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SLA Definition for Multi-Tenant DBMS and its Impact on Query Optimization

Shaoyi Yin , Abdelkader Hameurlain , and Franck Morvan

Abstract—In the cloud context, users are often called tenants. A cloud DBMS shared by many tenants is called a multi-tenant DBMS. The resource consolidation in such a DBMS allows the tenants to only pay for the resources that they consume, while providing the opportunity for the provider to increase its economic gain. For this, a Service Level Agreement (SLA) is usually established between the provider and a tenant. However, in the current systems, the SLA is often defined by the provider, while the tenant should agree with it before using the service. In addition, only the availability objective is described in the SLA, but not the performance objective. In this paper, an SLA negotiation framework is proposed, in which the provider and the tenant define the performance objective together in a fair way. To demonstrate the feasibility and the advantage of this framework, we evaluate its impact on query optimization. We formally define the problem by including the cost-efficiency aspect, we design a cost model and study the plan search space for this problem, we revise two search methods to adapt to the new context, and we propose a heuristic to solve the resource contention problem caused by concurrent queries of multiple tenants. We also conduct a performance evaluation to show that, our optimization approach (i.e., driven by the SLA) can be much more cost-effective than the traditional approach which always minimizes the query completion time.

Index Terms—Cloud computing, cost-efficiency, multi-tenancy, query optimization, service level agreement

1 INTRODUCTION

A multi-tenant DBMS can be used by a PaaS (Platform as a Service) provider to manage the data of all its customers (which become tenants in the cloud context). This kind of service is often called DBaaS (Database as a Service). As in any other cloud-based service, the resource consolidation allows the tenants to only pay for the resources that they consume (pay-as-you-go), while providing the opportunity for the provider to increase its economic gain. Examples of such systems include MS SQL Azure [23], Amazon RDS [2] and Oracle Data Cloud [17]. With these systems, a Service Level Agreement (SLA) is established between the provider and a tenant. However, they are often defined by the provider, while the tenant should agree with it before using the service. In addition, only the availability objective is described in the SLA of these services, but not the performance objective. Indeed, defining performance objectives and above all, guaranteeing them is very challenging. Database queries have different levels of complexity, so defining a unique performance objective for all queries is not realistic.

In the research community, some work [13], [19] has introduced the performance SLO (Service Level Objective) to the DBaaS systems, for OLTP applications [13] and for OLAP applications [19] respectively. In this paper, we are interested in OLAP applications. Similar to but slightly different from

[19], we will include the performance objective in the SLA by fixing a threshold for each query template¹ and associate a price to it. In order to do so, we will define a negotiation framework such that the tenant and the provider could define this threshold together in a rather fair way. The aim is to find a performance objective that is satisfactory or at least acceptable by the tenant and reachable (i.e., technically achievable and financially profitable) for the provider. In the SLA, we also fix the pricing policy, which is used to adjust the price according to the real performance and the parameter values. If the query answer is delayed or the query is rejected, a penalty should be paid by the provider.

In a multi-tenancy environment, the performance for an individual tenant can be degraded because of the interference of other tenants. Guaranteeing the satisfaction of a tenant in terms of performance is a critical problem. A possible solution is to enforce performance isolation [16], [6], i.e., to specify the performance objective in the SLA by fixing the absolute amount of required resources (e.g., CPU, I/O, memory, and network) and the penalty in case of violation. This solution requires a lot of responsibility from the tenant: the tenant has to know in advance how many resources will be needed for its query, which is a very difficult task with OLAP applications. Thus, in our work, we will define the SLA in a different way such that the tenant does not need to know the resource consumption in advance. During the SLA negotiation, the tenant only provides the query templates with some basic statistics, and it is the provider who is responsible for estimating the resource requirements of a query in order to propose a reasonable price. Then,

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1. A query template is a parameterized SQL query, i.e., to use variables instead of constant values in the selection predicates, as can be seen in the TPC-H benchmark.

controlling the real resource consumption for a specific query becomes an important task of the query optimizer.

Once the SLA is defined, the objective of the query optimizer is to find an execution plan for a given query such that the performance expectation of the tenant is satisfied and the economic benefit of the provider is maximized. Sometimes, the optimizer detects that there are not enough resources to reach the performance objective, or that the economic benefit could be negative. In these cases, the optimizer should decide whether to wait for resources to be released, or to reject the query, or to start the current query but suspend other running queries which are relatively less beneficial. In other words, the query optimizer should be revisited to solve these problems.

The contributions of this paper are: (1) we define a framework which allows a fair negotiation between both the provider and the tenant. The tenant prepares a test case containing a small set of query templates, specifying a performance expectation for each template, and the provider proposes a pricing function with regard to the real performance and the parameter values. The tenant could compare offers from different providers and choose the most appropriate one; (2) we study the impact of the SLA on query optimization to demonstrate the feasibility and the advantage of our framework. We formally define the problem by taking into account the economic aspects. We revise the cost model, the search space and some search methods to adapt to the new context. We also propose a heuristic to solve the resource contention problem caused by concurrent queries of multiple tenants.

The rest of the paper is organized as follows. Section 2 analyzes the related work. Section 3 defines the SLA negotiation framework. Section 4 studies the impact on query optimization, including the problem formulation, a cost model, the search space and two search methods. Section 5 shows the experimental results. Finally, Section 6 concludes the paper and points out future work.

2 RELATED WORK

As said above, in this paper, we deal with two main challenges: (1) the SLA definition for multi-tenant DBMS, which takes into account the performance objectives, and (2) cost-effective query optimization. Below, we study the related work corresponding to these two directions.

2.1 Performance Concerned SLA Definition

In the DBaaS context, [13] is one of the first research work which takes the performance SLO into consideration for query processing. This work has been done for OLTP applications and the performance metric is transactions per second (tps). Two types of SLO are distinguished: (1) H, associated with a high performance of 100 tps and (2) L, associated with a lower performance of 10 tps. The authors present a framework that takes as input the tenant workloads, their performance SLOs, and the available hardware resources, and outputs a cost-effective recipe that specifies how much hardware to provision and how to schedule the tenants on each hardware resource.

A recent work [19] which focuses on OLAP applications introduces the notion of Personalized Service Level

Agreement (PSLA). The main idea is that a tenant should specify the database schema with basic statistics (e.g., base table cardinalities), and then the cloud provider shows different levels (tiers) of services that can be provided. Each service tier contains a set of query templates, the estimated performance for each template and the price (dollars/hour) corresponding to this level of service. The advantage is that the tenant does not need to specify its query templates in advance, but only needs to choose a service level. However, PSLA has some constraints. In fact, each defined service tier is generated based on a specific hardware configuration, for example, a shared-nothing architecture with 4 nodes, 6 nodes or 8 nodes. Thus, inside a tier, the performance degrades with the complexity of the query. Once the tier is chosen, a tenant cannot expect a good scalability (i.e., having more or less the same performance for simple and complex queries by allocating different amounts of resources).

In our paper the target workload is OLAP applications, and the performance metric is the Query Completion Time (QCT)². Unlike in [19], we allow a tenant to specify an expected performance threshold for each query template independently, and each query will be invoiced separately. It is the query optimizer of the provider which decides how many resources should be dedicated to a given query and issues performance isolation if necessary. Indeed, the tenant has to provide in advance a small set of query templates that he will make. However, in the context of OLAP applications, this is not a hard problem.

2.2 Monetary-Cost-Aware Query Optimization

Some research work treats monetary-cost-aware query optimization as a multi-objective optimization problem [27]. QCT and Monetary Cost (MC) are defined as independent cost metrics. The query optimizer tries to find the best trade-off.

Algorithms like Dynamic Programming (DP) [21] that prune plans based on a single cost metric rely on the following principle of optimality: replacing subplans within a query plan by better subplans with regard to that cost metric cannot worsen the entire query plan. This principle breaks when there are multiple cost metrics [7]. Based on that insight, Ganguly et al. [7] proposed an extended DP algorithm that uses a multi-objective version of the principle of optimality. This algorithm guarantees to generate optimal query plans. However, it is too computationally expensive for practical use, as shown in [27]. Thus, Trummer et al. [27] proposed two approximation schemes for multi-objective query optimization problem which formally guarantee to return near-optimal query plans while speeding up optimization by several orders of magnitude in comparison with exact algorithms. However, as we will demonstrate in Section 4.4.1, when the parallelism of query execution is considered, the pruning strategy used in [7] and [27] becomes invalid.

Kllapi et al. [12] also tackled the problem of multi-objective optimization, but it focuses on the resource allocation phase of data processing flows in the cloud. The authors proposed some heuristics based on greedy algorithms and simulated annealing [8] to find the optimal schedule for three types of problems: (1) minimize QCT given a fixed budget,

2. QCT is defined to be the elapsed time between the query submission and the return of the complete result (Section 4.1).

(2) minimize MC given a deadline, and (3) find trade-offs between QCT and MC without any a-priori constraints. Indeed, resource allocation is also an important step in query optimization. However, it is not the focus of our paper. We deal mainly with the join order determination problem, as in [27].

Although multi-objective optimization is relevant to our work, it is a general approach, and for our specific problem described in Section 1, we think that it is more appropriate to define it as a single objective optimization problem. We try to maximize the provider's benefit, while treating the query completion time threshold and the maximum resource consumption as constraints to meet. The reason of doing this is twofold: first, the tenant does not need to choose a plan from a set of proposed plans for each query. Thus, the query processing is transparent; second, the constraints can be used by the optimizer to prune some intermediate results, so that the search method is more efficient, as will be shown in Section 5.5.

3 SLA NEGOTIATION FRAMEWORK

In the existing SLAs for DBaaS systems, the performance objective (i.e., the QCT) is not explicitly described [3], [18], [22]. The main reasons are as follows. First, even if the tenant may have a rough expectation for the QCT, it is not sure that this expectation could be met by the provider. Second, if we let the provider define the QCT threshold and the price, it may trick the tenant. In fact, the commonly used pricing policy is that the price is a function of the consumed resources. However, for a database query, the resource consumption depends on the execution plan chosen by the optimizer. If the optimizer chooses a bad plan, not only will the QCT be larger, but also the bill will be higher, which is not fair for the tenant. Therefore, neither the tenant nor the provider should decide alone the performance objective and the corresponding price for a query. In this section, we will define a framework which allows a fair negotiation between both sides. The negotiation is aided by an automated Offer Generation Tool (OGT) at the provider's side. The design of a good OGT is not trivial. It should follow some guidelines: (1) the generated offer should be simple enough so that the tenant can easily understand it, (2) the defined performance objective should be reachable by the provider for any instantiated query, (3) the defined objectives should be auditable by the tenant, and (4) the communication during the negotiation between the provider and the tenant should be minimized.

The main idea of our negotiation framework is as follows. For each template, the tenant specifies an expected QCT (QCT_{EXP}) and a tolerance threshold λ . The OGT estimates the shortest QCT (QCT_S) with the corresponding price, and the lowest price with the corresponding QCT. If QCT_{EXP} is smaller than QCT_S , the expected QCT will be automatically adjusted to QCT_S . Then, the OGT defines a price function with regard to the actual QCT. The tenant could compare this offer with the offers from other providers. Once the provider is chosen, the tenant can add new query templates whenever he wants, and the OGT can automatically extend the SLA. Note that the statistics the tenant provides may be inaccurate so the

estimation may be irrelevant. In this case, a renegotiation may be triggered. These steps will be discussed in detail in Section 3.1. An example will be given in Section 3.2.

3.1 Steps for Generating the SLA Offer

The main steps are explained in detail below.

Step 1: Fixing the QCT threshold for each query template. The input to the OGT includes: (a) the schema of the database (i.e., relations, attributes, data types, and constraints, etc.), (b) the estimated number of tuples in each base relation, (c) a set of query templates with parameterized predicates (as in the benchmark TPC-H), (d) a QCT_{EXP} and a tolerance threshold λ for each template, and (e) some other statistics that are needed to estimate cardinalities of intermediate results (e.g., numbers of distinct values of the attributes), if available. If (e) is not provided by the tenant, the OGT will use some default values. The inaccuracy problem is addressed in *Step 4*.

For each query template, the OGT first supposes the highest selectivity for each parameter and calculates the following information, by running its query optimizer: (1) the shortest query completion time QCT_S and the corresponding price PR_S , and (2) the lowest price PR_L and the corresponding query completion time QCT_L .

If QCT_{EXP} is smaller than QCT_S , the expected QCT will be automatically adjusted to QCT_S . For example, for a given query template, the tenant has an initial expected query completion time, which is 15s. If the optimizer returns the following result: $QCT_S = 5s$, $PR_S = 50 \text{ cents}$; $QCT_L = 10s$, $PR_L = 5 \text{ cents}$, then the threshold 15s will be maintained, and the price will be 5 cents. However, if the optimizer returns: $QCT_S = 20s$, $PR_S = 30 \text{ cents}$; $QCT_L = 50s$, $PR_L = 5 \text{ cents}$, then the tenant's expectation will be adjusted automatically by the OGT to 20s.

If $QCT_S \leq QCT_{EXP} \leq QCT_L$, the corresponding price PR_{EXP} is fixed by using the following function:

$$PR_{EXP} = PR_L + \frac{PR_S - PR_L}{QCT_L - QCT_S} \times (QCT_L - QCT_{EXP}). \quad (1)$$

For the last example, if the threshold was 30s, then according to this function, the expected price is 22 cents.

Step 2: Defining the price function with regard to the real QCT. A naïve pricing policy could be that: if the real QCT is not larger than QCT_{EXP} , the provider returns back the query result and the tenant will be billed with the expected price; otherwise, the provider does not give back the result and pays a penalty instead. However, we find it too strict. In fact, very often, the tenant could tolerate a small delay if the price is reduced correspondingly. Thus, in our framework, we allow the tenant to define a factor λ such that a penalty is only paid if $QCT > \lambda * QCT_{EXP}$. More precisely, the following function is applied to compute the price to be invoiced (denoted by PR_{SLA}):

$$PR_{SLA} = \begin{cases} PR_{EXP}, & \text{if } QCT \leq QCT_{EXP} \\ \left(\frac{QCT_{EXP}}{QCT}\right) \times PR_{EXP}, & \text{if } QCT_{EXP} < QCT \leq \lambda \times QCT_{EXP} \\ -PR_{EXP}, & \text{if } QCT > \lambda \times QCT_{EXP} \end{cases} \quad (2)$$

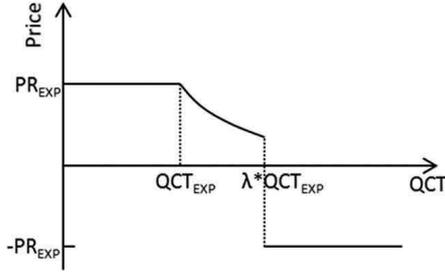


Fig. 1. Pricing function.

This is illustrated by Fig. 1. Once the price functions are defined, the tenant compares them with the offers from other providers and chooses the best one for him.

We define the price as a piecewise function with respect to the QCT value, but it does not mean that each point is achievable, since the solutions for a query are discrete points. However, we think that it is not a problem, and the most important thing is that the way that we fix the QCT threshold and define the price function is fair for both sides. On the one hand, the tenant cannot trick the provider to acquire a penalty by defining a lower QCT_{EXP} . First, as said above, QCT_{EXP} cannot be smaller than QCT_S , so there is always a chance that the provider meets the threshold. Second, if the tenant picks a low QCT_{EXP} and the provider meets it, the tenant has to pay a high price. Thus, the best strategy for the tenant is to show his expectation honestly. On the other hand, the provider cannot trick the tenant by offering higher PR_S and PR_L either, due to the pressure that the tenant may choose another provider.

Step 3: Varying the price according to the selectivity.

Since the price PR_{EXP} in Step 1 is computed by supposing the highest selectivity for each parameter, there might be an overpricing problem. To avoid this, it is better to define a finer pricing function with respect to the selectivity for each parameter. However, unfortunately, such a function can be extremely complex, especially when there are multiple parameters in a query template. In order to make a tradeoff between the fairness and the ease of comprehension, we propose to compute three expected prices (PR_{EXP_LOW} , PR_{EXP_MEDIUM} and PR_{EXP_HIGH}) corresponding to three levels of selectivity: low, medium and high. For example, if a query template contains two parameters X and Y , the selectivity interval of X is $[0.1, 0.5]$ and the selectivity interval of Y is $[0.3, 0.9]$, then the OGT will estimate three prices: for example, 10 cents for $(0.1, 0.3)$, 30 cents for $(0.3, 0.6)$, and 100 cents for $(0.5, 0.9)$.

For a specific query, when we generate the invoice, we will compute the Euclidean distances between its selectivity vector and the three pre-defined vectors respectively. The one with the shortest distance decides the price.

Step 4: Renegotiating and extending the SLA. The reliability of the OGT relies on the cost model of the query optimizer, especially the cardinality estimation module. In fact, cardinality estimation is itself a complicated subject which has been well-studied in the literature [14], [1]. With the proposed techniques, estimation errors can be reduced but are still inevitable. Therefore, we accept that the first estimation of the OGT can be inaccurate. This is not a problem for the tenant, because the main objective of the initial negotiation is

to compare offers from different providers. Since all providers receive the same statistics, the comparison remains valuable. However, for the provider, it may cause some financial loss. Our solution is to periodically detect the estimation inaccuracy by using execution traces and propose a renegotiation if it is significant enough (e.g., the overall economic loss during the last month reaches 5 percent due to this inaccuracy). During the renegotiation, since the OGT can extract exact cardinalities from the execution traces, the new cost estimations become much more accurate. The provider can even get refunded for the past queries. Of course, the refunding policy should be written clearly in the SLA to avoid that malicious tenants refuse to be responsible. The execution traces can be used by the tenant to prepare a new test case to see if other providers could propose cheaper offers. Evidently, the provider should minimize the renegotiation risk. A possible track is to adapt robust query optimization methods [28] to the cloud context.

Another case is that the database grows with time, so the statistics become obsolete. In this case, the provider can update the SLA periodically without renegotiations. The tenant is not obliged to check each updated version of the SLA, but he can make a control whenever he wants.

As said before, once the initial SLA is established, it can be dynamically extended. That is to say, new templates can be added at any moment and the corresponding price functions will be generated immediately. Thus, ad-hoc queries can be handled easily. To insure that the provider treats new query templates equally with those defined in the initial SLA, he is obliged to provide a detailed invoice and necessary execution traces for each query, so the tenant can carry out an audit process if in doubt. To insure the credibility of the traces, fraud detection techniques should be designed. However, in our paper, we do not address this issue.

3.2 An Example

Let us consider the query template given in Step 3. The OGT uses the query optimizer to make estimates and gets the following information: for the highest selectivity, the shortest time $QCT_S = 52s$ and $PR_S = 150$ cents; the lowest price $PR_L = 50$ cents and $QCT_L = 60s$.

We assume that the expected QCT of the tenant is 56s and the tolerance factor is 2. Then, QCT_{EXP} is accepted as 56s and the expected price for the high selectivity is 100 cents. After that, the optimizer estimates the lowest prices for medium and low selectivities, under the constraint of $QCT \leq 56s$. Suppose that they are 30 cents and 10 cents.

Now, let us consider a query with selectivity vector $(0.3, 0.7)$. Normally, the provider could answer it in at most 56s and the price should be 30 cents. However, if the provider is overloaded and answers the query in 80s, the tenant will accept it, even though he is less satisfied. The good news is that he only needs to pay a bill of 21 cents.

4 IMPACT ON QUERY OPTIMIZATION

In order to meet the defined SLA while maximizing the provider's benefit, in this section, we reformulate the query

optimization problem and revisit the principle components of the query optimizer.

4.1 Problem Formulation

In this study, we assume that the database server is a parallel DBMS running on top of a shared-nothing architecture. We deal with SPJ (Select-Project-Join) queries, which are the most frequent queries in OLAP applications. Thus, a query Q can be represented as a connected graph, where each vertex is a relation, and each edge is a join predicate.

Before defining the optimization problem, we first introduce some important cost metrics for a query execution plan.

Query Completion Time (QCT): the elapsed time between the query submission and the return of the complete result.

Maximum Parallelism Degree (MPD): the maximum number of nodes occupied at the same time during the query execution.

Monetary Cost (MC): the economic cost with regard to resource consumption.

$$MC = \sum_{i=1}^N DR_i \times PR_{Node} + V_{tr} \times PR_{net}, \quad (3)$$

where N is the number of nodes used for the query execution, DR_i is the duration that *Node* i is occupied, PR_{Node} is the monetary cost of a node during a time unit (e.g., cents/s), PR_{net} is the monetary cost of the network to transfer a bit, and V_{tr} is the total volume of data (number of bits) transferred during query execution.

Note that the MC is the monetary cost for the provider, but not the price provided to the tenant. In order to have some benefit, the provider defines a gain factor α ($\alpha > 0$), and the proposed price is:

$$PR = (1 + \alpha) * MC. \quad (4)$$

When the query is submitted, the optimizer needs to estimate the economic benefit of each plan with regard to the defined SLA. Thus, we add the following metric:

Unit Benefit Factor (UBF): the average benefit in a time unit.

$$UBF = (PR_{SLA} - MC)/QCT. \quad (5)$$

Using the above cost metrics, we define our problem as follows:

SLA-driven Cost-effective Query Optimization is a process which finds, for a query Q , the execution plan P that maximizes the UBF, while satisfying the conditions $QCT(P) \leq QCT_{th}$ and $MPD(P) \leq MPD_{th}$, where:

$QCT(P)$ and $MPD(P)$ are the QCT and MPD of the plan P , respectively;

*QCT_{th} is the threshold of the query completion time ($QCT_{th} = \lambda * QCT_{EXP}$);*

and MPD_{th} is the maximum number of nodes that can be used to execute the query, which is decided by the system's resource manager according to the current load.

Note that the query optimization cost is not negligible. It has an impact on the QCT, the MC and thus the UBF. However, this cost cannot be considered directly by the optimization process. Therefore, we divide the problem into two steps: the first step is to choose an appropriate search method

which minimizes the optimization cost; and the second step is to find the optimal plan by using the chosen method.

Compared to a traditional query optimization problem which simply minimizes the QCT, our problem is more complex. First, the objective function is specific, so the cost model needs to be redesigned (see Section 4.2), the existing search space restriction rules need to be rechecked (see Section 4.3). Then, due to the constraint checks, pruning strategies like Dynamic Programming (DP) often used by classical enumerative search methods cannot work efficiently. This will be seen in Section 4.4.1. In order to make the optimization process more efficient, we will also revise a randomized search method in Section 4.4.2. Finally, it is possible that no solution can be found for our optimization problem when there is a resource contention caused by concurrent queries of other tenants. We will propose a heuristic to solve the resource contention problem in Section 4.4.3.

We point out that maximizing the UBF for each query does not mean the maximization of provider's overall profit in a long term. However, it can be seen as a greedy strategy. In Section 5, we will experimentally show that, with our proposal, the overall profit can truly be increased, compared to the traditional approach which does not consider the economic aspects.

4.2 Cost Model

To illustrate our proposal, we use a classical execution model: a query execution plan is represented as a binary operator tree, and the join algorithm is parallel hash join [11], [20]. Details are given in Section 4.2.1. The reason to choose this model is that, our target applications are OLAP queries, which deal with huge volumes of data, and executing a single query usually requires multiple nodes running in parallel. For simplicity, we assume that the nodes are homogeneous. We also assume that queries from the same tenant are launched sequentially. Actually, concurrent queries from a tenant are much more difficult to take care of, because they share the same data. Either they should be serialized to avoid data migration, or some data should be (statically or dynamically) replicated to increase the parallelism. We will study this problem deeply in future work.

Obviously, new cost models should be designed when other execution models are used. For example, new multi-way join operators and data shuffling algorithms have been proposed recently in [4] which aim to reduce the communication cost for complex multi-join queries. This section can be served as an example for designing other cost models.

4.2.1 Query Execution Paradigm

A query execution plan is represented as an operator tree. The relationship between two operators could be: (i) sequential, meaning that one operator cannot start until the other one finishes, (ii) independent, so both operators can be executed in parallel, or (iii) pipelined, meaning that one operator consumes the output of the other operator and they are executed in parallel. Thus, the plan tree can be seen as a set of pipeline chains (PC). At a given time, if all the inputs of a PC are available (i.e., the preceding operators are all executed), this PC is called an executable pipeline chain (EPC).

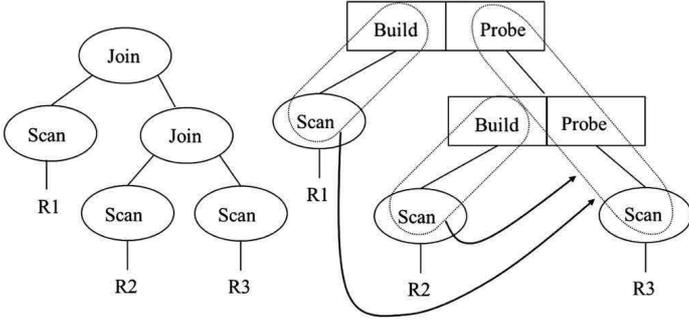


Fig. 2. An operator tree and its dependency graph.

```

Let PCS = the set of all pipeline chains;
While (PCS is not empty)
{
    Execute all EPCs in parallel;
    Remove these EPCs from PCS;
    Update the status of other PCs in PCS;
}

```

Fig. 3. Generalized operator scheduling model.

The relationships between operators can be represented through an operator dependency graph [20]. Fig. 2 shows an operator tree (left side) and the corresponding dependency graph (right side). A PC is enclosed by a dashed line. A dependency between PCs is represented by a bold directed arc. [20] proposed the following scheduling strategy for this example operator tree:

```

Seq
Par
    Pipe scan R2 – build R2 End_Pipe
    Pipe scan R1 – build R1 End_Pipe
End_Par
Pipe scan R3 – probe R2 – probe R1 End_Pipe
End_Seq

```

This operator scheduling model can be generalized using the notion of pipeline chains defined above, as shown in Fig. 3. Thereafter, an iteration will be called an execution phase (EP).

To summarize, a query plan is executed in a sequence of phases. An execution phase contains one or more pipeline chains, which are executed in parallel. A pipeline chain has one or more physical operators, which are executed in pipeline. In addition, a physical operator is executed by multiple nodes in parallel (i.e., intra-operation parallelism). Note that, at any given moment, a resource is used by only one query, and there is no interference of other queries. We argue that the resource isolation [16] is very important to make the estimation more accurate, and above all, to avoid unexpected SLA violations.

In order to estimate the cost of a query plan, we distinguish the following three types of executable pipeline chains (see Figs. 4, 5, and 6). Type I: Scan-Build (a scan operator followed by a build operator), Type II: Scan-Probe...-Probe (a scan operator followed by one or more probe operators), and Type III: Scan-Probe...-Probe-Build (a scan operator followed by one or more probe operators and then by a build operator).

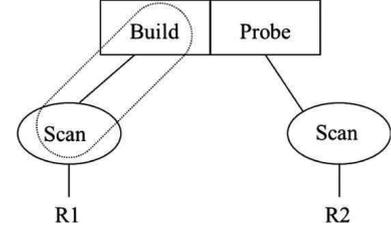


Fig. 4. EPC Type I.

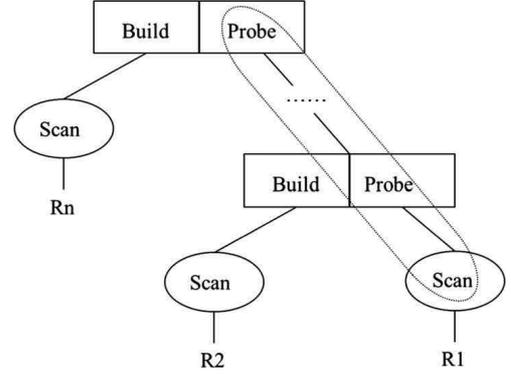


Fig. 5. EPC Type II.

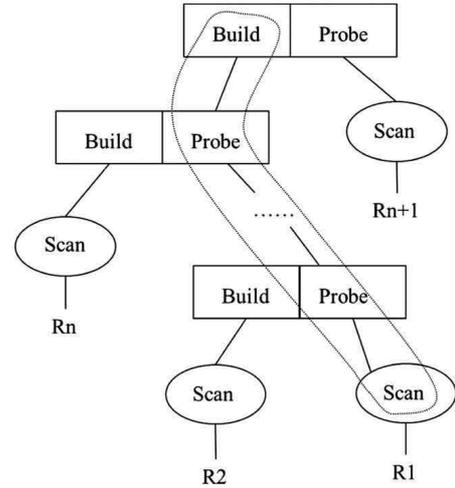


Fig. 6. EPC Type III.

To make the analysis more concise, we can further generalize these three types of EPCs into the following form: Scan-(Probe)*-(Build), where () means the operation is optional, and * means the operation can be repeated. Consequently, in section 4.2.3, we will give only the cost formulas for Type III. Those for Type I and Type II can easily be extracted.

4.2.2 Parameters

The parameters of the cost model and some values that we will use are listed in Table 1. The relation R_x is initially distributed on dd_x nodes. The data placement problem is outside of our scope. An algorithm can be found in [5]. For simplicity, we choose the values of the parameters dd_x and pd_x in such a way that all data partitions could fit into the main memory during the query execution.

Note that the price of the data storage is not included in our cost model, because the data storage cost is independent of the query optimization problem.

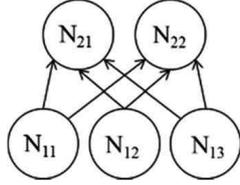


Fig. 7. An example of data transfer.

4.2.3 Cost Estimation

We first give the cost model for a PC of Type III, then for an execution phase, and finally for the complete query.

For a PC of Type III. The scan operator and the build operator are executed in pipeline by different nodes. The elapsed time of a scan operator is the sum of the time to load the data into memory, the time to execute the select operator and the time to prepare the tuple partitioning. The time of transferring b bytes of data from N nodes to M nodes is estimated using the following formula:

$$T_{tr} = (b/(M*N)/nb + nd)*MAX(N, M). \quad (6)$$

For example, in Fig. 7, there is 60 MB data stored on 3 nodes. Suppose that the network bandwidth $nb = 10$ GB/s and the network delay is 1 ms. Thus, the time for transferring the data to 2 nodes is 6 ms. In fact, each destination node has to receive sequentially 3 packages of 10 MB, which constitutes a bottleneck.

Based on this formula, we estimate the elapsed time for a PC of type III as follows:

$$\begin{aligned}
& \text{Elapsed time } ET = \\
& MAX(ET_Scan(R1); ET_Transfer(R1); ET_Probe(R1); \\
& \dots; ET_Transfer(R12 \dots (n-1)); ET_Probe(R12 \dots (n-1)); \\
& ET_Transfer(R12 \dots n); ET_Build(R12 \dots n)), \text{ where} \\
& ET_Scan(R1) = \\
& SUM(|R1|*|S1|/dd.1/db + dl; //read the pages from disk \\
& |R1|*|S1|*ipc/dd.1/cpu; //executethe select operator \\
& |\sigma(R1)|*|S1|*iph/dd.1/cpu \\
& //prepare the tuple partitioning); \\
& ET_Transfer(R1) = \\
& (|\sigma(R1)|*|S1|/(dd.1*pd.2)/nb + nd)*max(dd.1; pd.2); \\
& ET_Probe(R1) = \\
& SUM(|\sigma(R1)|*|S1|*iph/pd.2/cpu; //execute the probe \\
& |R12|*|S12|*iph/pd.12/cpu \\
& //prepare the repartitioning); \\
& ET_Transfer(R12 \dots (n-1)) = \\
& |R12 \dots (n-1)|*|S12 \dots (n-1)|/(pd.(n-1)*pd.n)/nb + nd \\
& *max(pd.(n-1); pd.n); \\
& ET_Probe(R12 \dots (n-1)) = \\
& SUM(|R12 \dots (n-1)|*|S12 \dots (n-1)|*iph/pd.n/cpu; \\
& //to execute the probe operator \\
& |R12 \dots n|*|S12 \dots n|*iph/pd.n/cpu \\
& //to prepare the tuple repartitioning); \\
& ET_Transfer(R12 \dots n) = \\
& (|R12 \dots n|*|S12 \dots n|/(pd.n*pd.12 \dots n)/nb + nd) \\
& *max(pd.n; pd.12 \dots n); \\
& ET_Build(R12 \dots n) = \\
& |R12 \dots n|*|S12 \dots n|*iph/pd.12 \dots n/cpu.
\end{aligned} \quad (7)$$

TABLE 1
Some Required Parameters

Parameter	Signification	Value used
$ R_x $	number of tuples in Rx	
$ S_x $	size of a tuple in Rx (bytes)	
$ R_x - y $	number of tuples in Rx $\bowtie \dots \bowtie$ Ry (estimated)	
dl	average disk latency	2ms
db	disk I/O bandwidth	100 MB/s
cpu	CPU processing speed	100 GIPS
iph	number of instructions for hashing a byte	3
ipc	number of instructions for comparing two bytes	3
nd	network delay	1ms
nb	network bandwidth	80 Gb/s
m	main memory size	3 GB
pr_node	price of a node	1 cent/s
pr_net	price of the network transfer	0.0125 cent/Mb
dd_x	distribution degree of the relation Rx	
pd_x	parallelism degree of the build operator for Rx	

The transferred data volume is:

$$TDV = |\sigma(R1)|*|S1| + |R12|*|S12| + \dots + |R12 \dots (n-1)|*|S12 \dots (n-1)| + |R12 \dots n|*|S12 \dots n|. \quad (8)$$

The maximum number of occupied nodes is:

$$MNN = dd.1 + \sum_{i=2}^n pd.i + pd.12 \dots n. \quad (9)$$

For an execution phase EP_i composed of k pipeline chains: $EP_i = \{PC_1, PC_2, \dots, PC_k\}$.

These pipeline chains are executed in parallel, so the elapsed time of an execution phase is computed like:

$$ET(EP_i) = MAX(ET(PC_1); ET(PC_2); \dots; ET(PC_k)). \quad (10)$$

The transferred data volume is the sum of the TDV of all pipeline chains:

$$TDV(EP_i) = \sum_{j=1}^k TDV(PC_j). \quad (11)$$

The maximum number of occupied nodes is:

$$MNN(EP_i) = \sum_{j=1}^k MNN(PC_j). \quad (12)$$

The monetary cost is:

$$MC(EP_i) = MNN(EP_i)*ET(EP_i)*PR_{Node} + TDV(EP_i)*PR_{net}. \quad (13)$$

For a complete query composed of m phases:

The query Q is a sequence of m execution phases:

$$Q = \{EP_1, EP_2, \dots, EP_m\}.$$

The query completion time is the total elapsed time of these phases:

$$QCT = \sum_{i=1}^m ET(EP_i). \quad (14)$$

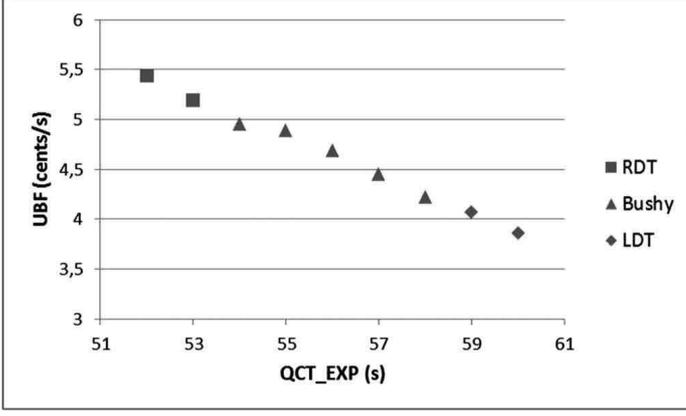


Fig. 8. Impact of the QCT_{EXP} on the UBF .

The maximum number of occupied nodes is:

$$MPD = \text{MAX}(MNN(EP_1); MNN(EP_2); \dots; MNN(EP_m)). \quad (15)$$

The monetary cost is:

$$MC = \sum_{i=1}^m MC(EP_i). \quad (16)$$

4.3 Study on Three Operator Tree Formats

To make the optimization more efficient, the search space is often restrained to one of the following tree formats: left deep tree, right deep tree or bushy tree [10], [20]. In this section, we use an example to show that it is better to explore all these tree formats in our context. The analysis is based on the above cost model.

For the example query, we first enumerate all possible execution plans except those with Cartesian products and estimate the QCT , MC and MPD for each plan. Based on this result, we get the QCT_S , PR_S , QCT_L and PR_L , as well as the maximum value and the minimum value of MPD . We then analyze the impact of QCT_{EXP} and MPD_{th} on the UBF , in order to discover the behavior of different tree formats under various conditions.

The impact of QCT_{EXP} is shown in Fig. 8. The x-axis represents the QCT_{EXP} varying between QCT_S and QCT_L . The y-axis represents the UBF . Each point represents a query plan which has the highest UBF for the given QCT_{EXP} value. The three formats of trees are distinguished by different symbols. For this experiment, the MPD_{th} is fixed as infinity. We can see that, when the tenant's expectation on QCT is very strict, the right deep tree brings the highest UBF , because it can meet the QCT_{EXP} due to the high degree of parallelism. An interesting phenomenon is revealed by this figure: the UBF decreases when the QCT_{EXP} grows. However, this is logical, because a low QCT_{EXP} implies a high risk of not being met, and thus corresponds to a high reward if it is met.

The impact of MPD_{th} is shown in Fig. 9. The x-axis represents the MPD_{th} . The y-axis represents the UBF . Each point represents a query plan which has the highest UBF for the given MPD_{th} value. Again, the three formats of trees are distinguished by different symbols. For this experiment, the QCT_{EXP} is fixed as 53s. We can see that when the system resources are limited (i.e., MPD_{th} is low), the left deep tree could be used to avoid the rejection of the query.

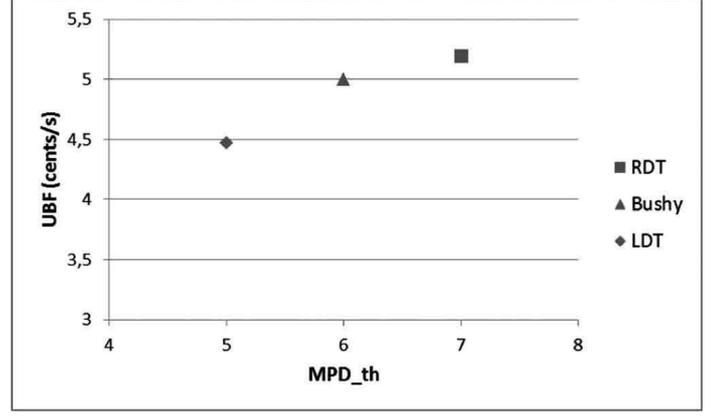


Fig. 9. Impact of the MPD_{th} on the UBF .

To summarize, the right deep tree is useful when the expectation of the tenant is strict, the left deep tree is necessary when the resources are very limited, while the bushy tree is the most beneficial in other cases. Therefore, we propose to consider all these three tree formats.

4.4 Search Strategy

In this section, we first revise two types of search strategies: enumerative and randomized. Then, we propose a heuristic for solving the resource contention problem.

4.4.1 Enumerative Method

The plan enumeration method that we have revised is the one proposed in [15], which has been shown to be efficient for the generation of optimal bushy join trees. A query is represented as a connected graph with n relations R_0, R_1, \dots, R_{n-1} . The algorithm is based on the notion of *csg-cmp-pairs*, where *csg* means connected subgraph and *cmp* is the abbreviation of *complement*. Suppose that, S_1 is a non-empty subset of $\{R_0, \dots, R_{n-1}\}$, and S_2 is another non-empty subset of $\{R_0, \dots, R_{n-1}\}$, the pair (S_1, S_2) is called a *csg-cmp-pair*, if: (1) S_1 is connected, (2) S_2 is connected, (3) $S_1 \cap S_2 = \phi$, and (4) there exist nodes $v_1 \in S_1$ and $v_2 \in S_2$ such that there is an edge between v_1 and v_2 in the query graph. The algorithm to efficiently list all the *csg-cmp-pairs* is given in [15]. Once the *csg-cmp-pairs* are enumerated, the algorithm uses dynamic programming to construct the optimal bushy join tree recursively. Therefore, the method is named as *DPccp* (i.e., Dynamic Programming with *csg-cmp-pairs*).

If we use directly the *DPccp* algorithm for our problem, the following pruning strategy should be applied: *given two equivalent sub-plans SP_1 and SP_2 , if $UBF(SP_1) > UBF(SP_2)$, then we can eliminate SP_2 .*

However, this is not a valid pruning strategy in our context. Here is a counter example. For a subset $\{R_1, R_2\}$, we compare two sub-plans $SP_1 = R_1 \bowtie R_2$ and $SP_2 = R_2 \bowtie R_1$, supposing that $UBF(SP_1) > UBF(SP_2)$. Consider the following two cases: (1) $QCT(SP_1) > QCT_{th}$ or $MPD(SP_1) > MPD_{th}$; (2) $QCT(SP_1) \leq QCT_{th}$ and $MPD(SP_1) \leq MPD_{th}$. For case (1), if we eliminate SP_2 , then no solution will be found, because the entire plan constructed from the sub-plan SP_1 will violate the optimization constraints. For case (2), it is not sufficient to guarantee that the entire plan constructed from SP_1 will meet the constraints, so we still cannot eliminate SP_2 . Therefore, in both cases, we should keep SP_2 .

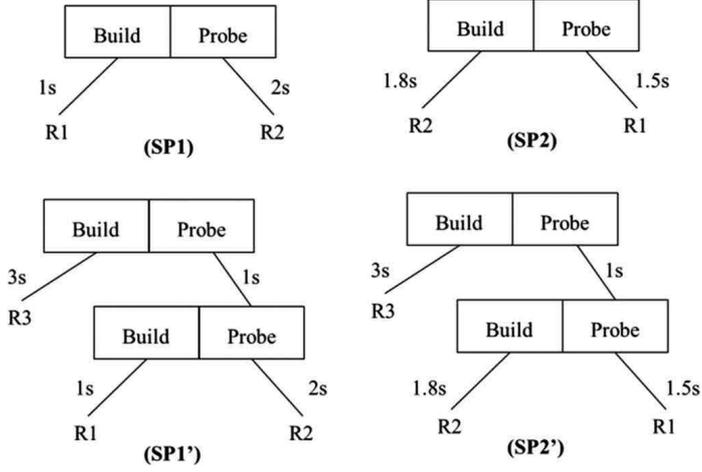


Fig. 10. Counter example for a pruning strategy.

Another pruning strategy, as used by [7], [27], is: *given two equivalent sub-plans $SP1$ and $SP2$, if $QCT(SP1) \leq QCT(SP2)$, $MC(SP1) \leq MC(SP2)$ and $MPD(SP1) \leq MPD(SP2)$, we say that $SP1$ dominates $SP2$ and we eliminate $SP2$.*

Again, it is invalid in our context due to the use of the independent and pipeline parallelism. We show this by a counter example, illustrated in Fig. 10. For a subset $\{R1, R2\}$, we take the two sub-plans $SP1 = R1 \bowtie R2$ and $SP2 = R2 \bowtie R1$. Suppose that $|R1| < |R2|$. For $SP1$, the operation $Build(R1)$ takes 1s, $Probe(R2)$ takes 2s, and for $SP2$, $Build(R2)$ takes 1.8s, $Probe(R1)$ takes 1.5s. We have $QCT(SP1) = 1 + 2 = 3s$, and $QCT(SP2) = 1.8 + 1.5 = 3.3s$. It is possible that $MPD(SP1) = 2$, $MPD(SP2) = 3$, $MC(SP1) = 8$ cents, and $MC(SP2) = 10$ cents. In this case, we can say that $SP1$ dominates $SP2$. Now we compare an entire plan generated from $SP1$ which is $SP1' = R3 \bowtie (R1 \bowtie R2)$, with the plan generated in the same way from $SP2$ which is $SP2' = R3 \bowtie (R2 \bowtie R1)$. Suppose that $Build(R3)$ takes 3s and $Probe(R12)$ takes 1s. We have $QCT(SP1') = \max(1, 3) + \max(2, 1) = 5s$ and $QCT(SP2') = \max(1.8, 3) + \max(1.5, 1) = 4.5s$, so $SP1'$ does not dominate $SP2'$. Thus we cannot eliminate $SP2$.

Nevertheless, there exists a valid pruning strategy in our context: as said above, if $QCT(SP1) > QCT_{th}$ or $MPD(SP1) > MPD_{th}$, the entire plan constructed from the subplan $SP1$ will violate the optimization constraints. Thus, $SP1$ can be eliminated.

In Fig. 11, we show the new enumerative algorithm using this pruning strategy, where the procedure $ConstraintsMet(Plan)$ checks if the sub-plan meets the optimization constraints.

4.4.2 Randomized Method

We propose an extension of the Iterative Improvement (II) algorithm [24], as shown in Fig. 12. First, we randomly choose several plans as starting points. For each starting point, we check a certain number of adjacent plans. This number is a tunable parameter called "runs". We do not check all the adjacent plans, because there could be a huge number. If no adjacent plan is found better, the current plan is considered to be a local optimal plan. If an adjacent plan is better, we move to that plan and repeat the same check procedure. The number of moves is also limited by the value of the parameter runs. Finally, we compare the obtained local optimal plans and return the global optimal one.

Algorithm 1: getOptimalPlanEnum()

Input: Query Q with a set of relations $R = \{R0, \dots, Rn-1\}$, cardinalities of base relations and intermediate relations, parameters listed in section 4.2

Output: an optimal plan tree

Begin

For all $Ri \in R$

BestPlans ($\{Ri\}$) = $\{Ri\}$;

End For

For all csg-cmp-pairs ($S1, S2$), $S=S1 \cup S2$

For each $p1 \in$ BestPlans ($S1$) and each $p2 \in$ BestPlans ($S2$)

NewPlan = $p1 \bowtie p2$;

If (**ConstraintsMet**(NewPlan))

BestPlans (S) = BestPlans (S) \cup {NewPlan};

NewPlan = $p2 \bowtie p1$;

If (**ConstraintsMet**(NewPlan))

BestPlans (S) = BestPlans (S) \cup {NewPlan};

End For

If ($S == R$)

Return the plan p with the highest UBF;

End For

End

Function Boolean ConstraintsMet(Plan)

Begin

Return ($QCT(Plan) \leq QCT_{th}$ and

$MPD(Plan) \leq MPD_{th}$);

End

End function

Fig. 11. Revised enumerative algorithm.

Algorithm 2: getOptimalPlanRand()

Input: Query Q , cardinalities of base relations and intermediate relations, parameters listed in section 4.2

Output: an optimal plan tree

Begin

Randomly choose X (e.g. 3) plans;

For each plan P

Popt = P ;

numTests = numMoves = 0;

While(numTests < runs && numMoves < runs)

/ randomly get an adjacent plan */*

newP = $P.getNeighbour()$;

/ if the new plan meets the constraints or the current plan does not meet the constraints, check whether the new plan brings more benefit. If so, move to the new plan. */*

If ($(QCT(newP) \leq QCT_{th} \&\& MPD(newP) \leq MPD_{th})$

$|| QCT(P) > QCT_{th} || MPD(P) > MPD_{th}$)

$\&\& UBF(newP) > UBF(P)$)

$P = newP$;

Popt = newP;

Increase numMoves;

Reset numTests;

Else

Increase numTests;

End If

End While

End For

*/*compare the local optimal plans, and choose the one which brings the highest benefit and meets all constraints.*/*

Return the best Popt;

End

Fig. 12. Extended II algorithm.

In the *getNeighbour()* function, we randomly pick a join operation in the plan, and check the following transformation rules [9]:

Join commutativity: $a \bowtie b = b \bowtie a$

Join associativity: $(a \bowtie b) \bowtie c = a \bowtie (b \bowtie c)$

Left join exchange: $(a \bowtie b) \bowtie c = (a \bowtie c) \bowtie b$

Right join exchange: $a \bowtie (b \bowtie c) = b \bowtie (a \bowtie c)$

A transformation which produces a Cartesian product is considered as invalid. Among the valid transformation results, we randomly choose one.

4.4.3 Heuristic for Resource Contention

In the above algorithms, the value of the parameter *MPD_{th}* is decided by the system's resource manager according to the current load. Assuming that, at the query optimization time, the number of available nodes in the system is *nb_{avb}*, we first run the optimizer using *MPD_{th} = nb_{avb}*. If no solution is found, it means that, there are not enough resources to run the query. In this case, we use the following heuristic: first, we run the optimizer without constraint on *MPD* to find an optimal plan; then, we decide whether to execute this plan later when enough resources will be available, or suspend some other running queries to release resources, or give up the current query, according to the estimated costs.

More precisely, the heuristic includes the following steps:

- 1) If the optimizer cannot find a solution due to the resource limitation, we set *MPD_{th} = ∞* and run the optimizer. Suppose that the *MPD* of the obtained plan is *MPD_{opt}*, the *QCT* is *QCT_{opt}* and the *UBF* is *UBF_{opt}*.
- 2) Rank the running queries by their completion time in ascending order. Take the first *n* queries such that $\sum_{i=1}^n MPD_i + nb_{avb} \geq MPD_{opt}$. Assume that these queries are expected to finish in time *t*.
- 3) If $t + QCT_{opt} \leq QCT_{th}$, then we wait the *n* queries to finish and start executing the query *Q* after.
- 4) Otherwise, rank the running queries by their *UBF* in ascending order. Take the first *k* queries such that $\sum_{i=1}^k MPD_i + nb_{avb} \geq MPD_{opt}$. We suspend these queries if the following condition holds:

$$UBF_{opt} * t - \sum_{i=1}^k PIt_i > \sum_{i=1}^k UBF_i * QCT_i - PIt(Q), \quad (17)$$

where, *PIt_i* is the penalty to pay if we stop the query *i*, and *PIt(Q)* is the penalty to pay if we refuse the query *Q*.

- 5) If the above condition does not hold, we reject the query *Q* and pay the penalty.

Note that, if there are too many query rejections, the provider should consider adding new computing resources or canceling some service contracts. In this paper, we do not discuss this problem further.

5 EXPERIMENTAL EVALUATION

We have implemented the cost model and the proposed search methods inside a query optimizer. Experiments have been made to evaluate the cost-effectiveness of our SLA-driven optimization approach. We have also compared different plan search methods in terms of optimality and query

optimization cost. The latter includes optimization time and memory consumption.

5.1 Experiment Setting and Evaluated Methods

For the evaluation of cost-effectiveness of our SLA-driven approach, we use a simulated multi-tenant parallel DBMS running on top of a shared-nothing architecture. Each node is composed of a 100 GIPS CPU, a 3 GB RAM, and a hard disk whose I/O bandwidth is 100 MB/s. The average disk latency is 2ms. The multi-tenant DBMS is simulated in the following way: (1) the execution of a query is simulated by using several parameters like start-time, end-time and number of nodes used, (2) we assume that, at the beginning, *N* queries from *N* different tenants arrive at the same time, and the optimizer chooses an execution plan for each query one after the other according to their session numbers. The chosen plan depends on the still available resources. Once the query plans are chosen, we assume that they start being executed in parallel at time 0, (3) when the execution of query *i* of tenant *j* is finished, the optimizer chooses a plan for query *i + 1* of the same tenant under the current resource constraints. If there are enough resources, the plan starts being executed immediately. Otherwise, the execution is postponed or the query is rejected.

We compare the average *UBF* of the following two methods: (1) Enumerative method using the traditional approach *ENUM_TRAD* which always minimizes the *QCT* under the system resource constraints, and (2) Enumerative method using the cost-effective approach *ENUM_CEM* which maximizes the *UBF* under the system resource constraints and the *QCT* threshold constraint of the SLA. To be fair, they are implemented by using the same cost model for the *QCT* estimation.

For the comparison of the plan search methods, we run our optimizer (implemented in JAVA) on a PC with Intel Core i5-3570 CPU 3.4 GHz, 8 GB RAM, Windows 10 (64 bits). We compare the optimality, optimization time and memory consumption of three methods: (1) *ENUM_CEM*, (2) our proposed randomized method *RAND_CEM*, and (3) the Iterative-Refinement Algorithm (IRA) method proposed in [27], which adopts the Multi-Objective Optimization (MOO) approach: *IRA_MOO*.

The way that we do the optimality measurement of *RAND_CEM* is as follows: for each sample query, we run the method 100 times, calculate the average *UBF* value and compare it with the *UBF* of the optimal plan generated by the method *ENUM_CEM*.

5.2 Benchmark Description

We selected a subset of TPC-H [26] queries (*Q3, Q4, Q5, Q8* and *Q10*) which represent different levels of complexity (2, 1, 5, 7 and 3 joins respectively). For each query template, we first define the SLA under the proposed negotiation framework (see Section 5.3). The scale factor that we use for the TPC-H dataset is 10. Then, we optimize the queries according to the SLA and simulate a parallel execution of queries launched simultaneously by several tenants. The workload that we use is similar to the workload for the throughput test in TPC-H benchmark. There are 3 parallel sessions which represent 3 tenants. The query sequences in these sessions are shown below:

TABLE 2
Defined SLA

	QCT _s (s)	PR _s (cents)	QCT _L (s)	PR _L (cents)	QCT exp (s)	PR exp (cents)
Q3	51.6	459	55.2	370	55	375
Q4	51.7	569	51.7	569	55	569
Q5	51.7	1672	72.5	925	55	1553
Q8	32.1	821	55.3	689	55	691
Q10	51.7	563	59.1	457	55	516

Session 1: Q3, Q5, Q10, Q8, Q4
 Session 2: Q10, Q8, Q5, Q4, Q3
 Session 3: Q8, Q5, Q4, Q10, Q3

For each query, we note the start time, end time, *UBF* and *MPD*, in order to compute the average *UBF* for the complete workload.

5.3 Defined SLA

In Table 2, we show the shortest *QCT* with the corresponding price, the lowest price with the corresponding *QCT*, and the expected *QCT* of the tenant with the expected price. We suppose that the tolerance threshold of the tenant is 2 and the gain factor of the provider is 1. In this section, for illustration purpose, we suppose the highest selectivity for each parameter of all queries.

5.4 Cost-Effectiveness of the SLA-Driven Approach

We evaluate the cost effectiveness under two different configurations. In the first configuration, we assume that the system has enough resources. In the second configuration, we assume that the system resources are limited, for example, there are only 16 nodes available for the workload.

5.4.1 With Enough Resources

Under this configuration, a query can be processed as soon as it arrives. Fig. 13 shows the result of the *ENUM_TRAD* method which always minimizes the query completion time. Fig. 13a is a Gantt chart illustrating the progress of the three sessions. They start at the same time and finish at the same time. The elapsed time is 238.8 seconds. Fig. 13b shows the benefit (i.e., revenue - cost) gained by each query. Note that, when the deadline is met, the benefit is often positively correlated to the price. This is normal, because a high price is usually due to high resource consumption, and a high reward is deserved. The total benefit is 4407.34 cents. Fig. 13c is the number of occupied nodes at each point of time during the execution. The maximum number is 25 nodes. Based on the obtained numbers, we compute the average *UBF* as follows:

$$UBF_{avg} = total\ benefit / elapsed\ time \\ = 4407.34 / 238.8 = 18.46(cents/s).$$

Fig. 14 shows the result of our method *ENUM_CEM* which maximizes the *UBF* for each query. We can see that, the elapsed time is 246.4 seconds, a little longer than the *ENUM_TRAD* method. However, the benefits of some queries are higher, and the total benefit is 5612.17 cents, 21 percent higher than *ENUM_TRAD*. The reason is that fewer resources are consumed, as can be seen in Fig. 13c: the maximum number of occupied nodes is 18. The average *UBF* is computed as follows:

$$UBF_{avg} = 5612.17 / 246.4 = 22.78(cents/s).$$

5.4.2 With Limited Resources

We assume that there are only 16 nodes available for the workload. When a query arrives, if there are not enough resources, it cannot be processed until some other queries

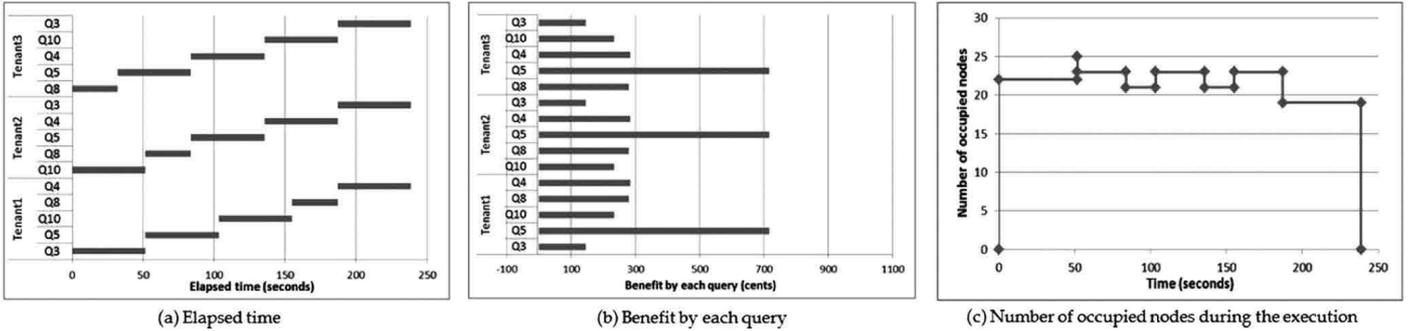


Fig. 13. Method *ENUM_TRAD* with enough resources.

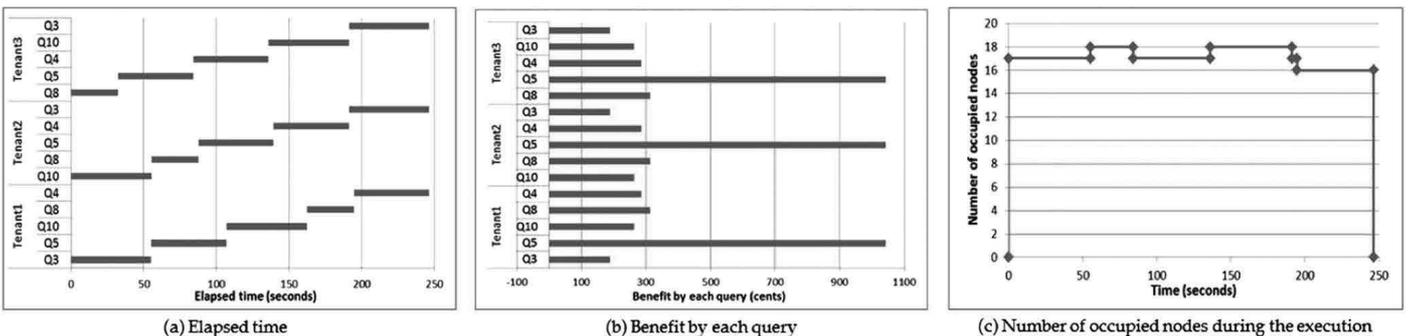


Fig. 14. Method *ENUM_CEM* with enough resources.

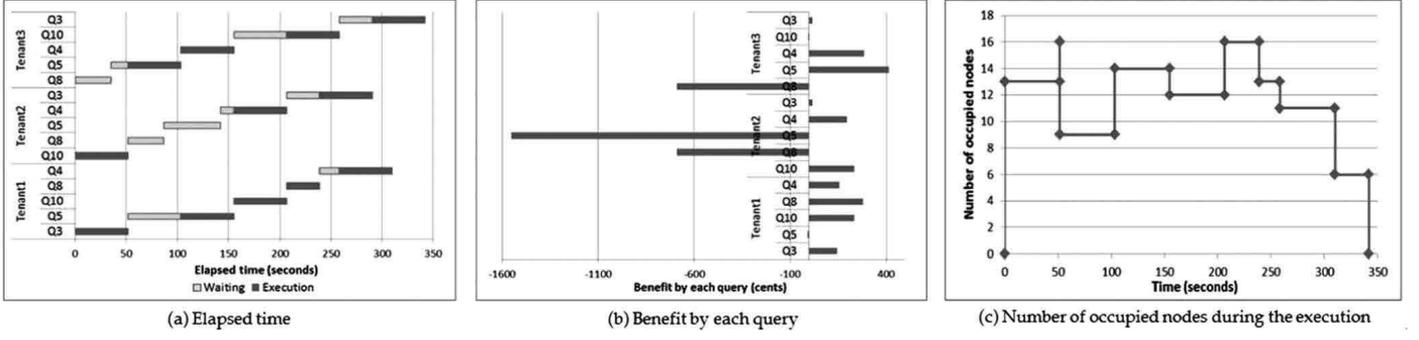


Fig. 15. Method *ENUM_TRAD* with limited resources.

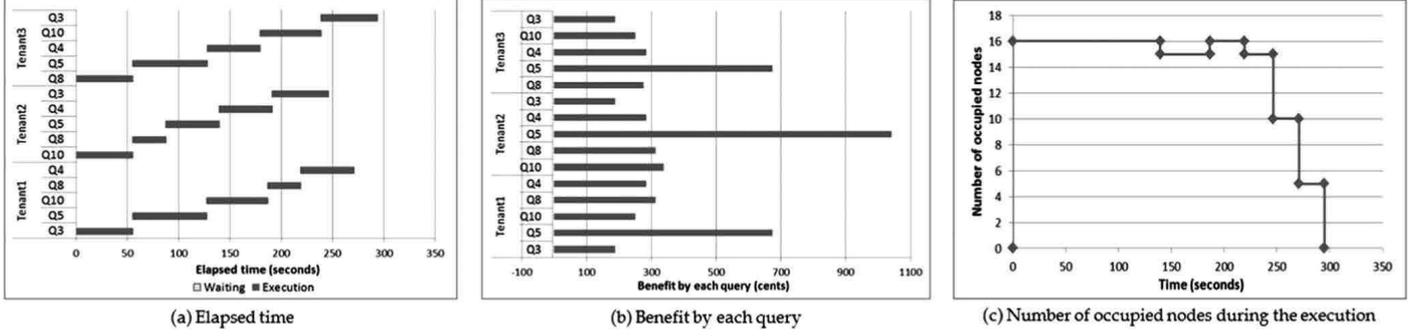


Fig. 16. Method *ENUM_CEM* with limited resources.

TABLE 3
Overview of the Results

	With enough resources		With limited resources	
	<i>ENUM_TRAD</i>	<i>ENUM_CEM</i>	<i>ENUM_TRAD</i>	<i>ENUM_CEM</i>
Total elapsed time (seconds)	238.8	246.4	342	294
Total benefit (cents)	4407.34	5612.17	-1162.42	4892.59
Average <i>UBF</i> (cents/s)	18.46	22.78	-3.4	16.64

finish. Fig. 15 shows the result of *ENUM_TRAD*. In Fig. 15a, we see that some queries have to wait due to resource limitation, and some others have to be rejected because the SLA cannot be met. For example, the first query *Q8* of tenant 3 and two queries of tenant 2 have been rejected. The second query of tenant 3 waited 16.6 seconds. Therefore, the total elapsed time is longer (342 seconds). The benefits for some queries are negative, for example, *Q5* of tenant 1, *Q5* and *Q8* of tenant 2, etc. The total benefit is -1162.42 cents, as shown in Fig. 15b. Fig. 15c shows the number of occupied nodes at each point of time during the execution. The average *UBF* is negative:

$$UBF_{avg} = -1162.42/342 = -3.4(\text{cents/s}).$$

The result of our method *ENUM_CEM* can be found in Fig. 16. The total elapsed time is 294 seconds, and the total benefit is 4892.59 cents. So the average *UBF* is:

$$UBF_{avg} = 4892.59/294 = 16.64(\text{cents/s}).$$

5.4.3 Summary

With enough resources, the *ENUM_TRAD* method spends very little time to finish the queries, but its economic cost is rather high, so the benefit is low. Our method *ENUM_CEM*

has a better trade-off between the query completion time and the economic cost, so the overall benefit is higher.

With limited resources, both methods need more time to finish the queries, because some queries have to wait for resources to be released. In addition, some queries may be rejected. This situation happens less frequently for *ENUM_CEM*, so its total elapsed time is shorter than that of *ENUM_TRAD*. The average *UBF* of *ENUM_CEM* is always higher due to the SLA-driven cost-effective optimization problem definition.

The experimental results are summarized in Table 3. We can conclude that, under both configurations, our method is more cost-effective than the method *ENUM_TRAD*. With enough resources, *ENUM_CEM* gains 23 percent more than *ENUM_TRAD*. With limited resources, *ENUM_CEM* still gains, but *ENUM_TRAD* starts losing due to query rejections.

5.5 Comparison of the Plan Search Methods

The *RAND_CEM* method does not enumerate all possible execution plans, so the optimal plan may be skipped by the search algorithm. As for the method *IRA_MOO*, since its pruning strategy is not valid when parallel execution is considered, as demonstrated in Section 4.4.1, the optimal plan may be eliminated in an early stage. When a sub-optimal plan is

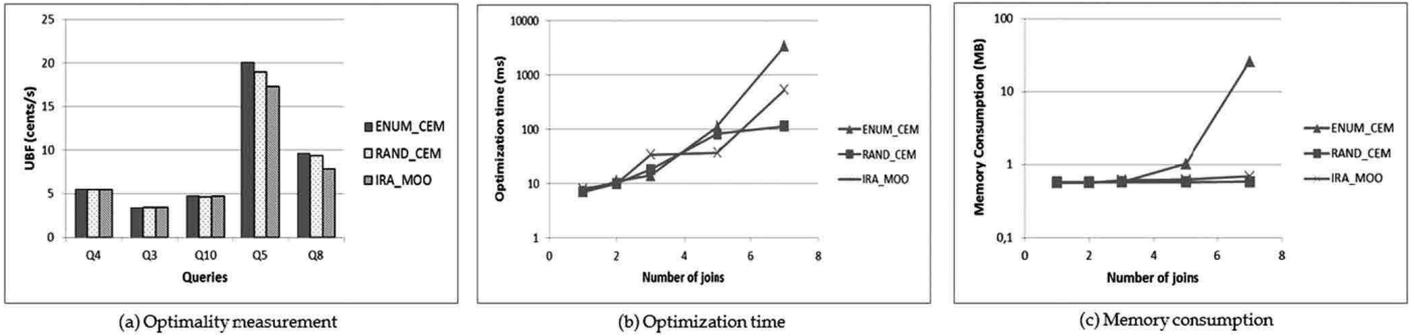


Fig. 17. Comparison of plan search methods.

proposed, the *UBF* becomes lower. Therefore, we compare the optimality of *RAND_CEM* and *IRA_MOO* with the exact method *ENUM_CEM*. For *RAND_CEM*, we run 100 times the method for each query template and compute the average *UBF*, in order to measure the long term consequence on the *UBF*. In this experiment, we assume that there are enough resources. The result is shown in Fig. 17a. We can see that, compared to the optimal *UBF*, the degradation of *RAND_CEM* is no more than 6 percent, while the degradation of *IRA_MOO* can reach 19 percent. Note that the value of runs of *RAND_CEM* for each query template has been tuned to make the result close to optimal. The approximation factor of *IRA_MOO* is 1.15 which was shown to be a good trade-off between the optimality and the optimization cost in [27].

For fairness, based on the same setting, we measure the optimization time and memory consumption for the example queries and compare the three methods. The optimization time is shown in Fig. 17b and the memory consumption is shown in Fig. 17c. With the *ENUM_CEM*, both the optimization time and the memory consumption become very high when there are 7 joins. Even though some plans can be eliminated by the pruning strategy, the number of generated plans is still proportional to the total number of possible plans, which grows exponentially with regard to the number of joins [25]. With the *RAND_CEM* method, the optimization time also grows when there are more joins, because the number of runs should be increased to find a near optimal plan. However, it is always much more efficient than the *ENUM_CEM* method. As for the memory consumption of the *RAND_CEM* method, it is almost a constant. The *IRA_MOO* method is often less expensive than *ENUM_CEM*, but more costly than *RAND_CEM*.

Despite the expensive optimization cost, we believe that in some situations, the *ENUM_CEM* method could be more advantageous than the other methods. For example: (1) when there are less than 7 joins, all methods have equivalent optimization costs, but the *ENUM_CEM* method guarantees the optimality; (2) when the QCT_{EXP} is very large due to the huge size of the database, the optimization time of the *ENUM_CEM* method becomes relatively small compared to the query execution time thus can be ignored; (3) when the QCT_{EXP} is very close to the QCT_S , or the MPD_{th} is very close to the minimum value of MPD , the *ENUM_CEM* method could eliminate many intermediate sub-plans thus becomes very efficient. On the other hand, the *RAND_CEM* and *IRA_MOO* methods will have a high risk of not being able to find the optimal plan.

6 CONCLUSION AND FUTURE WORK

In this paper, we first proposed a SLA negotiation framework such that a tenant could define the performance objective together with the provider. The tenant does not have to know the query execution detail, but he should not worry about being cheated, because he can compare offers from different providers and choose the best one. As for the provider, the offer that he proposes is based on its own estimation, so the performance objective is achievable and the benefit could be maximized by using appropriate techniques. For this purpose, we then formally defined the cost-effective query optimization problem. We included the economic cost and benefit into our cost model. We explored a large search space with different tree formats. We revised an enumerative search method and a randomized search method to make the optimization more efficient.

Experimental results show that: (1) our optimization method *ENUM_CEM* is much more cost-effective than the *ENUM_TRAD* method which always minimizes the query completion time (e.g., more than 23 percent); (2) for our optimization problem, the enumerative search method *ENUM_CEM* may become prohibitive when there are more than 6 joins, while the randomized search method *RAND_CEM* has reasonable query optimization time and memory consumption, and it is superior in all aspects to a related work *IRA_MOO*; (3) however, the *ENUM_CEM* method can be a good choice in some special cases.

In the future, we will include the aggregation operators into our cost model. After that, as previously said, a further research direction could be adapting robust query optimization methods [28] to the cloud context, in order to minimize the renegotiation risk.

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