larger the $rp(r)$ value the better the quality of the current offer, and therefore, the more positive the influence on the rating of the retailer. Factor k_p ($k_p \geq 1$) determines the relative significance of the new outcome with respect to the old one. In essence, this value determines the memory of the system. Small k_p value means that the memory of the system is large. Therefore, good offers will gradually improve the retailer's rating position.

It should be noted that a deterioration of the quality of the offer of retailer r, with respect to that made by other retailers, leads to a decreased post rating value, since then the $\left(rp(r) - E\left[rp(r)\right]\right)$ quantity is negative. The $rp(r)$ function may be implemented in several ways. In the result sections of this paper, it was assumed without loss of generality that the $rp(r)$ values vary from 0.1 to 1.

4.2.2 Reliability Related Rating Mechanism-Update Formulae

This subsection introduces the formulas used for the rating of users according to the reliability criterion. In general, the approach is similar to that of the previous subsections.

Each retailer r may be rated according to the reliability criterion through the following formula:

$$RR_{post}(r) = RR_{pre}(r) + k_r \cdot \left(rr(r) - E\left[rr(r)\right]\right) \tag{7}$$

where $RR_{post}(r)$ and $RR_{pre}(r)$ are the retailer-r reliability-based rating before and after the updating procedure, $rr(r)$ is a (reward) function reflecting whether the service quality is compliant with the picture established during the negotiation phase, and $E\left[rr(r)\right]$ is the mean (expected) value of the $rr(r)$ value. The k_r factor plays the same role as in the performance rating case.

It should be noted that the reliability value of the selected retailer is updated after the user finally accesses the service. Moreover, this rating requires a mechanism for evaluating whether the service quality was compliant with the picture promised during the negotiation phase. This mechanism should allow for a fair evaluation that will protect both sides (user and retailer).

4.3 Revised retailer selection algorithm and role of computational components (UA and RA)

In this sub-section we describe the algorithm, on which the SUAs and the RAs base the accomplishment of their tasks. The algorithm should be seen as a more detailed description of their sub-tasks involved, taking also into account the schemes of this section.

Step 1. The UA is acquainted with the preferences, requirements and constraints of user u regarding service s. These are expressed by the following data. First, the set of the service features $SF(u,s)$ that are of interest (relevant) to the user. Second, for each service feature i ($i \in SF(u,s)$) the corresponding set of allowable quality levels $Q(u,i)$. Third, the values $b_{SQ}(i,j)$ that describe the benefit (user satisfaction) stemming from the provision of service feature-i at quality level-j ($j \in Q(u,i)$). Fourth, the upper limit on the price $p_{\max}$ and the lower limit on the user satisfaction $B_{\min}$ that the user may afford, or wants to experience, respectively, during the service usage. Fifth, the estimated retailer rating values formed according to the formulas presented in the previous section.

Step 2. The UA obtains the list of candidate retailers, R, and the references of the RAs.

Step 3. The UA forms the confined set of candidate retailers, R_c ($R_c \subseteq R$), based on the rating mechanisms presented previously in this section, in case the pertinent fundamental information is not outdated.

Step 4. The UA activates the appropriate negotiator entities for undertaking the interactions with the retailers in the confined set of candidate retailers, R_c.

Step 5. Each negotiator entity obtains an offer from retailer r ($r \in R_c$) for the user preferences, requirements and constraints regarding service-s. These are expressed by the prices $p\big(r, A_{SQ}(r)\big)$ associated with the provision of service feature-i at quality level-j.

Step 6. Each negotiator entity evaluates the quality of the offer of retailer r ($r \in R_c$) by solving the appropriate instance of problem 1. The result (if feasible) is sent to the UA.

Step 7. The UA selects a retailer by comparing the objective function values that each retailer has scored.

Step 8. The retailers' rating values (performance and reliability related) are updated on the basis of equations (6) and (7) respectively.

Step 9. End.

5. RESULTS

This section provides some indicative results on the behaviour of the retailer selection mechanisms that are proposed in this paper. More specifically, the contribution of this paper lies in the following areas. First, the definition of a business case through which the role of the best candidate-retailer selection problem was explained. Second, the definition and mathematical formulation of the evaluation of the quality of the retailer offer problem, which should be solved in the context of the retailer selection phase. Third, the presentation of a method for reducing the set of candidate retailers, and hence, the associated computations, interactions and resource consumption required.

The results of this section aim at the provision of indicative evidence on the following. First, the efficiency of the overall retailer selection scheme, with respect to a random retailer selection scheme. Second, the efficiency of the learning mechanisms that confine the set of candidate retailers. In the rest of this section two sets of experiments will be used for demonstrating these aspects. The experiments are differentiated from the specific assumptions made concerning user preferences and not from their focus which is as described above.

This section assumes the existence of an area that falls into the domains of R candidate retailers. Users access the area in order to initiate a service usage. In the context of our experiments, it is assumed that users request a videoconference service. A simple and well-known service has been chosen in order to explain more effectively the proposed scheme.

The videoconference service comprises two service features, namely audio and video. In the context of our study, four quality levels have been considered for these service features. Specifically, the quality levels that have been defined for audio correspond to 8 kbits/sec, 16 kbits/sec, 32 kbits/sec and 64 kbits/sec, respectively. In a similar manner, the defined quality levels for video correspond to 15 frames/sec, 20 frames/sec, 25 frames/sec and 30 frames/sec, respectively.

Regarding the different users that access the area, it is assumed that k user classes exist. In the definition of these user classes we have also assumed that all users in these classes are interested for both service features. However, each user class is interested in different quality levels of these service features.

Concerning the implementation issues of our experiment, the whole TINA access session has been implemented in Java [44]. The OrbixWeb CORBA compliant platform [45] was used for the inter-component communication. Moreover, the UA and the RA have been implemented as intelligent, mobile agents based on the use of the Voyager platform [46].

The profiles of each user class in the first experiment are presented in Table 1(a). It has been assumed that $k = 10$. More specifically, this table indicates the quality levels for audio and video, i.e., QA_j and QV_j ($1 \leq j \leq 4$), respectively, which are of interest to each user class. Regarding the user satisfaction level the simplest possible assumption has been made in this experiment. Specifically, it has been assumed that the users in each class are equally attracted by all the quality levels at which a service feature can be offered. This assumption will be changed in the second experiment. Nevertheless, in the first experiment it enables the acquisition of an initial set of indicative results that show the behaviour of our schemes. In the light of the assumption made, the problem is reduced to the selection, for each service feature, of the quality level that will minimally impact on the price. Moreover, it should be noted that, for each user class, the coefficients $b_{SQ}(i, j)$, indicating the user satisfaction level when a service feature i is to be provided at a given quality level j, are taken to be equal for each (i, j) combination. Specifically, the $b_{SQ}(i, j)$ co-efficients have been arbitrarily set to be equal to 50.

Table 1(b) describes the retailer policies regarding the features (audio and video) of the videoconference service and the respective quality levels. It has been assumed that $|R| = 10$ (i.e., 10 retailers are involved in the experiment). More specifically, this table indicates the offered quality levels for audio and video, for each retailer, as well as the price (expressed in arbitrary values) which is associated with the provision of a service feature at a given quality level. It can be observed that the price at which each retailer offers a service feature – quality level combination increases, as the quality level increases.

Another aspect that should be noted is that, in order to make the test case more realistic (or general), all retailers are not assumed to offer all possible quality levels. Retailers that do not offer the lowest allowable quality level for a service feature as indicated in the service profile of the user class u constitute the $E(u)$ set, which comprises retailers that should be excluded from the negotiation phase. Table 2 presents the set of retailers that should be excluded from the negotiation with certain user classes, taking into account the profiles and retailer policies described in table 1.

As previously mentioned, the objective of our experiment is to provide indicative evidence of the overall retailer selection scheme, with respect to a random retailer selection scheme. In this respect, table 3 presents the outcome of the application of the retailer selection scheme for the user classes and retailer policies described in table 1. Specifically, for each user class, the derived value of objective function (1), the selected retailer, and the decrease with respect to the random retailer selection scheme are shown. It is noted that the co-efficients $b_{SQ}(i, j)$ are taken to be equal to 50. Moreover, with reference to table 3, from the derived results it can be deduced that the desired service features are always offered at the lowest allowable quality level. This is justified since (a) the users are equally attracted by the different quality levels and (b) the considered allocation yields minimum cost.

In general, from the results of table 3 it is observed that the best candidate retailer-selection scheme exhibits a better performance, which on the average is in the order of 20%, with respect to the random retailer selection scheme. This decrease is due to the selection of the most suitable retailer taking into account the user preferences and the retailer policies.

As previously mentioned, the objective of our experiment is to provide indicative evidence on the efficiency of the learning mechanisms that confine the set of candidate retailers. In this respect, first, table 4(a) and 4(b) present the outcome of the application of the retailer rating mechanism according to the performance and reliability criterion, respectively, while table 4(c) presents the outcome of the application of both criteria. It should be noted that excluded retailers are not considered when deciding for the most promising retailers during the configuration of the confined sets. Relations (5) and (6) are used for computing the ratings. Specifically, the reward signal for each retailer r, $rp(r)$, is computed as $rp(r) = f\left(r, A_{SQ}(r)\right) \Big/ \max\limits_{k \in R}\left[f\left(k, A_{SQ}(k)\right)\right]$, where $f\left(k, A_{SQ}(k)\right)$ is the objective function value (see relation (1)) that is scored by retailer k ($k \in R$). In other words, the $rp(r)$ value is obtained by normalising the objective function value of retailer r, $f\left(r, A_{SQ}(r)\right)$, with respect to the maximum objective function value scored by the retailers in R.

As a next step, the confined set of candidate retailers is formed. Tables 5(a), 5(b), and 5(c) present the outcome of the application of the learning mechanisms and the retailer selection scheme. Specifically, for each user class, the confined set of candidate retailers, and the outcome of the retailer selection scheme (i.e., objective function value and selected retailer) are shown. In the context of our experiment, the 3 most appropriate retailers were selected to constitute the confined set of candidate retailers.

Apart from the observations above, it should also be stressed that for user classes k_1, k_3, k_4, k_8, k_9 and k_{10} different retailers have been selected when applying different criteria for the configuration of the confined set. Specifically, different retailers are selected when applying reliability ratings and total ratings, in comparison to the performance ratings, for the configuration of the confined set of eligible candidate retailers. This is due to the introduction of different degrees of reliability for different retailers. This introduction can cause the selection of a different retailer, which offers a higher “safety” feeling to the user, in case the reliability ratings are taken into account, even when the retailer’s performance (i.e., the usual quality of the offer) is lower in comparison to the others. A better balance between performance and reliability is achieved when the total ratings are considered for the selection of the most promising retailers. For example, for user class -k_3, when performance ratings are considered, retailer-9 is selected. In case, reliability ratings are taken into account, retailer-5 is the most appropriate one, since, for the specific user class, retailer-5 possesses the highest rating. In case, both criteria are to be taken into account retailer-7 is selected, since retailer-7 is the most promising one in terms of both performance and reliability (even though he is not the best one when these criteria are considered separately).

Figure 8 presents information regarding the specialisation of retailers in serving certain user classes. Specifically, the figure presents the percentage of the different user class requests that were handled by the retailers, when different decision criteria were applied. From the obtained results it is observed that in case performance ratings are considered for the configuration of the confined set, retailers 1 and 9 handle a great number of requests because of their suitability for adequately serving 3 out of the 10 user classes. In case reliability or total ratings are considered for the configuration of the confined set of candidate retailers, a significant decrease is observed in the number of requests that retailers 1, 9 and 10 handle. At the same time, a significant increase to the number of requests handled by retailers 5, 7 and 8 is noted. This is due to the lower reliability rating retailers 1, 9, and 10 are presenting with respect to retailers 5, 7, and 8.

Following figure 9 presents a comparison of the cost of providing the service features at allowable quality levels when the retailer selection scheme and the performance, reliability, and total rating criteria are applied. The obtained results indicate a decrease of the value of the objective function representing the evaluation of the quality of the retailer’s offer when the reliability and total rating criteria are applied. This applies for the majority of the user-classes and is due to the fact that the most appropriate retailer in terms of performance possesses a lower reliability rating value in comparison to other candidates. Therefore, this retailer is not included in the confined set, according to the selection criterion, which in our case is reliability, or reliability and performance. For the rest of the user classes the objective function value is not altered suggesting the re-selection of the same retailer in all cases. Another thing that should be noted is a quite big decrease in the value of the objective function for user class k_{10}, when the reliability criterion is applied for the configuration of the confined set. However, this decrease is almost eliminated in case the retailer's performance is also taken into account.

The profiles and service preferences of the different user classes in the second set of experiments are shown in table 6. However, in this test case it is assumed that the user satisfaction volume that derives from providing a service feature at a given quality level, i.e., the coefficients $b_{SQ}(i, j)$, for each user class are not equal for all allowable quality levels. In this respect, table 6 shows for each user class the different coefficients, which indicate the level of attraction for all the quality levels at which a service feature, which is of interest to them, may be offered. Furthermore, from table 6, it is derived that, in principle, higher quality levels are more attractive to the users. Hence, the objective of the retailer selection scheme is to find the assignment that maximises the value of objective function (1). Regarding the retailer policies, the ones shown in table 1(b) are also valid in this set of experiments.

Table 7 presents the outcome of the application of the retailer selection scheme for the user classes of table 6 and retailer policies described in table 1(b). Specifically, for each user class, the derived value of objective function (1), the selected retailer, and the decrease with respect to the random retailer selection scheme are shown. From the results of table 3 it is observed that the best candidate retailer-selection scheme exhibits a better performance, which is up to 3%, with respect to the random retailer selection scheme. This decrease is due to the selection of the most suitable retailer taking into account the user preferences and the retailer policies.

Similarly to the first set of experiments, tables 8(a), 8(b) and 8(c) present the outcome of the retailer rating mechanism taking into account performance criterion, reliability criterion and both, respectively, for the user classes described in table 6 and the retailer policies described in table 1(b). Tables 9(a), 9(b) and 9(c) present the outcome of the application of the overall retailer selection procedure. More specifically, the results provide for each user class, the confined set comprising the most promising candidate retailers for the specific service requested, the derived value of objective function (1), the selected retailer and the quality levels at which the service features (audio and video) were provided. Comparing to the corresponding results in the first set of experiments (tables 5(a), 5(b) and 5(c)), it may be observed that the value of objective function (1) is increased up to 5% approximately, for user class k_1. The increase is due to the higher attraction level for a specific quality level. For example, for user class $-k_1$, QA_2 is equal to 55 while in the first set of experiments the respective factor is taken equal to 50.

Apart from the above observations, we may also stress that for the user classes k_1, k_2, k_4, k_5, k_8 and k_{10} different retailers have been selected comparing to the first set of experiments. This is, again, owing to the introduction of different levels of attraction for different quality levels. This introduction entails the selection of a different retailer, which offers a better balance between user satisfaction and derived cost.

Similarly to the first set of experiments, regarding retailer specialisation, figure 10 presents the percentage of the requests that were handled by the retailers for the different user classes and for the application of the different decision criteria. From the obtained results it is observed that in case performance ratings are considered for the configuration of the confined set, retailers 2, 4, 9 and 10 handle a great number of requests because of their suitability for adequately serving user classes. In case reliability or total ratings are considered for the configuration of the confined set of candidate retailers, a significant decrease to the number of requests retailers 2, 4, 9 and 10 handle is observed. At the same time, a significant increase to the number of requests handled by retailers 5, 6, 7 and 8 is noted. This is due to the lower reliability rating retailers 2, 4, 9, and 10 are presenting in conjunction to retailers 5, 6, 7, and 8.

Finally, figure 11 presents a comparison of the cost of providing the service features at allowable quality levels when the retailer selection scheme and the performance, reliability, and total rating criteria are applied. Similarly to the first set of experiments, a small decrease is observed in the value of the objective function representing the evaluation of the quality of the retailer's offer when the reliability and the aggregate criteria are applied. This applies for the majority of the user-classes and is due to the fact that the most appropriate retailer in terms of performance possesses a lower reliability rating value in comparison to other candidates. Therefore, this retailer is not included in the confined set, according to the selection criterion, which in our case is reliability, or both reliability and performance. For the rest of the user classes the objective function value is not altered suggesting the re-selection of the same retailer in all cases.

It is noted that in our experiments we periodically update retailers rating values (UA re-negotiates with every potential candidate retailer) in order to count for non-stationary situations arising by the dynamic nature of our model. In a following version of this paper, UA will be attributed with an exploration specific library conforming to the general ideas presented in section 4.

6. Conclusions and Future Works

The highly competitive communications markets of the future should encompass mechanisms for enabling users to find and associate with the most appropriate retailers, i.e., those offering adequate quality services in a cost efficient manner. This paper presented such mechanisms. Our starting point was the definition of a business case, through which the role of the best candidate-retailer selection problem was explained. In the sequel, the problem was analysed and the identified sub-problems were concisely defined, mathematically formulated and solved. The identified components of the best candidate-retailer selection problem were targeted to the evaluation of the quality of a retailer offer and the reduction of the set of candidate retailers by exploiting learning from experience notions. At the final sections the paper results are provided and concluding remarks are made.

Directions for future work include, but are not limited to the following. First, the migration from simulation-based studies that were conducted for this paper, to the realisation of wide scale trials, so as to experiment with the applicability of the framework presented herewith. Second, the experimentation with alternate approached for evaluating the quality of the retailers. Third, the experimentation with exploration specific libraries supporting UA in his decision on the confined set of candidate retailers taking into account the dynamic nature of our model.

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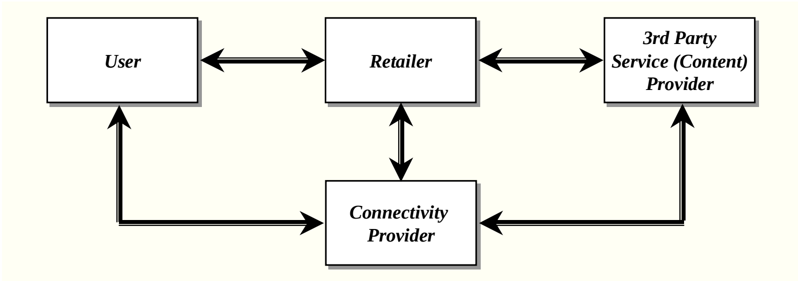

Figure 1. A view of the business level entities in the future competitive telecommunications environment

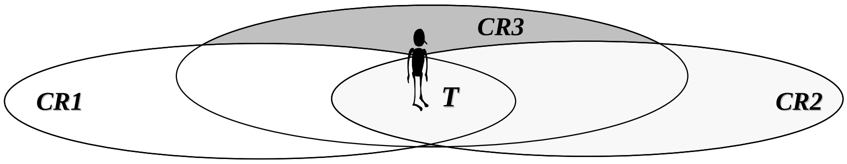

Figure 2. A user is found in an area from which he/she wishes to access a given service through the most appropriate retailer. The area falls into the domain of various candidate retailers.

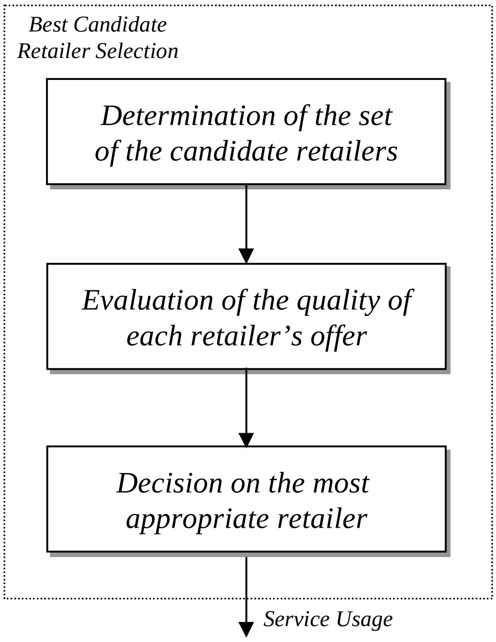

Figure 3. Approach for (phases in) the solution of the retailer selection problem

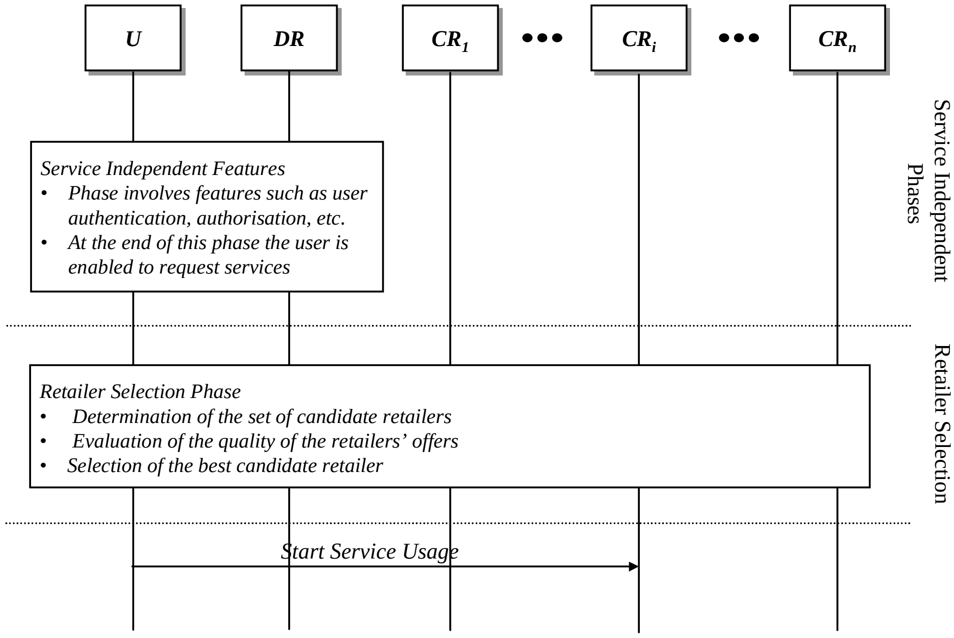

Figure 4. Interactions among the business level entities during the best, candidate retailer selection business case

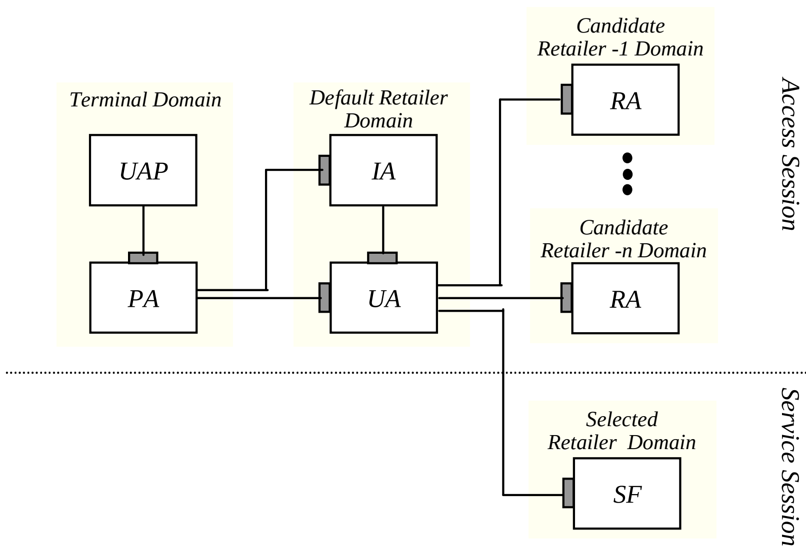

Figure 5. TINA-like computational model for the best candidate retailer selection business case

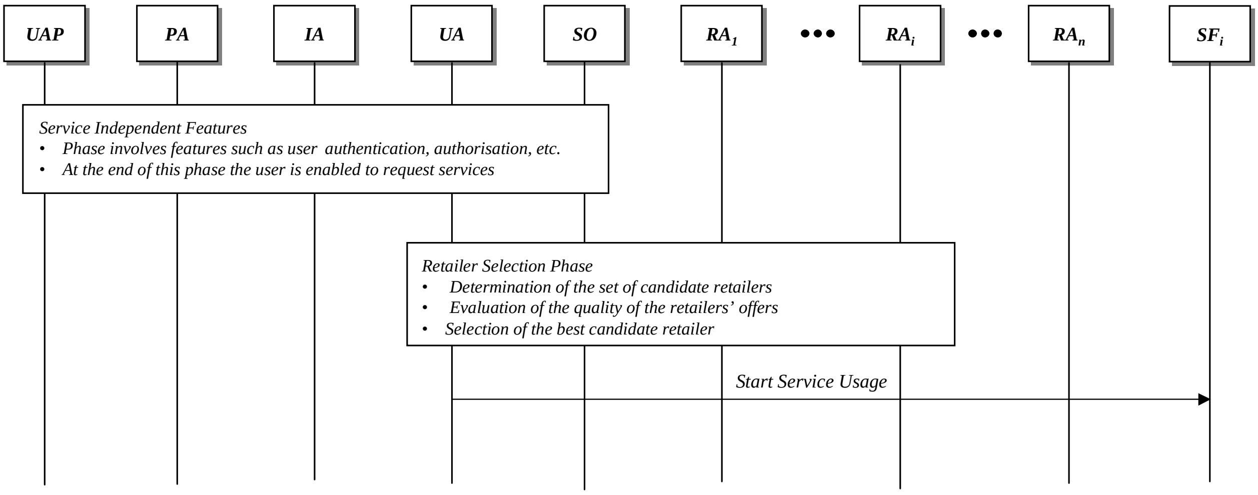

Figure 6. Interactions among the computational components in the context of the best, candidate retailer selection business case

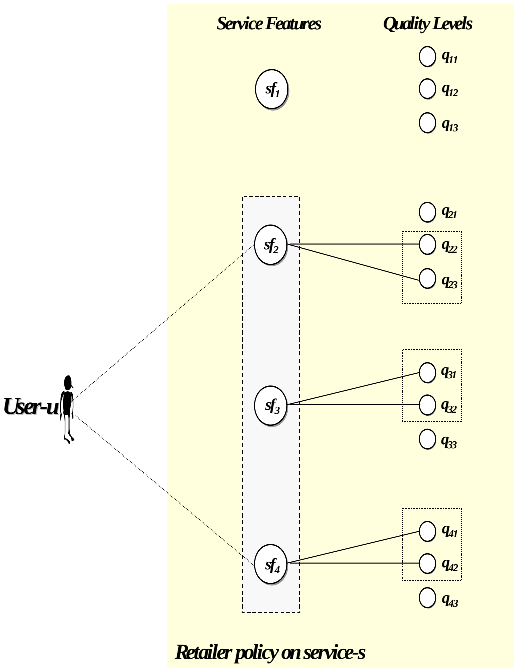

Figure 7. User-u wishes to access service-s, which is composed of different service features.

User Class	QA_1	QA_2	QA_3	QA_4	QV_1	QV_2	QV_3	QV_4
k_1	✓	✓			✓	✓		
k_2		✓	✓			✓	✓	
k_3	✓				✓	✓		
k_4	✓	✓				✓		
k_5			✓	✓		✓	✓	✓
k_6		✓					✓	✓
k_7				✓	✓	✓		
k_8	✓	✓	✓				✓	
k_9	✓						✓	
k_{10}	✓	✓	✓	✓	✓	✓	✓	✓

(a)

Retailer	QA_1	QA_2	QA_3	QA_4	QV_1	QV_2	QV_3	QV_4
R_1	**1**	**1.5**	**3**	**5**	**2**	**3**	**5**	**7**
R_2	**0,9**	**1,2**			**2**	**2,8**	**4**	
R_3	**1**	**1,4**	**2,5**		**1,8**	**2,5**		
R_4	**1**	**1,4**	**2,5**		**2**	**2,8**	**4**	
R_5	**0,9**	**1,2**			**1,8**	**2,5**		
R_6	**0,9**	**1,7**	**2,8**	**4,5**	**2,5**	**2,8**	**5,1**	**6,9**
R_7	**0,8**	**1,5**	**2,5**		**1,8**			
R_8	**1**				**2**	**2,3**	**4,1**	
R_9	**0,5**	**1,5**			**2**			
R_{10}	**0,8**				**1,8**	**2,3**		

(b)

Table 1. First set of experiments. (a) Description of service preferences in the profiles of the 10 user classes. The ticked boxes indicate that the users of the class are interested for the corresponding quality level at which the service feature can be provided. (b) Description of the retailer policies. Prices at which each service feature – quality level combination is provided. Empty boxes indicate that the corresponding service feature – quality level combination is not supported.

User Class	***Excluded Retailers***
k_1	-
k_2	7, 8, 9, 10
k_3	-
k_4	7, 9
k_5	2, 5, 7, 8, 9, 10
k_6	3, 5, 7, 8, 9, 10
k_7	2, 3, 4, 5, 7, 8, 9, 10
k_8	3, 5, 7, 9, 10
k_9	3, 5, 7, 9, 10
k_{10}	-

Table 2: The set of excluded candidate retailers for all user classes

User Class	***Objective Function Value***	***Retailer Selected***	***Improvement with respect to random retailer selection scheme (%)***
k_1	97,5	5	25.04
k_2	96,3	3	27.33
k_3	97,5	9	19.49
k_4	96,9	5	16.92
k_5	95	4	29.78
k_6	94,8	2	19.38
k_7	93	6	4.44
k_8	95,1	4	17
k_9	95,1	2	9.26
k_{10}	97,5	10	40.84

Table 3. First set of experiments. Outcome of the best candidate retailer selection scheme. Objective function value, selected retailer, and improvement with respect to the random retailer selection scheme, per user class involved in the experiment.

User Class	***Performance Ratings***									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**96,432**	**96,5185**	**96,6179**	**96,4224**	**96,7141**	**96,0217**	**96,8038**	**96,3936**	**96,128**	**96,7974**
k_2	**95,6345**	**96,041**	**96,1423**	**95,8884**	**96,3**	**95,6306**				
k_3	**97,0256**	**97,1205**	**97,2179**	**97,0205**	**97,3179**	**96,6077**	**97,4**	**97,0077**	**97,5**	**97,4128**
k_4	**96,016**	**93,3096**	**96,5128**	**96,2128**	**96,6096**	**96,3256**		**96,7**		**96,9**
k_5	**94,3158**		**95**	**94,7632**		**94,7053**				
k_6	**93,6097**	**94,8**		**94,6**		**93,2987**				
k_7	**92,7551**					**92,7**				
k_8	**93,8992**	**94,9054**		**94,8701**		**93,8938**		**94,6897**		
k_9	**94**	**95,1**		**95**		**94**		**94,9**		
k_{10}	**96,6719**	**96,5569**	**96,6531**	**96,496**	**96,7141**	**96,2425**	**96,8358**	**96,4512**	**96,9128**	**96,7974**

(a)

User Class	***Reliability Ratings***									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**100**	**93,6933**	**96,4774**	**93,4773**	**100,716**	**96,4773**	**100**	**100**	**94,9546**	**96,4773**
k_2	**100**	**93,6933**	**96,4774**	**93,4773**	**100,716**	**96,4773**				
k_3	**100**	**93,6933**	**96,4774**	**93,4773**	**100,627**	**96,4773**	**99,7106**	**100**	**94,9546**	**96,4773**
k_4	**100**	**93,6933**	**96,4774**	**93,4773**	**100,537**	**96,4773**		**100**		
k_5	**100**		**96,4774**	**93,4773**		**96,4773**				
k_6	**100**	**93,6933**		**93,4773**		**96,4773**				
k_7	**100**					**96,4773**				
k_8	**100**	**93,3039**		**93,4773**		**95,9879**		**99,1106**		
k_9	**100**	**93,3039**		**93,4773**		**95,9879**		**98,2211**		
k_{10}	**100**	**93,3039**	**95,988**	**93,4773**	**100,537**	**95,9879**	**99,7106**	**97,3317**	**94,9546**	**96,4773**

(b)

User Class	***Total Ratings***									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**196,432**	**190,212**	**193,095**	**189,9**	**197,43**	**192,499**	**196,804**	**196,394**	**191,867**	**193,275**
k_2	**195,634**	**189,739**	**192,62**	**189,366**	**197,016**	**192,108**				
k_3	**197,026**	**190,814**	**193,695**	**190,498**	**197,945**	**193,085**	**197,111**	**197,008**	**192,455**	**193,89**
k_4	**196,016**	**190,003**	**192,99**	**189,69**	**197,236**	**192,803**		**196,7**		**193,377**
k_5	**194,316**		**191,477**	**188,24**		**191,183**				
k_6	**193,61**	**188,493**		**188,077**		**189,776**				
k_7	**192,755**					**189,177**				
k_8	**193,899**	**188,209**		**188,347**		**189,882**		**193,8**		
k_9	**194**	**188,404**		**188,477**		**189,988**		**193,121**		
k_{10}	**196,672**	**189,861**	**192,641**	**189,973**	**197,341**	**192,23**	**196,257**	**193,783**	**191,867**	**193,275**

(c)

Table 4: First set of experiments. (a) Performance-based, (b) Reliability-based, and (c) Total (Aggregate) retailer rating, prior to the UA's decision on the confined set of candidate retailers.

User Class	***Confined Set of Retailers***	***Objective Function Value***	***Retailer Selected***	***Improvement (%)***
k_1	7, **9**, 10	97,5	9	25.04
k_2	2, 3, **5**	96,3	5	27.33
k_3	7, **9**, 10	97,5	9	19.49
k_4	5, 8, **10**	96,9	10	16.92
k_5	**3**, 4, 6	95	3	29.78
k_6	1, **2**, 4	94,8	2	19.38
k_7	1, **6**	93	6	4.44
k_8	**2**, 4, 8	95,1	2	17
k_9	**2**, 4, 8	95,1	2	9.26
k_{10}	7, **9**, 10	97,5	9	40.84

(a)

User Class	*Confined Set of Retailers*	*Objective Function Value*	*Retailer Selected*	*Improvement (%)*
k_1	1, 5, **7**	97,4	**7**	**21.8**
k_2	1, 3, **5**	96,3	5	27.33
k_3	1, **5**, 8	97,3	**5**	**13.04**
k_4	1, 5, **8**	96,7	**8**	**11.56**
k_5	1, 3, **6**	95	3	29.78
k_6	1, **2**, 6	94,8	2	19.38
k_7	1, **6**	93	6	4.44
k_8	1, 6, **8**	94,9	**8**	**13.61**
k_9	1, 6, **8**	94,9	**8**	**5.56**
k_{10}	**7**, 9, 10	97,4	**7**	**38.47**

(b)

User Class	*Confined Set of Retailers*	*Objective Function Value*	*Retailer Selected*	*Improvement (%)*
k_1	1, 5, **7**	97,4	**7**	**21.8**
k_2	1, 3, **5**	96,3	5	27.33
k_3	1, 5, **7**	97,4	**7**	**16.26**
k_4	1, 5, **8**	96,7	**8**	**11.56**
k_5	1, **3**, 6	95	3	29.78
k_6	1, **2**, 6	94,8	2	19.38
k_7	1, **6**	93	6	4.44
k_8	1, 6, **8**	94,9	**8**	**13.61**
k_9	1, 6, **8**	94,9	**8**	**5.56**
k_{10}	1, 5, **7**	97,4	**7**	**38.47**

(c)

*Table 5: First set of experiments. Decision on the confined set of candidate retailers, and outcome of the retailer selection scheme (i.e., objective function value and selected retailer), for each user class, on the basis of the (a) performance rating***,** *(b) reliability rating, and (c) total (aggregate) rating.*

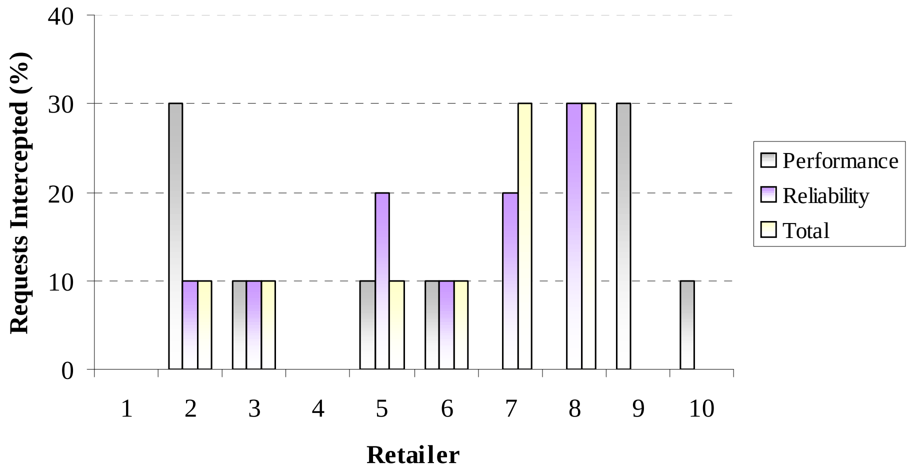

Figure 8: First set of experiments. Specialisation of the retailers with respect to the interception of requests of the various user classes, when the performance, reliability and aggregate criteria are considered for the configuration of the confined set.

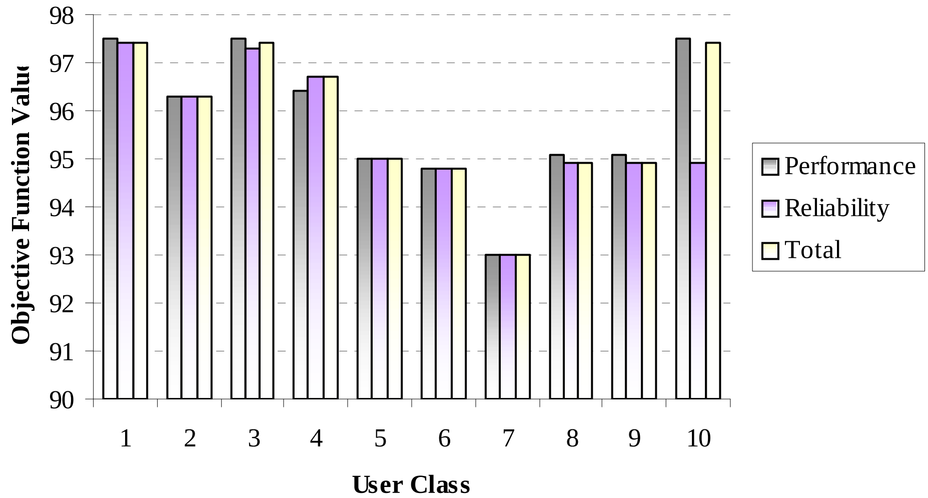

Figure 9: First set of experiments. Comparison of the retailers' selection scheme when the performance, reliability and aggregate criteria are applied for the selection of the retailers comprised in the confined set.

User Class	QA_1	QA_2	QA_3	QA_4	QV_1	QV_2	QV_3	QV_4
k_1	50	55			50	50,5		
k_2		50	51,5			50	50	
k_3	50				50	50,5		
k_4	50	51				50		
k_5			50	51		50	53	53
k_6		50					50	51
k_7				50	50	53		
k_8	50	50,3	53				50	
k_9	50						51	
k_{10}	50	50,3	51,5	50	50	51	51	53

Table 6: Second set of experiments. Description of service preferences in the user profiles of the 10 user classes that are involved in the experiments.

User Class	Objective Function Value	Retailer Selected	Improvement with respect to random retailer selection scheme (%)
k_1	102	5	3.13
k_2	96.5	3	1.09
k_3	97.5	9	0.41
k_4	97.3	5	0.66
k_5	96.5	4	2
k_6	94.8	2	1
k_7	93	6	1.53
k_8	96.5	4	1.71
k_9	96.1	2	0.5
k_{10}	97.9	10	1.21

Table 7. Second set of experiments. Outcome of the best candidate retailer selection scheme. Objective function value, selected retailer, and improvement with respect to the random retailer selection scheme, per user class involved in the experiment.

User Class	***Performance Ratings***									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**101,296**	**101,599**	**101,6**	**101,399**	**101,8**	**100,805**	**101,504**	**97,0128**	**101,304**	**97,2124**
k_2	**95,5725**	**96,0435**	**96,5**	**96,2435**	**96,3**	**95,9834**				
k_3	**97,0128**	**97,1077**	**97,2051**	**97,0077**	**97,3051**	**96,8**	**97,4**	**97,2**	**97,5**	**97,4**
k_4	**96,5**	**97**	**97,1**	**96,8**	**97,3**	**96,5**		**96,7**		**96,9**
k_5	**95,1088**		**95**	**96,5**		**95,1907**				
k_6	**93,5549**	**94,8**		**94,6**		**93,2439**				
k_7	**95**					**95,7**				
k_8	**95**	**95,1**		**96,5**		**95,1**		**94,9**		
k_9	**95**	**96,1**		**96**		**95**		**95,9**		
k_{10}	**97,1287**	**97,3257**	**97,5**	**97,2257**	**97,6**	**97,0137**	**97,4043**	**97,7386**	**97,515**	**97,9**

(a)

User Class	***Reliability Ratings***									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**100**	**93,6933**	**96,4774**	**93,4773**	**100,716**	**96,4773**	**100**	**100**	**94,9546**	**96,4773**
k_2	**100**	**93,6933**	**96,4774**	**93,4773**	**100,627**	**96,4773**				
k_3	**100**	**93,6933**	**95,988**	**93,4773**	**100,627**	**96,4773**	**100**	**100**	**94,9546**	**96,4773**
k_4	**100**	**93,6933**	**95,988**	**93,4773**	**100,627**	**96,4773**		**100**		**96,4773**
k_5	**100**		**95,988**	**93,4773**		**96,4773**				
k_6	**100**	**93,6933**		**93,4773**		**95,9879**				
k_7	**100**					**95,9879**				
k_8	**100**	**93,3039**		**93,4773**		**95,4984**		**100**		
k_9	**100**	**93,3039**		**93,4773**		**95,009**		**100**		
k_{10}	**100**	**93,3039**	**95,988**	**93,4773**	**100,537**	**95,009**	**99,7106**	**97,1106**	**94,9546**	**96,4773**

(b)

User Class	Total Ratings									
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9	R_{10}
k_1	**201,296**	**195,292**	**198,078**	**194,876**	**202,516**	**197,283**	**201,504**	**197,013**	**196,259**	**193,69**
k_2	**195,573**	**189,737**	**192,977**	**189,721**	**196,727**	**192,464**				
k_3	**197,013**	**190,801**	**193,193**	**190,485**	**197,932**	**193,277**	**197,4**	**197,2**	**192,455**	**193,877**
k_4	**196,5**	**190,693**	**193,088**	**190,277**	**197,927**	**96,3256**		**196,7**		**193,377**
k_5	**195,109**		**190,988**	**189,977**		**191,688**				
k_6	**193,555**	**188,493**		**188,077**		**189,232**				
k_7	**195**					**191,688**				
k_8	**195**	**188,404**		**189,977**		**190,598**		**194,9**		
k_9	**195**	**189,404**		**189,477**		**190,009**		**195,9**		
k_{10}	**197,129**	**190,63**	**193,488**	**190,703**	**198,137**	**192,023**	**197,115**	**196,849**	**192,47**	**194,377**

Table 8: Second set of experiments. (a) Performance-based, (b) Reliability-based, and (c) Total (Aggregate) retailer rating, prior to the UA's decision on the confined set of candidate retailers

User Class	*Confined Set of Retailers*	*Objective Function Value*	*Retailer Selected*	*Improvement (%)*	*Assigned QA_i*	*Assigned QV_j*
k_1	2, 3, **5**	102	5	3.13	QA_2	QV_1
k_2	**3**, 4, 5	96,5	3	1.09	QA_3	QV_2
k_3	7, **9**, 10	97,5	9	0.41	QA_1	QV_1
k_4	2, 3, **5**	97,3	5	0.66	QA_2	QV_2
k_5	1, **4**, 6	96,5	4	2	QA_3	QV_3
k_6	1, **2**, 4	94,8	2	1	QA_2	QV_3
k_7	1, **6**	93	6	1.53	QA_4	QV_2
k_8	2, **4**, 6	96,5	4	1.71	QA_3	QV_3
k_9	**2**, 4, 8	96,1	2	0.5	QA_1	QV_3
k_{10}	5, 8, **10**	97,9	10	1.21	QA_1	QV_2

(a)

User Class	***Confined Set of Retailers***	***Objective Function Value***	***Retailer Selected***	***Improvement (%)***	***Assigned QA_i***	***Assigned QV_j***
k_1	1, **5**, 7	102	5	3.13	QA_2	QV_1
k_2	1, **3**, 5	96,5	3	1.09	QA_3	QV_2
k_3	1, 5, **7**	97,4	**7**	**0.305**	QA_1	QV_1
k_4	1, **5**, 8	97,3	5	0.66	QA_2	QV_2
k_5	1, 3, **6**	95,1	**6**	**0.6**	QA_3	QV_3
k_6	1, **2**, 6	94,8	2	1	QA_2	QV_3
k_7	1, **6**	93	6	1.53	QA_4	QV_2
k_8	1, **6**, 8	95,1	**6**	**0.31**	QA_3	QV_3
k_9	1, 6, **8**	95,9	**8**	**0.3**	QA_1	QV_3
k_{10}	1, **5**, 7	97,6	**5**	**0.91**	QA_2	QV_2

(b)

User Class	***Confined Set of Retailers***	***Objective Function Value***	***Retailer Selected***	***Improvement (%)***	***Assigned QA_i***	***Assigned QV_j***
k_1	1, **5**, 7	102	5	3.13	QA_2	QV_1
k_2	1, **3**, 5	96,5	3	1.09	QA_3	QV_2
k_3	5, **7**, 8	97,4	**7**	**0.305**	QA_1	QV_1
k_4	1, **5**, 8	97,3	5	0.66	QA_2	QV_2
k_5	1, 3, **6**	95,1	**6**	**0.6**	QA_3	QV_3
k_6	1, **2**, 6	94,8	2	1	QA_2	QV_3
k_7	1, **6**	93	6	1.53	QA_4	QV_2
k_8	1, **6**, 8	95,1	**6**	**0.31**	QA_3	QV_3
k_9	1, 6, **8**	95,9	**8**	**0.3**	QA_1	QV_3
k_{10}	1, **5**, 7	97,6	**5**	**0.91**	QA_2	QV_2

(c)

Table 9: Second set of experiments. Decision on the confined set of candidate retailers, outcome of the retailer selection scheme (i.e., objective function value and selected retailer), and service configuration pattern (allocation of service features to quality levels), for each user class, on the basis of the (a) performance rating, (b) reliability rating, and (c) total (aggregate) rating.

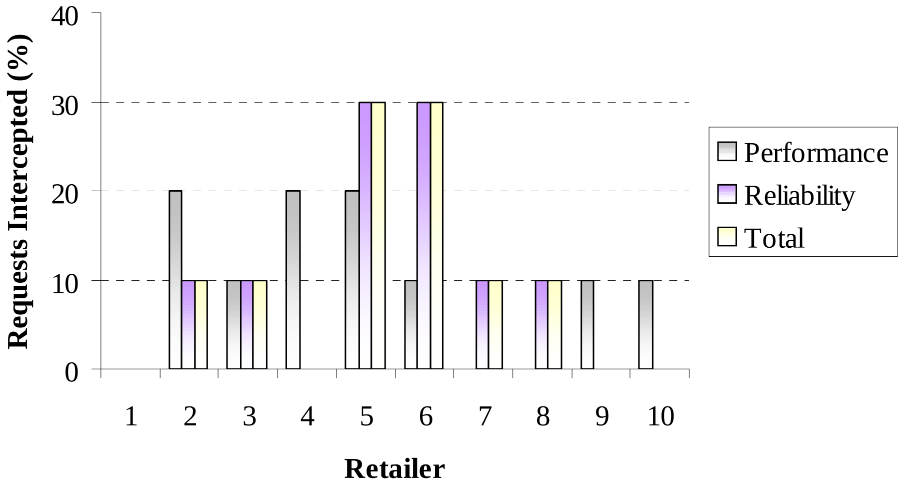

Figure 10: Second set of experiments. Specialisation of the retailers with respect to the interception of requests of the various user classes, when the performance, reliability and aggregate criteria are considered for the configuration of the confined set.

Figure 11: Second set of experiments. Comparison of the retailers' selection scheme when the performance, reliability and aggregate criteria are applied for the selection of the retailers comprised in the confined set.