Replication-Aware Query Processing in Large-Scale Distributed Information Systems[*]

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ABSTRACT

In this work, we address the problem of replica selection in distributed query processing over the Web, in the presence of user preferences for Quality of Service and Quality of Data. In particular, we propose RAQP, which stands for Replication-Aware Query Processing. RAQP uses an initial statically-optimized logical plan, and then selects the execution site for each operator and also selects which replica to use, thus converting the logical plan to an executable plan. Unlike prior work, we do not perform an exhaustive search for the second phase, which allows RAQP to scale significantly better. Extensive experiments show that our scheme can provide improvements in both query response time and overall quality of QoS and QoD as compared to random site allocation with iterative improvement.

1. INTRODUCTION

The Web has become the de-facto user interface and interconnection platform of modern life. Almost all collaborative, data-intensive applications are built for the Web or face obscurity. Many data-intensive applications are fueled by data from the physical world, thanks to the proliferation of (wireless) sensor technologies which are giving an unprecedented level of access and interaction with the real world.

In our Secure-CITI project (http://www.cs.pitt.edu/s-citi/), we envision a Web-based platform to be used to coordinate human response to disaster management. There is a pre-disaster component where different types of sensors are deployed in a networked fashion and are used to detect disasters (e.g., gas and water usage suddenly increase dramatically which could indicate a landslide in that area). There is also a critical component during the emergency, where in addition to sensor information, the same system is expected to be used to provide additional information (e.g., by providing real-time information about the capacity of area hospitals) and to coordinate human response (e.g., by identifying what is needed to perform a particular task and dynamically forming teams with the appropriate expertise to respond to it [2]). In such a scenario, many heterogeneous systems are glued together, facilitating the discovery and flow of critical information as a response to user requests.

To improve reliability, expedite data discovery, and increase performance, replication is expected to play a major role in large-scale distributed information systems, like the one we are exploring for Secure-CITI. By replicating information across multiple sites, crucial information can be accessed even in cases of disconnection or failure, which is common during disaster response (and most environments that are exposed to nature). Replication also allows for looser synchronization across multiple sites, which is necessary if the system spans different administrative or jurisdictional domains, which is typical in disaster management. In addition to data availability, replication allows for easier discovery of information, especially when catalogs are not present or not well maintained (i.e., the equivalent of unstructured overlay networks). Finally, replication is expected to drastically improve the overall performance of the system by reducing communication latency when requests are served locally or from close-by nodes. As such, we expect the most "valuable" data to be highly replicated across the entire system.

Although replication increases data availability and improves performance (i.e., Quality of Service, or QoS), it may have a detrimental effect to the Quality of the Data (QoD) that are being returned to the users. Getting results fast is crucial of course, but usually a limit to the degree of "staleness" is needed to make the results useful. Approaches for measuring QoD are traditionally grouped into three categories: *time-based* (where the time of last update is used), *divergence-based* (where the difference in value is used), and *lag-based* (where the number of unapplied updates is used) [9]. We concentrate on time-based measures of QoD, because we believe them to be the most general and the best fit for our case.

In this paper, we advocate going beyond simply measuring QoS and QoD. We introduce *Quality Contracts* (QC) as a novel way of specifying user preferences (with respect to QoS and QoD) and evaluating the system's adherence to them. The QC framework utilizes a market-based mechanism, which has been used in the past to solve resource allocation problems in distributed systems [11]. As such, it provides a natural and integrated way to guide the system towards efficient decisions that increase the overall user satisfaction. The QC framework also enables users to describe the relative importance of different queries and also the relative importance of the different quality metrics (e.g., preference for fast answers that are slightly stale). This results in "socially" optimal solutions for the entire system.

Using the QC framework, we propose a *Replication-Aware Query Processing* (RAQP) scheme that optimizes query execution plans for distributed queries with Quality Contracts, in the presence of multiple replicas for each data source. Our scheme follows the

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classic two-step query optimization [12, 7, 8]: we start from a statically-optimized logical execution plan and then apply a greedy algorithm to select an execution site for each operator and also which replica to use. The overall optimization goal is expressed in terms of ”profit” under the QC framework (i.e., the approach balances the trade-off between QoS and QoD), and as a special case, in terms of the traditional response time metric.

We provide the assumed system architecture and the QC framework in the next section. Section 3 contains the details of our RAQP scheme. We present extensive experimental results in Section 4. Section 5 describes related work. We conclude in Section 6.

2. SYSTEM OVERVIEW

2.1 System Architecture

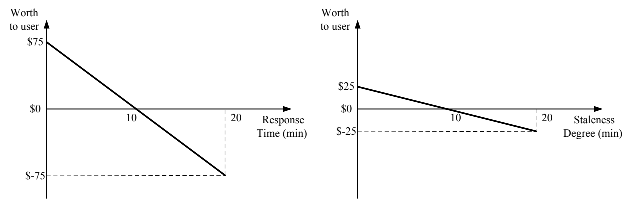
We envision a large-scale distributed information system, where heterogeneity in all aspects is the norm. Such a system is expected to bring together (1) a myriad of **receptors**, that are sensing the environment (e.g., RFID readers or sensors), contributing a tsunami of information, (2) a high number of **core nodes** that are providing a stable communications, storage, and query processing substrate, and, a plethora of **end-user access devices** (e.g., mobile PDAs or light-weight desktop machines) that are enabling their users to collaborate, contribute data and knowledge and cooperatively work towards a common goal (e.g., disaster response).

We assume that each data item is ”owned” by a specific node, but there is rampant replication in the system for availability and performance reasons. To facilitate data discovery, we build routing indexes[4] to direct the queries towards the nodes that are expected to hold relevant data. Each node maintains a local index, summarizing its local content. Core nodes maintain second-level indexes, that summarize index information from all nodes that connect to them, akin to a hybrid, unstructured P2P overlay network (e.g., Gnutella2). Core nodes can also exchange information among them, building merged indexes to summarize information on other reachable core nodes within a predefined horizon.

Query processing in our system is performed at core nodes. An end-user will send out a query message request along with a Quality Contract (QC) and a Time-To-Live (TTL) that controls the maximum number of hops the query could be routed in the network. After receiving a query message, a core node first checks its local index (in case it can answer the query), and then checks its merged index (in case a neighbor code node can answer the query). If there is a match (while abiding with the specified QC) an acknowledgment is sent back to the originator node which builds a query plan along with all the possible options for replicas. If there is no match, the query message is propagated further, until the TTL is reached.

2.2 Quality Contracts

In this work, we introduce *Quality Contracts* (QC) as a novel way of specifying user preferences (with respect to QoS and QoD) and evaluating the system’s adherence to them. The QC framework utilizes a market-based mechanism, which has been used in the past to solve resource allocation problems in distributed systems [11]. In our framework, users are allocated virtual money, which they “spend” to execute their queries according to their specifications for QoS (i.e., how fast they should get their results) and QoD (i.e., how fresh the results should be). Query servers (core nodes) execute queries and get virtual money in return for their services. The QC framework is general enough to also allow for *refunds*: servers pay virtual money back to the users if their queries were answered in an unsatisfying manner. In order to execute a query, both the user and the server must agree on a Quality Contract (QC). The QC



(a) QoS graph (b) QoD graph

Figure 1: QC example: combination of QoS and QoD requirements for one ad-hoc query

essentially specifies how much money the user is willing to pay to get their queries executed (according to their specifications for QoS and QoD). The amount of money paid to the server depends on how well the query is fulfilled, based on the user’s preferences.

We model Quality Contracts as a collection of graphs. Each graph represents a QoS/QoD requirement from the user. The X-axis corresponds to an attribute that the users want to use in order to measure the quality of the results, for example, response time. The Y-axis corresponds to the virtual money the user is willing to pay the server in order to execute his/her query. The QC graph is simply a function that maps quality (i.e., the user’s specification) to virtual money (i.e., the server’s reward). More than one graphs can be combined in a single QC, allowing for a user to consider multiple dimensions of quality of results, for example both QoS and QoD. The benefit of such approach is that users can easily specify the relative importance of the different quality metrics. For example, 75% of the “budget” of a given query can be allocated to QoS with the remaining 25% given to QoD; in this scenario, the system will give more attention to QoS instead of QoD (which will also be considered though). A server is expected to get ”paid” equally to the sum of all the virtual money from the different QC graphs.

In this work, we use linear functions for QCs; this can easily be extended to any monotonically decreasing function. Each QC is composed of two quality metrics: response time (QoS) and staleness degree, measured as time elapsed since the last update (QoD). An example of two such QC graphs is given in Figure 1a and 1b. In this example, the user has allocated $75 for optimal QoS, and $25 for optimal QoD.

2.3 Query Execution Plan

As in previous work [5], we assume that statistics regarding the cardinalities of the relations and the selectivities of the operators are available to the optimizer. We also assume that we can estimate the transmission cost between nodes and that it is relatively stable, so that the query optimizer can approximate the transmission cost incurred in transferring data. To estimate the latency between two arbitrary Internet end hosts, we utilize approaches from the networking community such as IDMaps[6] .

In this work, we extend traditional query execution plans with a *transmission operator* which will allow us to incorporate transmission costs in the query optimization process in a natural and integrated way. Transmission operators simulating transmission cost are simply incorporated between each pair of processing operators in the query execution plan. In this paper, we considered Select-Project-Join operators, however the framework and algorithms can be easily extended to handle non-relational operators, e.g., for querying XML documents (XQuery).

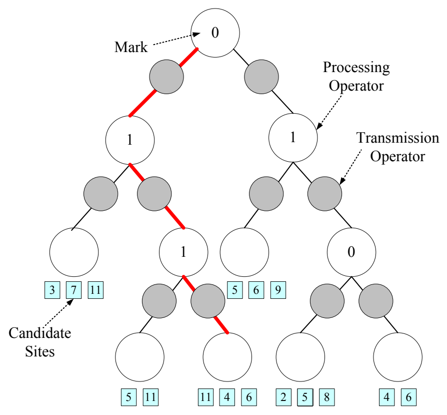


Figure 2: A query execution plan example

```
MARK-OPT-DIR()
for each node $i$
do if $i$ is a $leaf$
      then $LP(i) = Input\_Size\_i$
      else $LP(i) = estimated\_local\_processing\_i$
$PostOrderTraverse$
$//TR(i,j):$ $transmission\ amount\ from\ i\ to\ j;$
for each arc $i \rightarrow j$
do $W_{i,j} = (1-\alpha) \times LP(i) + \alpha \times TR(i,j)$
for each node $j$
do if $j$ is a $leaf$
      then $W_j = 0$
      else $i = Lchild(j);\ k = Rchild(j)$
            if $(W_{i,j} + W_i) \geq (W_{k,j} + W_k)$
               then $W_j = (W_{i,j} + W_i);\ M(j) = 0$
               else $W_j = (W_{k,j} + W_k);\ M(j) = 1$
return
```

Figure 3: Algorithm MARK-OPT-DIR

We present a QEP example in Figure 2. Processing operators and transmission operators are depicted as circles. Candidate sites (with replicas) are depicted as boxes. To generate an executable QEP, we need to select one site for each processing operator.

3. RAQP ALGORITHM

Our Replication-Aware Query Processing (RAQP) scheme follows the traditional two-step query optimization scheme[8] which has been extensively used in distributed database systems (e.g., XPRS[7] and Mariposa[12]). In the first phase, RAQP runs as if in a centralized system, generating the best query plan from a static point of view. In the second phase, RAQP dynamically chooses a replica for each data item and the execution site for each query operator, thus creating the final execution plan.

3.1 First Phase

In the first phase, we adopt the classic dynamic programming algorithm which has been proposed in system R[10]. However, we have lifted the constraint of left-deep trees from the system R optimizer and we are also looking at bushy trees, which is more appropriate in distributed systems, since they increase the parallelism.

3.2 Second Phase

In the second phase, we have two tasks to perform: replica selection (at the leaf nodes) and execution site selection (for the processing operators). We take the static query execution tree created from static planning phase as input and generate the physical execution plan as output.

Most previous work, assumed either that each data item has only one copy in the system, or that one replica has been selected prior to query optimization[8]. In most cases, the *Replica Selection Problem* (RSP) has been neglected. We expect high degree of replication in the types of systems that we are interested in (e.g., for disaster management), and as such, RSP is important. We define RSP formally as follows:

DEFINITION 1. *Assume a set of data items, D = {1, 2,. . . , m}, each of which has a set of replicas, S = $\{R_i^1, R_i^2, \ldots, R_i^n\}$, where $i \in D$. Each replica R_i^j is a tuple $\langle p_i^j, s_i^j, q_i^j \rangle$ where p_i^j is a price, s_i^j is the site replica R_i^j resides and q_i^j is the QoD of the replica. The Replica Selection Problem (RSP) attempts to label each replica as winning or losing, so as to maximize the processing node's revenue under the constraint that exactly one replica of each data item needs to be selected to form the best allocation.*

$$Max(B(alloc) - \sum_{s \in \mathcal{S}} p_i^j X_s)$$

$$s.t. \quad \forall s \in \mathcal{S}, \quad X_s \in \{0,1\} \quad and \quad \forall i \in D, \sum_{S|i \in D} X_s = 1$$

where B(alloc) is the sum of "profit" the processing node gets for fulfilling the quality contract.

Regarding site selection, previous work simply used exhaustive search to find the optimal allocation, since only one plan (which is selected by the first phase) will be explored. However, when we combine replica selection with site selection, exhaustive search is prohibitive for this NP-hard problem.

In our algorithm, we treat RSP and site selection in an integrated way. Our goal is to choose one site for each node in QEP, so that the final allocation is the best one in terms of either simply minimizing response time or maximizing the processing node's profit which is measured by total benefit from QCs minus the money "spent" on acquiring data. Specifically, we take query response time as QoS and aggregated staleness for QoD. We aggregate staleness by selecting either the highest staleness over the top data items or the average staleness of the top-k data items. Currently we assume that all replicas of a given data item have the same price and the same size. It is outside the scope of this work to determine how to effectively select such prices.

3.2.1 Initial Query Allocation

Given a statically optimized query plan, we first determine the allocation ordering. At each processing node, we set a flag to indicate our estimation of which subtree is more likely to be the bottleneck. Next, we will allocate that subtree first.

Formally, we traverse the tree in post order, for each arc $i \longrightarrow j$, assign weight as α times the transmission cost between i and j plus $(1-\alpha)$ times the local processing cost at node i. For each intermediate node, we calculate the aggregate working load from each subtree and mark M(i) to indicate the most expensive one. If it comes from left, M(i) = 0, otherwise M(i) = 1. This will be our optimization direction for future use. $\alpha \in (0,1)$ is a dynamic tuning factor to balance the transmission and processing cost. We use .5 in our experiment (i.e., giving equal importance). We provide the pseudo code for this MARK-OPT-DIR algorithm in Figure 3.

After the Query Execution Plan(QEP) is fully labelled, we start allocating in a bottom-up fashion. We traverse the estimated bot-

```
TRI-ALLOC()
$j = Lchild(i);$
$k = Rchild(i)$
$//BW(i,j):\ bandwidth\ between\ i\ and\ j;$
$\alpha = 1/avg(C(i)),\ i \in S_j \bigcup S_k$
$\beta = 1/avg(BW(i,j)),\ i,\ j \in S_j \bigcup S_k\ and\ i \neq j$
$T_{tr} = \beta \times \max(TR(j,i), TR(k,i))$
$T_{lp} = \alpha \times \min(LP(i), LP(j))$
switch
  case $T_{tr}/T_{lp}\ \geq \theta:\quad //Bandwidth - Bound$
      if $S_j \bigcap S_k \neq \emptyset$
        then $s = MC(S_j \bigcup S_k)$
             $L(i) = L(j) = L(k) = s$
        else $BW(m,n) = \max(BW(x,y))$
             $x \in S_j,\ y \in S_k\ and\ x \neq y$
             $L(j) = m; L(k) = n$
             if $TR(j,i) > TR(k,i)$
               then $L(i) = m$
               else $L(i) = n$
  case $T_{tr}/T_{lp}\ < \theta:\quad //CPU - Bound$
      if $LP(j) \geq LP(k)$
        then $C(p) = \max(C(s)), s \in S_j;\ L(j) = p$
             $C(q) = \max(C(s)), s \in \{S_k - p\};\ L(k) = q$
        else $C(q) = \max(C(s)), s \in S_k;\ L(k) = q$
             $C(p) = \max(C(s)), s \in \{S_j - q\};\ L(j) = p$
      $C(r) = \max(C(s)), s \in \{S_{st\_i} - p - q\};\ L(i) = r$
return
```

Figure 4: Algorithm TRI-ALLOC

tleneck path by starting from the root, go to left if M(i)=0, and go to right child otherwise, until we find the leaf (as depicted in Figure 2). We consider one triangle including three nodes as one allocation unit, and we start from the leaf, then its sibling and then their parent. Next time will be their parent, their parent's sibling and their grand-parent, and so forth. In each triangle, both children need to be either a leaf or both its subtrees to have been allocated, otherwise we allocate the subtrees first.

For each triangle, two allocation algorithms are applied. We call the first one **RAQP-L** which exhaustively explores the local search space to decide the optimal one. Alternatives include sending both relations to a third node, processing there; sending the smaller relation to the larger one, processing there, and assigning all three nodes on the same site, so that local processing is the only cost.

Another algorithm is a greedy one which we call **RAQP-G**. For each triangle, we calculate a score to estimate if this subquery is *CPU-bound*, i.e., local processing is the bottleneck, or *bandwidth-bound*, i.e, transmission cost dominates response time. If it is bandwidth-bound, we try to get rid of transmission by processing operators in groups. If the candidate sets of two children have an intersection, we allocate all three nodes on the same site. If there is no intersection, we allocate the parent to the same site as the slowest child in the transmission. Whenever more than one site satisfies the condition, we choose the site which covers most referenced data as the winner (since it has more of a chance to be improved in a later allocation), and use the QoD as the second tie breaker. If it is CPU-bound, we try to spread jobs to different sites so that the computation could be done in parallel. The two children choose the most powerful site from their own candidate set under the constraint that they are allocated in different ones. The parent node is allocated to the most powerful site in the union of its subtree's candidate set under the constraint that it's different from both its children.

We give the pseudo code of this greedy algorithm Tri-Alloc in Figure 4. S_i is the candidate set of node i, C(t) is the CPU capacity of site t, MC(S) is the most covered site in set S and L(i) is the running site we allocated for node i.

3.2.2 Iterative Improvement

After an initial allocation is determined, we iteratively adjust the bottleneck path/node according to our optimization goal.

As a special case, we optimize for *response time*, the traditional performance metric. We first locate the real bottleneck path under the initial allocation and try to improve the bottleneck node on this path. If the most costly node is a processing node, there are two cases. If more than one operator is running on the currently allocated site, we offload the heaviest job to the most light-loaded site. If there is only one job running, we move the job to another more powerful site. If the most costly node is a transmission node, we remove that by merging the two processing nodes into the one which has lighter load between the two. After each adjustment, the response time of the new plan is recalculated. The change is accepted if it leads to an improvement, and then the process is repeated. Otherwise, the improvement step stops and the current allocation is returned as final one.

In general, our optimization goal is to maximize the *overall "profit"* under the QCs. We need to consider both QoS and QoD in this case. Our improvement step is divided into two substeps. First, we locate and improve the bottleneck on response time in the same way as described above. The modification will be accepted if the total profit is improved, otherwise we label this try as failed. Second, we locate the bottleneck replicas in this plan based on their staleness degree. Once found, we replace those replicas with other ones that improve the overall QoD (thus satisfying more QCs). The process is repeated until neither QoS nor QoD can be further improved.

Simulation Parameter	Default Value
Core Node Number	100
Edge Node Number	1000
Unique Data Source	1000
Unique Data Number Per Data Source	U(10, 100)
Data Size	U(20, 200Mb)
# of Replicas Per Data	U(10, 30)
Bandwidth between each pair of Nodes	U(1, 50Mbps)

Table 1: Default System Parameters in Experiments

4. EXPERIMENTAL STUDY

We evaluated our proposed replication-aware query processing algorithm experimentally by performing an extensive simulation study using the following algorithms:

- **Exhaustive Search (ES):** Explore the whole search space exhaustively, thus guaranteeing to find the optimal allocation.
- **RAQP-G:** Greedy replication-aware initial allocation plus iterative improvement.
- **RAQP-L:** Bottleneck breakdown, local exhaustive search plus iterative improvement.
- **Rand(k):** Random initial allocation plus k steps of iterative improvement. In each step, the bottleneck node is identified and a random replacement is selected, if our optimization goal is improved. We use it as a "sample" of the search space.

We implemented an initial prototype of our distributed system, as described in section 2. The system parameters used in our experiments are reported in Table 1.

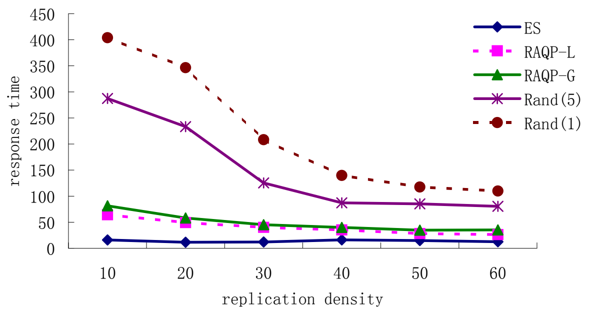


Figure 5: Response time under various degree of replication

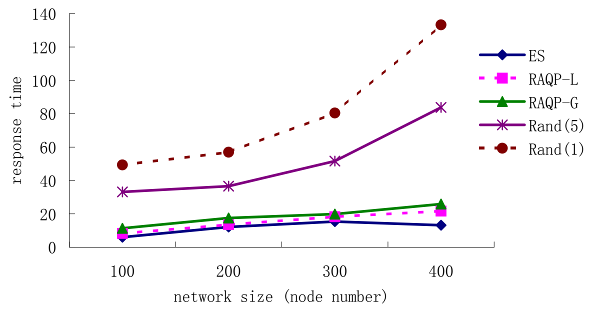


Figure 6: Response time under various network sizes

4.1 Optimizing for Response Time

In the first set of experiments, our optimization goal is to minimize the response time. We evaluate the different optimization algorithms under various circumstances. To avoid bias in the results, we repeated each experiment 5 times with different random seeds, and report the average values.

4.1.1 Effect of Replication Degree

We artificially varied the number of replicas per data item in the system. We optimize queries with 6 joining relations. The quality of the resulting plans is reported in Figure 5. Clearly, our RAQP algorithms greatly outperformed Rand(5), and RAQP-L was a bit better than RAQP-G. As expected, ES always finds the optimal plan.

An obvious observation is that the quality of the resulting plans is improved as the number of replicas is increased. There are two reasons. First, as the number of replicas increases, we get more nearby candidate sites (which improves response time). Second, more replicas mean more candidate sites for execution, which increases the search space (and improves the overall response time).

4.1.2 Optimization Overhead

Exhaustive search can always find the optimal plan, however, its running time is prohibitive in large-scale systems. We fixed the number of replicas to 20 and looked at the running time of different algorithms versus the quality of the resulting plans. We report our findings in Table 2(a). Clearly, ES took around 2 days to find the optimal plan, while our RAQP-G algorithm took around 70 ms.

We also report the optimization time for queries with 3 and 1 joins in Table 2(b) and 2(c). We found similar trends in all three experiments. We did not increase the number of joins beyond 6 as we would not have been able to compare with the exhaustive algorithm.

	ES	RAQP-L	**RAQP-G**	Rand(5)	Rand(1)
resp. time	11.62s	49.23s	58.11s	233.2s	346.5s
opt. time	**1.9days**	**53min**	**70ms**	**28ms**	**15ms**
total time	1.9days	54min	58.18s	233.2s	346.5s

(a) Optimization time for queries with 6 joins

	ES	RAQP-L	**RAQP-G**	Rand(5)	Rand(1)
resp. time	16.57s	20.34s	25.14s	87.08s	94.25s
opt. time	**9.58min**	**2.61min**	**33ms**	**20ms**	**11ms**
total time	9.86min	2.95min	25.17s	87.1s	94.26s

(b) Optimization time for queries with 3 joins

	ES	RAQP-L	**RAQP-G**	Rand(5)	Rand(1)
resp. time	10.38s	10.87s	11.28s	20.01s	25.27s
opt. time	**40ms**	**23ms**	**5ms**	**2ms**	**1ms**
total time	10.42s	10.9s	11.28s	20.01s	25.27s

(c) Optimization time for queries with 1 joins

Table 2: Optimization time for join queries

4.1.3 Effect of Network Size

In the second set of experiments, we varied the network size to observe the changes in optimization quality. In order to show the trend clearly, we chose 100 to 400 as the network size. The results are reported in Figure 6. A jump, from 100 to 200 makes small difference in the relative quality change. However, when the network size increased to 300, 400, the random algorithm showed much worse performance compared to others. The reason is when the system enlarges, our search space becomes sparser. Not surprisingly, the blind random search performed much worse than our informed heuristic search. For the above sets of experiments, we also confirmed that our algorithm scaled very well in both running time and the optimization quality. RAQP is also relatively stable under various network size and data loads.

4.2 Optimizing for Profit

In this set of experiments we tune our algorithms to optimize for the overall QC profit instead of simply response time.

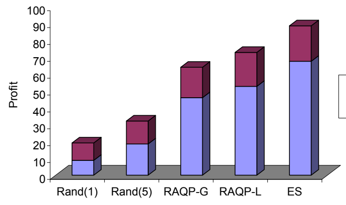
One of the important features Quality Contracts hold is that users can easily specify the relative importance of each component of the overall quality by allocating the query budget accordingly. In order to observe the algorithm performance under different environments, we classify the users' quality requirements into 6 classes. We have three values for QoS and QoD: high (75), low (25), same (50) and two types of slope for the QC function: small and large, which produce 6 seperate classes. Each data item had 20 replicas. We report our results in Figure 7.

Since our allocation initialization algorithm was aimed at response time improvement, QoS got more improvement than QoD in all the cases. Especially when QoS was assigned higher budget, the effect on both QoS and total profit were obvious. When QoD was assigned higher budget, the relative improvement of QoD also increased compared to the lower budget case.

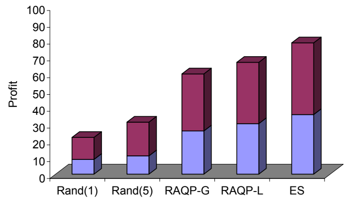
Our results clearly confirmed the functionality of Quality Contracts and our RAQP algorithm. Assigning higher "budget" to a quality dimension ends in that dimension getting better performance by our optimization algorithm. The larger the budget difference the larger the difference in the resulting quality. This is behavior is unique to our algorithm and is an important feature to have when both QoS and QoD are of concern to users.

5. RELATED WORK

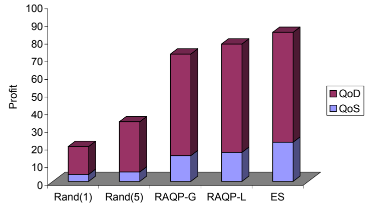
Mariposa[12] is the first distributed DBMS to use economic schemes as the underlying paradigm. Queries are submitted to the Mariposa system with a bid curve on delay; a broker sends out requests,



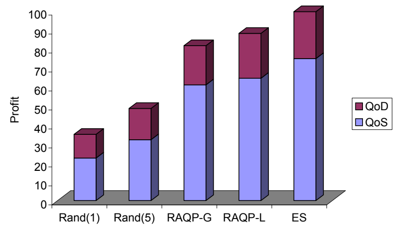
(a) QoS ≫ QoD, QCslope:Large



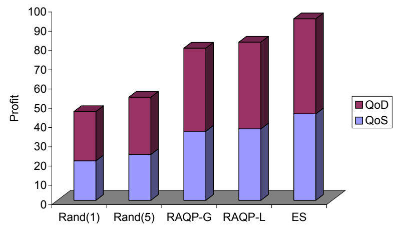
(b) QoS = QoD, QCslope:Large



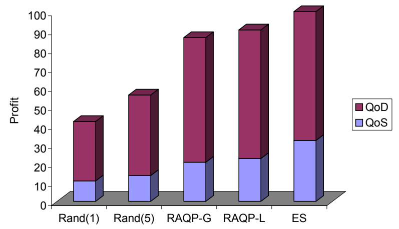
(c) QoS ≪ QoD, QCslope:Large



(d) QoS ≫ QoD, QCslope:Small



(e) QoS = QoD, QCslope:Small



(f) QoS ≪ QoD, QCslope:Small

Figure 7: Total profit of the algorithms under different classes

collects bids and decides on the best plan; bidders are discovered through name servers. The main difference from our work is that we addressed QoD as another quality measure. Second, we applied different query processing schemes in our system. Third, we avoid the cost of building and maintaining name servers in our system.

Another system close to ours is Borealis[1], a distributed stream processing engine, which inherits stream processing functionality from Aurora[3]. Aurora adopted a utility-function based QoS model on the processing delay of output tuples. Borealis also uses multi-dimensional quality metrics which could include response time, quality of data and etc. The difference from our work (QC) is that Borealis simply measures the overall quality by calculating an aggregated value from a global weight function, and the weight for each quality dimension is fixed. In our work, each user can allocate these weights and differentiate among queries and quality metrics.

There is a lot of work on distributed query optimization, but to the best of our knowledge, we are the first to address the problem of replica selection under quality guarantees.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we introduced Quality Contracts (QC) as a unifying framework to enable users to specify their QoS and QoD requirements and their relative importance. Additionally, we proposed a replica-aware query processing scheme and demonstrated that it works fairly well for both optimization goals, response time and total profit from multi-dimensional quality requirements. In this paper, we focused on SPJ queries, however, we believe the proposed framework and algorithms can be easily extended to cover XML data and XQuery.

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