A Proposed Query Optimization Strategy For Autonomous Distributed Database Systems

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Abstract- *Distributed database is a collection of logically related databases that cooperate in a transparent manner. Query processing uses a communication network for transmitting data between sites. It refers to one of the challenges in the database world. The development of sophisticated query optimization technology is the reason for the commercial success of database systems, which complexity and cost increases with increasing number of relations in the query. Mariposa, query trading and query trading with processing task-trading strategies developed for autonomous distributed database systems, but they cause high optimization cost because of involvement of all nodes in generating optimal plan. In this paper, we proposed a modification on the autonomous strategy ye K-QTPT that make the seller's nodes with the lowest cost have gradually high priorities to reduce the optimization time. We implement our proposed strategy and present the results and analysis based on those results.*

Keywords- Autonomous strategies, distributed database systems, high priority, query optimization.

I. INTRODUCTION

QUERY processing includes translation of high-level queries into low-level expressions that can used at the physical level of the file system.

Query Optimization is the process of finding the best strategy in order to execute the given query from a set of alternatives [1][2]. Query optimization and actual execution of the query needed to get the result consists of three steps: parsing and translation, optimization and execution of the query submitted by the user. These steps shown in Fig.1[2].A relational algebra operations and communication primitives like send or receive operations describe a distributed query execution strategy to transfer data between sites[3].

The query optimizer that follows this approach consists of three components: A search space, a search strategy and a cost model [3][4]. The search space is the set of alternative execution for representing the input query. The search strategies are equivalent, in the sense that they produce the same result but they differ on the execution order of operations and the way these operations are implemented [5] [6]. The search strategy explores the search space and selects the best plan. It defines which plans are examined and in which order [5]. The cost model predicts the cost of a given execution plan which may consist of the following components[6].

- Secondary storage cost: It is the cost of searching for reading and writing data blocks on secondary storage.
- Memory storage cost: This cost related to the number of memory buffers needed during query execution.
- Computation cost: It is the cost for performing in memory operations on the data buffers during query optimization.
- Communication cost: This cost responsible for shipping the query and its results from the database site to the site or terminal where the query originated.

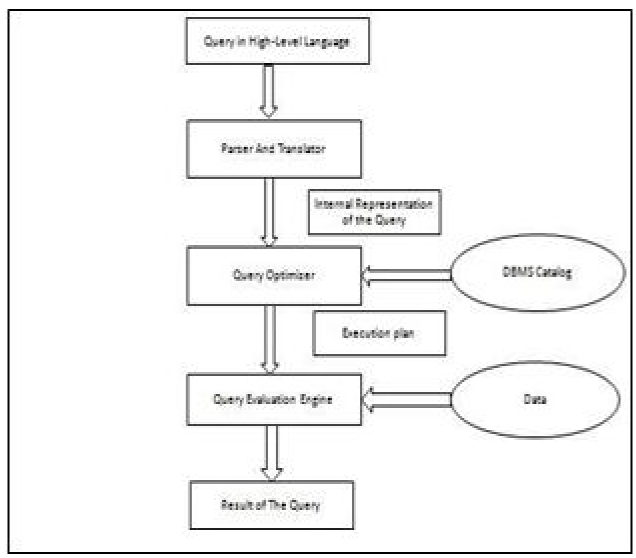


Fig. 1. Query processing steps.

Homogeneous distributed database systems strategies divided to non-autonomous and autonomous strategies. For non-autonomous strategies, all node saw are of physical schema, logical schema, data statistics such as deterministic and randomized strategies with their types. For autonomous strategies, all nodes are independent and unaware of each other.

II. BACKGROUND

There is a central optimizer, which does not support total node autonomy, a non-autonomous distributed database system. On the contrary in autonomous distributed database system, there is no central optimizer where each site has

Elsayed A. Sallam is with Computers and Control Engineering Dept. Tanta University, Egypt. Work as Emeritus Professor (phone: 002-01155411019; e- mail: sallam@f-eng.tanta.edu.eg). complete control over its resources, we mean that, the participating nodes in query execution independently decide whether to participate or not according to the node's resource capacity and data availability [7][8]. So, all participating nodes identified before actual query execution.

Authors in [9] proposed an economic model in order to identify all participating nodes and to support node autonomy in autonomous system. According to this economic model, as showninFig.2[10],there are two types of nodes-buyer nodes and seller nodes. The buyer node is the node where a query is initiated (initiator node)where the seller is then ode that execute the query.

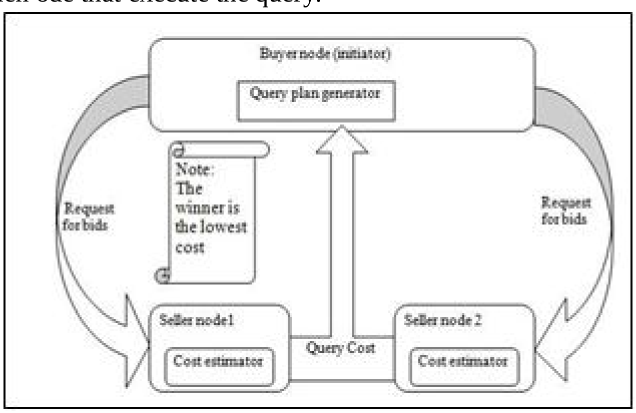


Fig. 2. The Economic model.

Mariposa [11] and Query Trading algorithms [9]depending on this economic model. In general, both algorithms follow the process as stated below:

- Buyer node prepares Request for bids (RFB) for sub-queries that require cost estimation
- Buyer node sends RFB to the seller nodes requesting cost for the sub-query.
- Seller nodes calculate the costs for sub-queries and send replies back to buyer node.
- Buyer node, based on replies, decides on an execution plan for the query; if required repeat steps 2 and3.

III. EARLIER WORK ON QUERY OPTIMIZATION STRATEGIES FOR AUTONOMOUS DISTRIBUTED DBMS

In an autonomous distributed database management system, all nodes are independent and unaware of physical schema, logical schema, and data statistics.

In this paper, we discuss the query optimization strategies for autonomous Distributed Database Management System (DDBMS). These strategies are Mariposa strategy, Query Trading (QT) strategy, and variations of Query Trading strategy.

A. Mariposa Strategy

In Mariposa strategy, a buyer node submit queries, a query starts with a budget that once is decided, query is parsed and given to a single site optimizer that make optimization for

Whole query as if data is not fragmented and prepares a plan [7]. A fragmenter convert single site plan into fragmented plan depending on number of fragments in query. The fragmented query plans prepared by fragmenter will collected and advertised for bids to various sites. After that buyer decides which one to accept, as shown in Fig 3. Each Mariposa site is free to accept or reject, therefore it has total local autonomy [2][12]. Mariposa generates optimal plans and is suitable for autonomous distributed database management system. However, it does not support fully autonomous environment, as it needs data statistics, indices information and partitioning information for generating good quality of plans. This disadvantage of Mariposa is solved by Query Trading strategy [10][13].

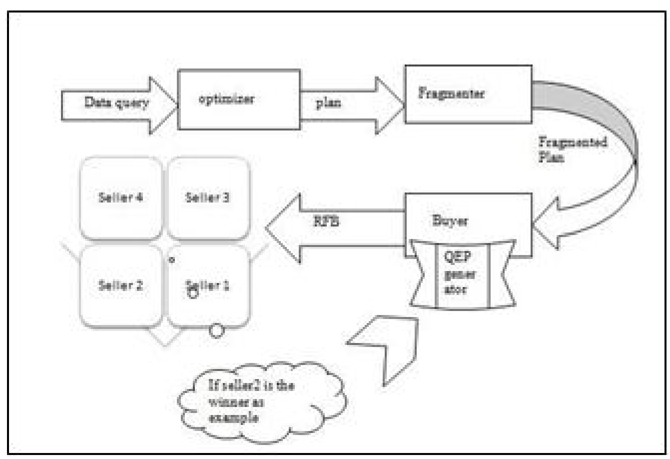


Fig. 3. Architecutre of Mariposa strategy.

B. Query Trading (QT) Strategy

Comparing to Mariposa, this strategy asks distant nodes for information but these information are less than required information by Mariposa, which allow higher node autonomy to participate in executing the queries [7]. QT strategy is considering the queries and query answers as produces and the query optimization procedure as a trading of query answers between nodes.

The query trading strategy means that there are two algorithms, buyer side algorithm and the seller side algorithm. The buyer send request for all seller asking it for help in evaluating some queries [12]. The seller nodes based on their fragmentation of data will rewrite query and use local optimizer to generate partial query execution plan. They offer that execution including answer's cost of the queries and processing tasks involved in solving query. Buyer decides winner with lowest bid according to seller's bids. Finally, the buyer query plan generator build possible execution plans for the original query by combination of the winner bids [13], as shown inFig.

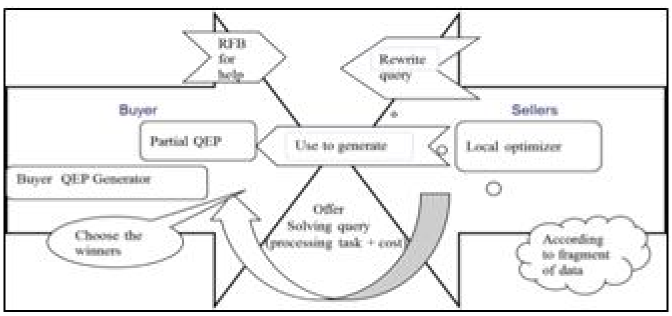


Fig. 4. Architecutre of Query Trading.

4. In a distributed query optimization, the selection of nodes that will eventually process the data is considered as an important factor affecting on the overall performance of distributed execution plans [12][14]. The processing can performed either at seller nodes or at buyer nodes. In a query trading, the seller only processes data that is locally available, while the buyer performs all leftover processing on the data received from the sellers [13]. These restrictions may lead to non-optimal plans, especially when the buyer is overloaded. Hence, to handle such situation a variant of query trading strategy, query trading with final step of processing task-trading (QTPT) is proposed [15][16].

C. Query Trading with Processing Task Trading(QTPT) Strategy

QTPT is an extension of query trading strategy. It works in two phases [7]. In the first phase, it determine the initial distributed query execution plan while in the second phase it repeat the same process at first phase, again send RFBs for all seller nodes for all processing tasks involved in plan (i.e.,QTPT strategy run the QT strategy twice), as shown in Fig 5. QTPT produces better plans compare to QT, however the times required for optimization increases due to an additional phase [13].

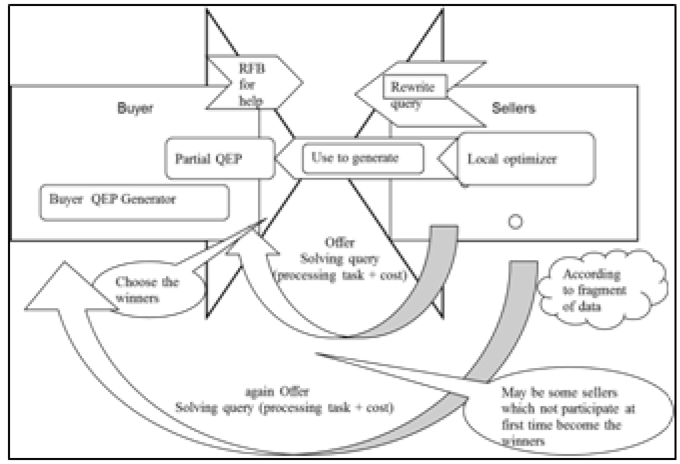


Fig. 5. Architecutre of QTPT Strategy.

D. K-QTPT Strategy

The K-QTPT strategy works in two phases, such as QTPT [10]. In the first phase, the K-QTPT is typically like QTPT, it determines initial query execution plan [13]. In the second phase, from the winners of first phase, buye rnode buffers a list of K winning nodes then; RFBs for processing task will requested from only these k nodes selected in first phase, instead of requesting from all nodes. This reduce optimization time substantially. Deciding appropriate value of k is one of the challenges for implementing K-QTPT. Figure 6 shows the architecture of K-QTPT strategy.

In autonomous systems, to increase local autonomy the optimizer consults the data sources involved in an operation to find the cost of that operation [17]. Hence, the main cost in optimization becomes the cost of contacting the underlying data sources, thus we show that Mariposa produces less efficient plans compared to Query Trading (QT) strategy and requires more information for query optimization than QT strategy[18].

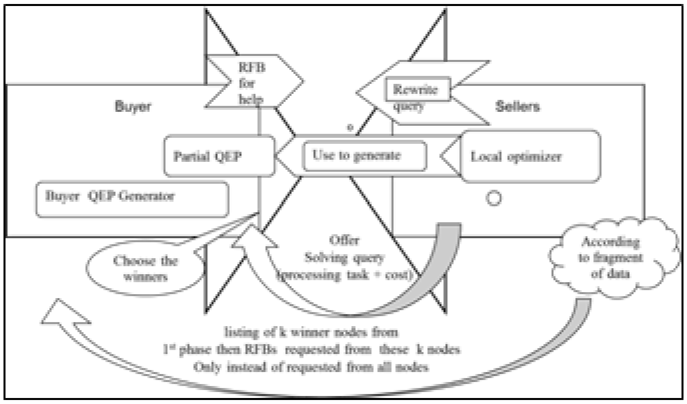


Fig. 6. Architecture of K-QTPT Strategy.

Inthenextsection,wepresentourproposedstrategyandthen we compare it with the various optimization strategies for autonomous distributed database systems based on parameters like time delay and startup cost[19].

IV. THE PROPOSEDSTRATEGY

The proposed strategy also works in two phases, like k- QTPT. The first phase is the same as that in k-QTPT strategy, it determines initial query execution plan (QEP). In the second phase, depending on the winners resulting from the first phase, buyer node buffers a list of K winning nodes then RFBs for processing task that requested from only these selected K nodes , instead of requesting from all nodes. After that, the buyer give high priorities for the winner nodes to increase RFBs and receive quick responses from these winners. This will reduce the optimization time, as shown in Fig 7.In then ext subsection, we present the flowchart, pseudocode, challenged faced, and the experimental evaluation for the proposed strategy followed by the analysis of the results compared with the QT, QTPT, K- QTPT strategies.

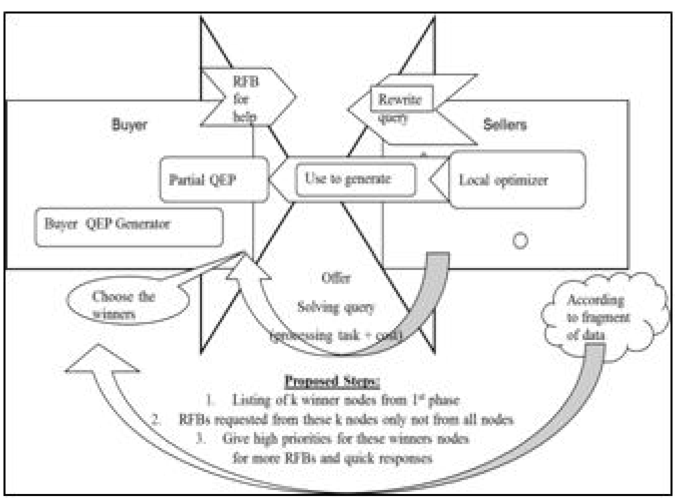


Fig. 7. Architecture of proposed strategy.

A. Flowchart

The following flowchart in Fig. 9 explains the steps of our proposed strategy. In the beginning, the user start entering the query at the initiator node, the buyer node. The buyer sends RFBs for all sellers to ask them for help in evaluating the query execution time. All the seller nodeses tima te the query cost and send the response back to thebuyer.

objectiveofthisproposedstrategyistoreducetheoptimization time taken by KQTPT Strategy. According to our proposed strategy, the buyers end RFB stoall sellers for estimation of the query cost and every selle rreply with the query cost depending on its available resources. The buyer compares the costs to find the seller node with the lowest cost to be the winners. Then, the buyer sorts these winners according to the costs withpriorities. The lowest cost of winners take high priority and gradually complete the winners' priorities. The buyer ignore low priorities and again send RFBs for high priorities winners. Finally, the buyer generator take the high priorities winners' costs and produce the QEP that will be close enough to the optimal.

Our proposed strategy starts with implementing a network consists of one buyer and a number of sellers. The user enters the required query, the buyer asks the sellers to calculate the query execution cost (c). Each seller replies with its c. The buyer collects all the costs and put them ordered in an array list. After that, it compare all costs to find the minimum that is the winner seller node. Once the number of winner nodes k equal 2, the buyer compares the two winners and set high priorityfor the winner node that has the lowest cost. Then, it displays the costofthehighprioritywinner fromthesellernode.Afterthat, the winner sends RFBs for this high priority winner for quick responses. The pseudocode of the proposed strategy shown in Fig.9.

Fig. 8. Flowchart of the proposed strategy.

The buyer determines the seller winner nodes that have the lowest cost. Then, sort these winners with priorities. The high priority winner only, which the buyer will send RFB to and finally produces the QEP to answer query [20].

B. Pseudocode

In this paper, we propose a modification on the autonomous strategy KQTPT that we call the proposed strategy.

```
Pseudocode
Input: query
Output: query execution plan
1. Calculate the query execution costs(c) at each seller
node
2.      Put c in the array listarrList[]
3.      Ifc<min
   - Set min=c
4.      Endif
5.      For number of winnersk<=2
   1. If arrList[k] < minthen
   2. Put arrList[] = min & display c of winner with high
      priority
   3.   End if
6.      End for
```

Fig. 9. Pseudocode of the proposed strategy.

C. Experimental Setup

We built our experiment starting with a designing a DDBMS on a 64bit workstation device, Core i7 processor and 16GB of RAM for studying the performance of QT, QTPT, K-QTPT and proposed algorithm. Our design consists of seven nodes (one buyer and six sellers) interconnected by a network asshowninFig8.AllnodesconnectedusingaLANwithspeed of 100 Mbps. We create eight tables using MYSQL database. Horizontal fragmentation has done on each table. We have used java1.7 and MYSQL 5.1 to simulate the DDBMS[21].

Each node is equipped with MYSQL 5.1. the seven nodes in the emulation setup were having Microsoft windows7 ultimate as operating system. Each node was equipped with NetBeans IDE 8. In order to connect java with MYSQL each node was added mysql-connector-java-5.1.14-bin.jar for the librariesand classpath[22].

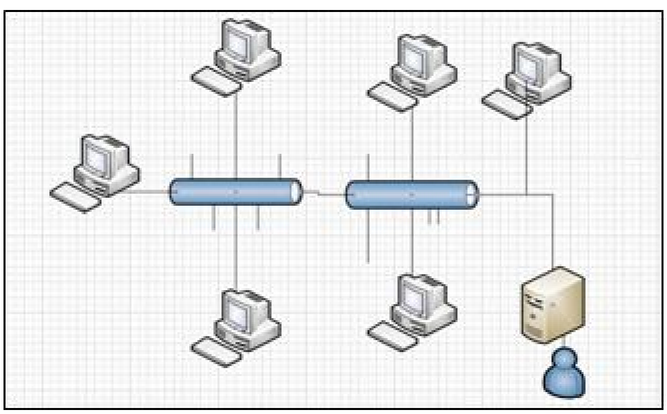


Fig. 10. Organization of the proposed strategy nodes.

D. Challenges faced

We initially tried to make a LAN network consists of three real computers using Microsoft windows 7 operating system.

Formerly, we faced a problem in the socket port number and we solved it by making different port numbers for the socket and the database. After that, a new problem was found which is the missing of the jdbc driver and solved by adding mysql- connector-java-5.1.14-bin.jar into classpath andlibraries.

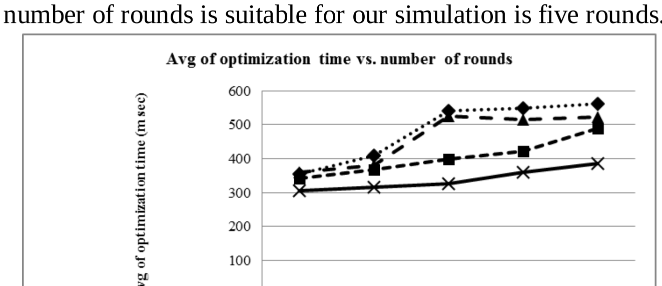
Then, we met a heap space problem at adding random number of tuples and attributes in db but it is overcomed by setting the privilege of MYSQL. Because the nodes are not multi threading we programmed a class, which we called socket thread, and the server import it. Later, we attempted to simulate our work on a workstation device on virtual machine because the results were produced from the real network were not suitable because the network was very bad and waste a lot of packets and the number of available devices were not useful for our work. Based on the above experimental setup, we analyzed performance of the QT, QTPT, k-QTPT strategies and the proposed strategyalgorithm.

E. Results and Analysis

In this section, we have measured optimization time, time takentoperformprocessingtaskatqueryinitiatingnode,buyer node, time taken to perform processing task at query an answering node, seller node, and total response time, total execution time. The main object of our work is to reduce the optimization time of proposedalgorithm.

In our experiment, the number of rounds assumed to find best optimization plan is five and in each round we ran the experimentfivetimesandtookaverageofoptimizationtime(in mille seconds) the results of average of optimization time comparison of QT, QTPT, K-QTPT and our proposed algorithm is as shown in Fig.11.

Figure 11 describes the average of optimization time with the number of rounds. It shows that the optimization time increases with the increase of the number of rounds. The least number of rounds is suitable for our simulation is five rounds.



	1	2	3	4	5
QT ALGORITHM	356	410.4	540	549.6	561.5
QTPT ALGORITHM	360	381	525	515	522
KQTPT ALGORITHM	341.8	367	399.5	421.7	488.5
Proposed ALGORITHM	306.7	315.84	327.1	360.7	386.56

Fig. 11. Average of optimization time vs. number ofrounds.

The average of the query execution time at each node with the number of rounds is illustrated in Fig. 12. It shows that the average of query execution time increases with the increase of the number of rounds. In addition, the least number of rounds is suitable for our simulation is five rounds. The figures hows that our proposed strategy is better than both the QTPT and the KQTPT strategies. However, due to the small load caused by the minimum number of seller nodes, the QT strategy still the best and produces a QEP is closed and near to the optimal.

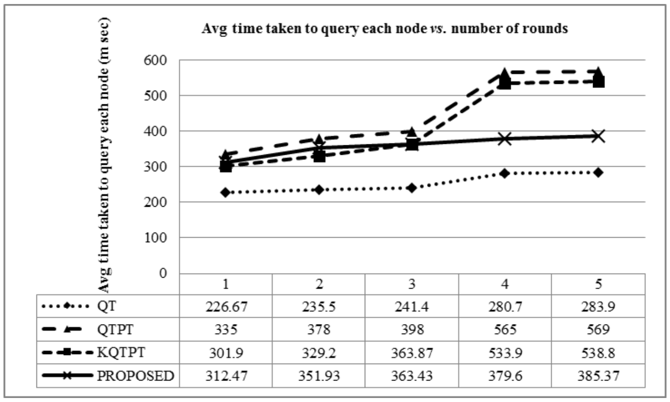


Fig. 12. Average of execution time at each node vs. number of rounds.

In Fig. 13, the average of the query execution time at each nodewiththenumberofsellernodesisexplained.Itisseenthat the average of the query execution time increases with the increaseofthenumberofsellernodes.Whenweadded6seller nodes connected at the buyer, the query execution time at each node was very high. The figure shows that our proposed strategy is better than the QTPT and the KQTPT strategies,but the traditional QT Strategy still gives the best QEP when the buyer was not overloaded.

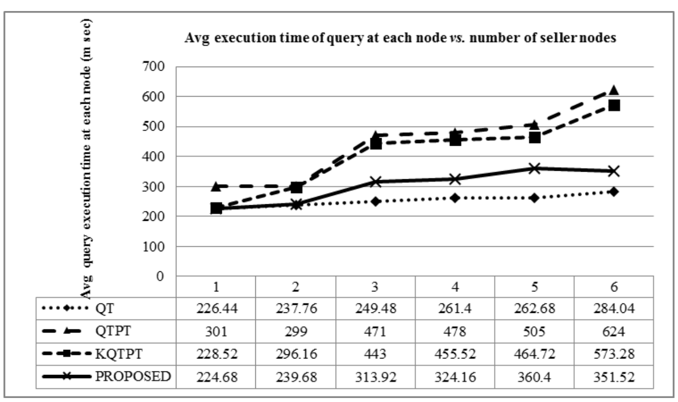


Fig. 13. Average of query execution time vs. number of seller nodes

Inourexperiment,weavoidtheMariposastrategyfromour comparison because it is not support the full node autonomy. Conclusion

In this paper, the different optimization autonomous strategies are presented. The performance of a distributed database system depends on efficient query optimization. In a non-autonomous environment, the algorithms produces best plansbutrequirecompleteinformationaboutothernodesinthe system. Mariposa, QT, and QTPT are optimization strategies that proposed to support autonomous environment. QTPT generates optimal plans compared to QT, but incurs high optimization cost. To reduce the increase of optimization cost, an enhancement of the K-QTPT autonomous strategy is proposed which only the K nodes participate in generating the optimal plans. The high priority for the winner seller nodes are chosen to reduce the optimizationcost.

Our simulation results demonstrate that the proposed strategyefficientlyreducesoptimizationcostespeciallyinwith theincreaseofthenumberofrounds,minimizesthetimedelay, and generate the bestplan.

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