Local Cost Estimation for Global Query Optimization in a Multidatabase System

Dr. Qiang Zhu
The University of Michigan - Dearborn

Outline

- **Introduction**
- **Challenges for QO in MDBS**
- **Query Sampling Method**
- **Qualitative Approach**
- **Fractional Analysis and Probabilistic Approach**
- **Conclusions**

1. Introduction

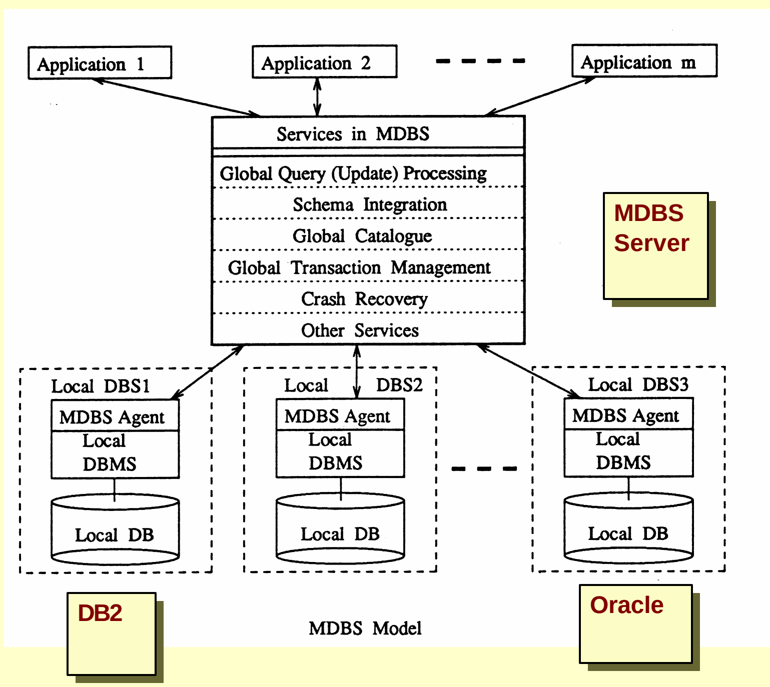
- **Multidatabase System (MDBS)**
  - **What:** a distributed system that integrates data from various **pre-existing** databases managed by **heterogeneous** local DBMSs
  - **Key feature:** **local autonomy**

- **Why Global Query Optimization (GQO)**

  MDBS ⇒ Global query

  ⇒ Global query optimization

  ⇒ Good overall **system performance**



2. Challenges for Global Query Optimization in MDBS

- **GQO for Traditional DDBS**

  developed for a **homogeneous** environment

  – **Techniques:**
    - optimal vs heuristic searches
    - join vs semijoin strategies
    - static vs dynamic optimization
    - sequential vs parallel execution

  ⇒ many **not suitable** for an MDBS

- **Challenges for GQO in MDBS**

  Caused by **local autonomy**:

  – Some local optimization information may **not be available** at global level

  – **Different and changing** local capabilities are assumed

  – **Heterogeneous** data formats and models may be used

  – Implementation of local DBMSs **cannot be changed**

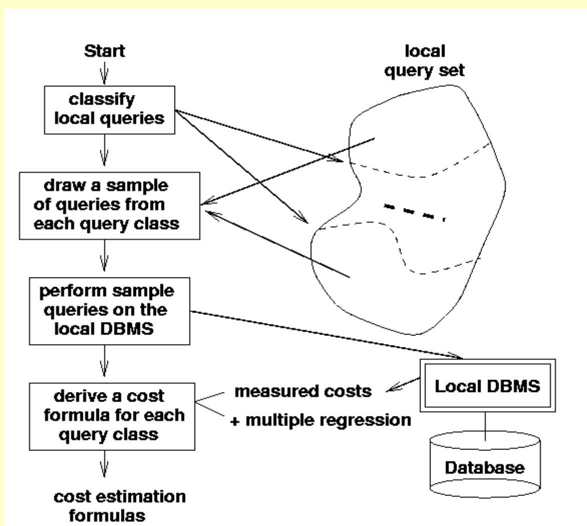
  – **More constraints** need to be considered during global query optimization

  ⇒ **Crucial challenge:** incomplete local information

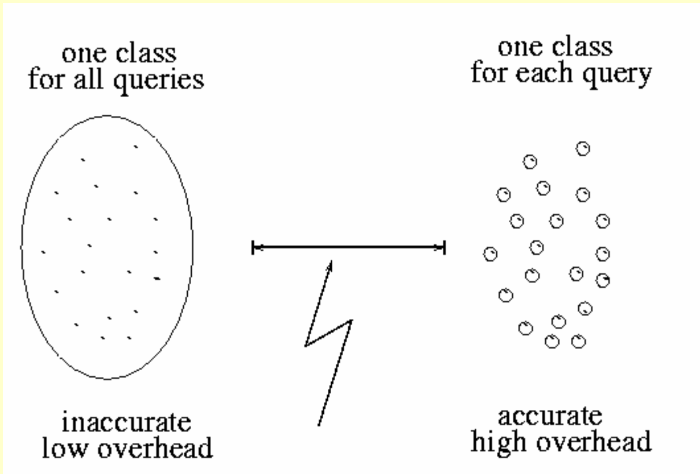
- **Proposed Techniques**
  - Calibration method (*Du et al. 92*)
  - Fuzzy approach (*Zhu et al. 94*)
  - Extended calibration method (*Gardarin et al.96*)
  - Cost vector database approach (*Adali et al.96*)
  - Generic cost model approach (*Naache et al.98*)
  - Garlic approach (*Roth et al. 99)*
  - Query sampling method *(Zhu et al. 94 &98)*
  - Qualitative approach *(Zhu et al. 00)*
  - Fractional analysis approach *(Zhu et al. 00)*
  - Probabilistic approach *(Zhu et al. 00)*

3. Query Sampling Method

- **Key idea**



- **Classification of Queries**
  - **Two extreme cases**



- **Information available**
  - **Characteristics of queries:** e.g., unary queries, join queries
  - **Characteristics of operand tables:** e.g., number of tuples, indexed columns
  - **Characteristics of local DBMSs:** e.g., supported access methods

- **Classification goal:** each query class corresponds to one access method

- **Classification rules:** based on common rules for access methods, such as
  - A unary query and a join query use different access methods
  - A clustered-index-based method is preferred to an (non-clustered) index-based method
  - An index-based method is preferred to a sequential scan method
  - A clustered-index-based method is chosen for a query if it has a conjunctive term that can use a clustered-index, e.g., for query

$$\sigma_{R.a=2 \wedge (R.b<3 \vee R.c<4)}(R)$$

clustered - indexed

etc.

- **Classification methods**
  - Bottom-up method
  - Top-down method
- **Example of classification**

G = { all queries }

$G = G_1 \cup G_2$

unary queries   join queries

$G_1 = G_{11} \cup G_{12} \cup G_{13}$ $G_2 = G_{21} \cup G_{22} \cup G_{23}$

$$G_{11} = \{ \, p_{b_1,\ldots,b_k}(s_{F_1 \wedge \ldots \wedge F_m}(R)) \mid \text{at least one } F_i \ (1 \le i \le m)$$
$$\text{is } R.a = C, \text{ where } R.a \text{ is a clustered-indexed column} \}$$
$$G_{12} = \{ \, p_{b_1,\ldots,b_k}(s_{F_1 \wedge \ldots \wedge F_m}(R)) \mid \text{at least one } F_i \ (1 \le i \le m)$$
$$\text{is } R.a = C, \text{ where } R.a \text{ is an indexed column} \} - G_{11}$$
$$G_{13} = G_1 - (G_{11} \cup G_{12})$$

….. classification can be further refined

– **Relevant issues**
  - Composition of rules
  - Redundancy of rules
  - Classification algorithms
  - Membership testing

- Sampling and cost formulas
  – **Sampling method: mixed** judgment and probability sampling
    - Use some knowledge to restrict a query class to a **representative** subset
    - Apply one or more types of **probability sampling**, e.g., simple random sampling and cluster sampling, to draw a sample

  – **Example**

For G_{11} : $\{ \, p_{b_1,\ldots,b_k}(s_{F_1 \wedge \ldots \wedge F_m}(R)) \, \}$

F_i : $R.a = C$ -- key conjunctive term

clustered-indexed

Sample : $SP_{11} = \{ \, p_a(s_{R.a=C \wedge F}(R)) \, \}$

– **Derivation of cost formulas**

- **Explanatory variables**

Basic set:

- Cardinality of operand table(s)
- Cardinality of result table
- Size of intermediate result(s)

Secondary set:

- Operand tuple length(s)
- Result tuple length
- Characteristics of index tree
- …… etc

- **Selection of variables**

A **mixed** forward and backward procedure

- **Backward:** remove insignificant variables from the basic set
- **Forward:** add more significant variables from the secondary set

- **Example of cost formula**

For a unary query class:

$$C_1 = \underbrace{b_1 + b_2}_{\text{coefficients}} * N + b_3 * \underline{N * S}$$

coefficients

inputs

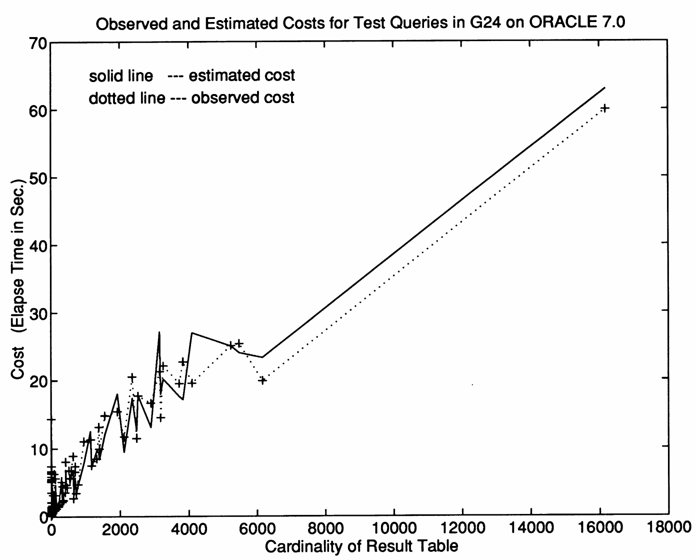
N – – operand table size

S – – selectivity

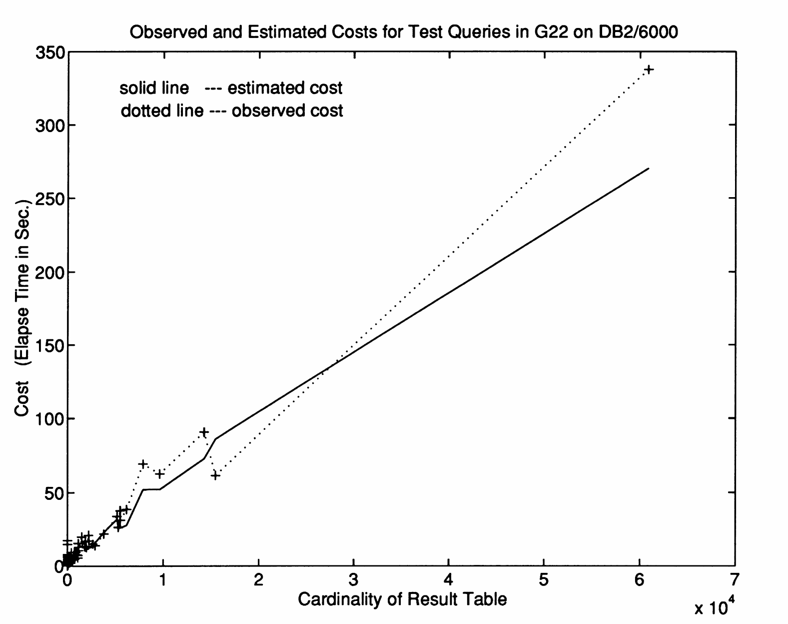
- **Estimation of coefficients**
  - Multiple regression analysis

- **Validation of cost formulas**
  - Standard error of estimation
  - Coefficient of total determination
  - F-test
  - Test queries

- **Experiment results on Oracle**



- **Experiment results on DB2**



For more details:

Q. Zhu and P.-A. Larson:

- “Solving local cost estimation problem for global query optimization in multidatabase systems”, ***Distributed and Parallel Databases***, Vol. 6, No. 4, 1998
- “Classifying local queries for global query optimization in multidatabase systems” ***Int’l Journal of Coop. Inf. Sys***., Vol. 9, No. 3, 2000
- “A query sampling method for estimating local cost parameters in an MDBS”, ***Proc. of 10th IEEE Int’l Conf. On Data Eng***., 1994

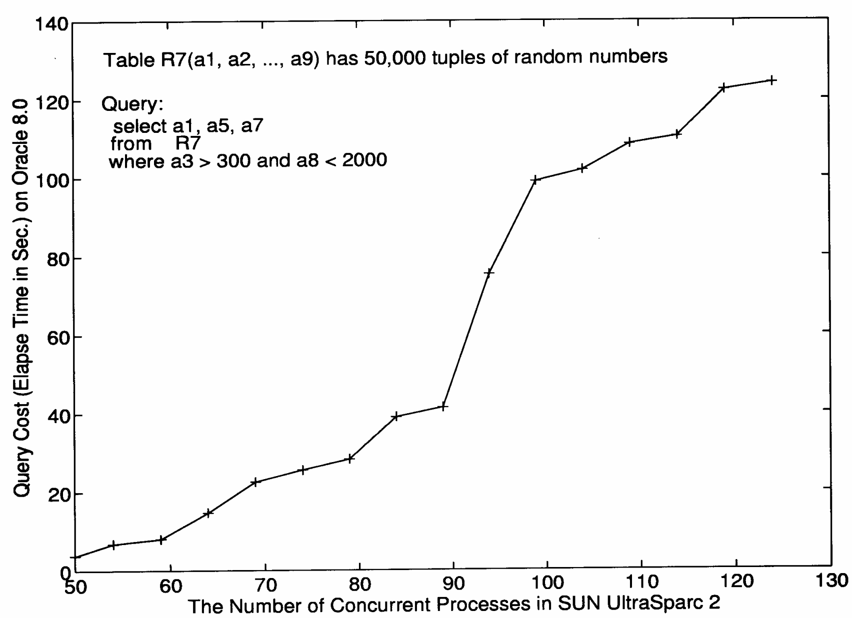
4. Qualitative Approach

- **Motivation:** query cost may **change dramatically** in a dynamic environment
- **Types of dynamic factors**
  - **Frequently-changing factors**

    E.g., CPU load, I/Os per sec., amount of memory being used
  - **Occasionally-changing factors**

    E.g., DBMS configuration parameters, data physical distribution, physical memory size
  - **Steady factors**

    E.g., CPU speed, DBMS release and type



- **Capture dynamic factors in cost models**
  - **Steady factors**
    - usually don't cause problem
  - **Occasionally-changing factors**
    - periodically rebuild the cost model via the query sampling method
  - **Frequently-changing factors**
    - infeasible to rebuild frequently
    - difficult to include all dynamic variables: (1) too many; (2) unknown interaction forms

  $\Rightarrow$ use a new **qualitative approach**

- **Key idea**
  - ***Consider the combined effect*** of all dynamic factors on query cost
  - ***Use the cost of a probing query*** to measure the system contention level
  - ***Divide the contention level*** into a number of discrete states: e.g., high contention, medium contention, low contention, no contention, etc.
  - ***Use a qualitative variable*** in a cost model to indicate contention states

- **Cost model with qualitative variable**
  - **Qualitative variable**
    - a qualitative variable with **m states** is represented by **m-1 indicator variables**

$$
\begin{aligned}
S_1: &\quad Z_1 = 1,\ Z_2 = 0,\ \ldots,\ Z_{m-1} = 0 \\
S_2: &\quad Z_1 = 0,\ Z_2 = 1,\ \ldots,\ Z_{m-1} = 0 \\
&\quad \ldots\ldots \\
S_m: &\quad Z_1 = 0,\ Z_2 = 0,\ \ldots,\ Z_{m-1} = 0
\end{aligned}
$$

  - **Cost model**

$$Y = (b_0^0 + \sum_{j=1}^{m-1} b_0^j Z_j) + \sum_{i=1}^{n} (b_i^0 + \sum_{j=1}^{m-1} b_i^j Z_j) X_i$$

- **System states determination**

  How to determine the system contention states?
  - **two extremes:** one state $\leftrightarrow$ infinite states
  - determination via **iterative uniform partition with merging adjustment**
    - **Phase I :** **uniformly partition** the range of probing query cost with an incremental number of states until $|(R_{new}^2 - R_{old}^2)/R_{old}^2|$ and $|(s_{new} - s_{old})/s_{old}|$ are sufficiently small, where

R^2 -- coefficient of total determination

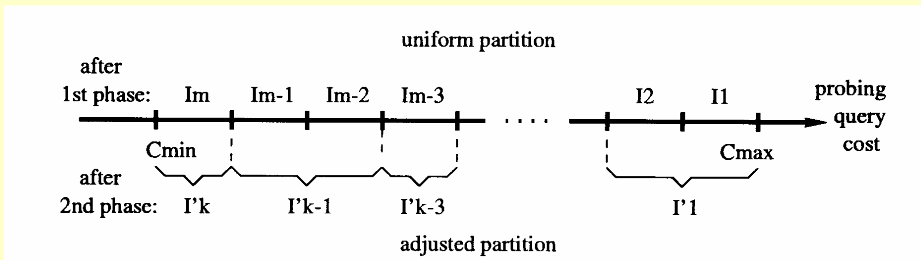
s -- standard error of estimation

- **Phase II :** **merge two states** S_{k-1} and S_k *if* no significant difference in coefficients for the cost model, i.e., if

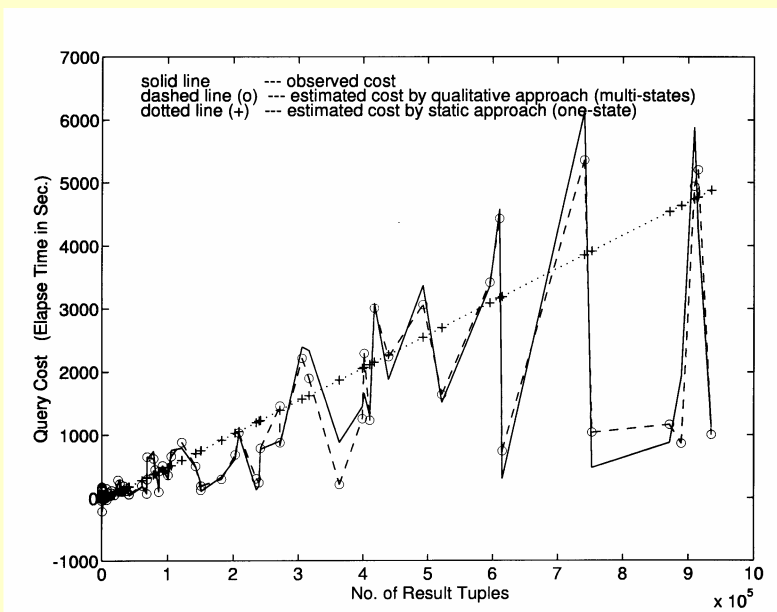
$$r_k = \max_{i \in \{0,1,2,...,n\}} \{|(q_i^{k-1} - q_i^k)/q_i^k|\}$$

is too small, where

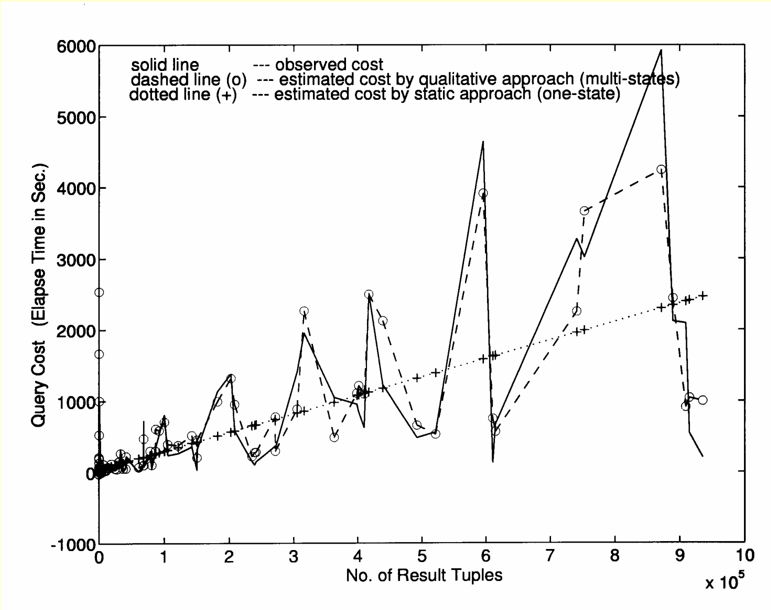
$q_i^j = b_i^0 + b_i^j$ -- adjusted coefficient of X_i for state S_j



- **Experiment results on Oracle**



- **Experiment results on DB2**



For more details:

Q. Zhu, Y. Sun, S. Motheramgari:

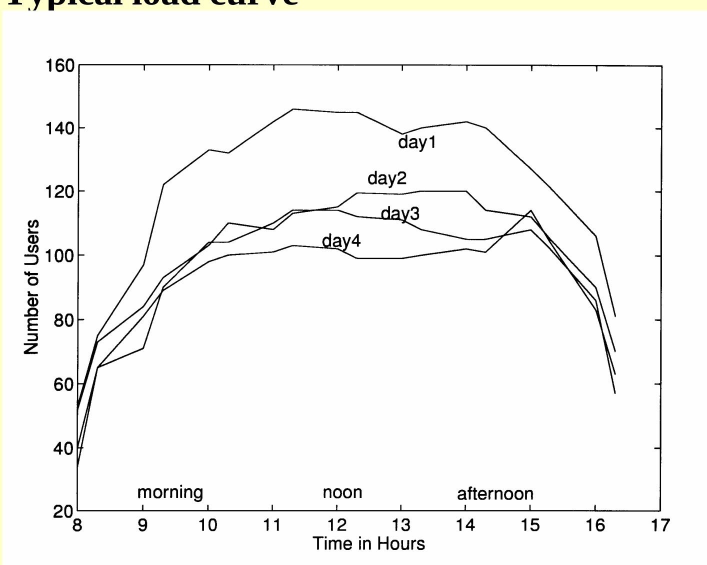
- “Developing Cost Models with Qualitative Variables for Dynamic Multidatabase Environments”, ***Proc. of 16th International Conf. on Data Eng. (ICDE’2000),*** Feb. 2000

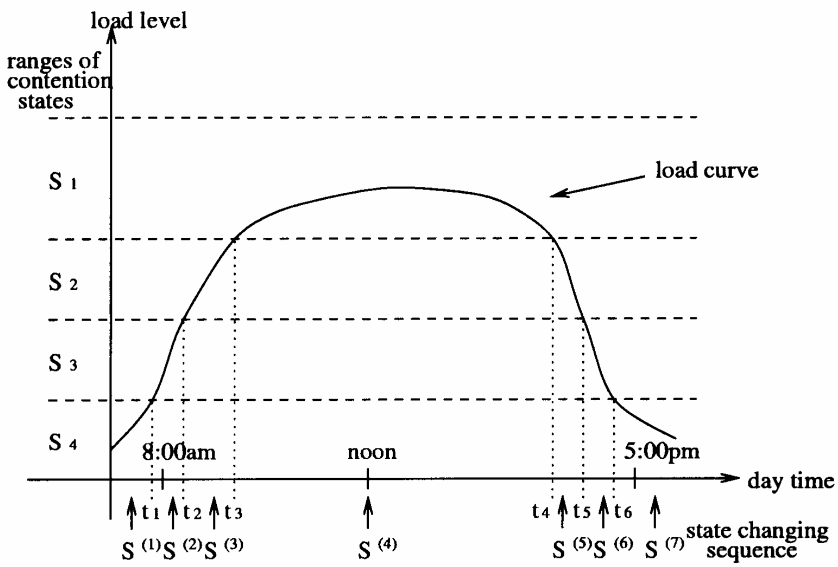
5. Fractional Analysis and Probabilistic Approach

- **Motivation:** a large (cost) query may experience multiple states during its execution, how to estimate its cost?
- **Simple solutions**
  - *single state analysis*: consider only one prevailing contention state, e.g., the initial state
  - *average cost analysis*: take average of costs in all contention states

⇒ **Better solutions?** Yes

- **Fractional Analysis Approach**
  - **Typical load curve**





– **Key idea**

- Calculate the fraction of cost in each state and add them up
- Let

$\Delta = \{S_1, S_2, \ldots, S_M\}$ – all possible states

$S^{(1)}, S^{(2)}, \ldots, S^{(N)}$ – sequence of states occurred along the load curve

$t^{(i-1)}, t^{(i)}$ – starting and ending times for $S^{(i)}$

Q – query starting at $t_Q^{(s)}$ in state $S^{(k)}$

$T^{(k)} = (t^{(k)} - t_Q^{(s)})$ – max time interval for Q in $S^{(k)}$

$T^{(i)} = (t^{(i)} - t^{(i-1)})$ for $i > k$ – time interval for $S^{(i)}$

$C(Q, S^{(i)})$ – cost estimate of Q in $S^{(i)}$

- **Case 1:** if $C(Q, S^{(k)}) \le (t^{(k)} - t_Q^{(s)})$, then $C(Q) = C(Q, S^{(k)})$
- **Case 2:** if $C(Q, S^{(k)}) > (t^{(k)} - t_Q^{(s)})$, then

  estimated fraction of work done for Q in $S^{(k)}$ is :

  $$(t^{(k)} - t_Q^{(s)}) / C(Q, S^{(k)})$$

  remaining fraction of work for Q is :

  $$[1 - (t^{(k)} - t_Q^{(s)}) / C(Q, S^{(k)})]$$

  - **Sub-case 1:**

    if $[1 - (t^{(k)} - t_Q^{(s)}) / C(Q, S^{(k)})] * C(Q, S^{(k+1)}) \le (t^{(k+1)} - t^{(k)})$,

    then

    $$C(Q) = \underbrace{(t^{(k)} - t_Q^{(s)})}_{\text{work done in } S^{(k)}} + \underbrace{[1 - (t^{(k)} - t_Q^{(s)}) / C(Q, S^{(k)})] * C(Q, S^{(k+1)})}_{\text{work done in } S^{(k+1)}}$$

- **General cost estimation formula:**

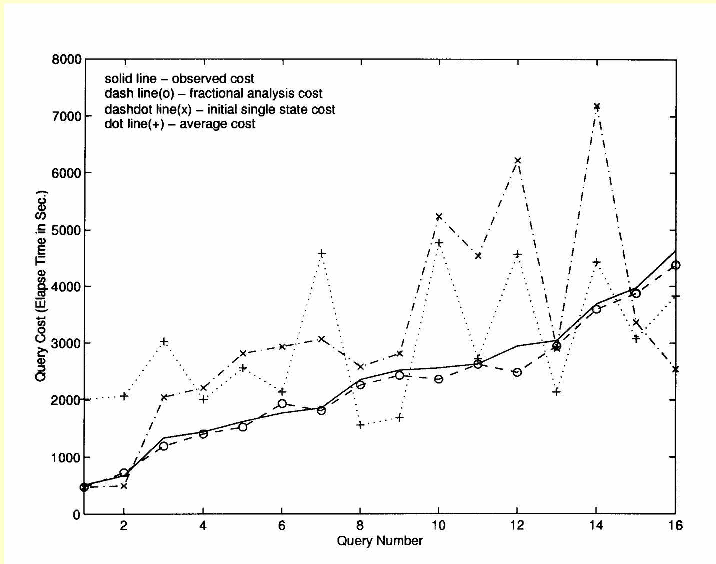
  $$C(Q) = \sum_{i=k}^{m} T^{(i)} + [1 - \sum_{i=k}^{m} T^{(i)} / C(Q, S^{(i)})] * C(Q, S^{(m+1)})$$

  where m is the minimum integer such that

  $$[1 - \sum_{i=k}^{m} T^{(i)} / C(Q, S^{(i)})] * C(Q, S^{(m+1)}) \le T^{(m+1)}$$

- **Assumptions:**
  - Load curve is prior known
  - Load changes gradually

– **Experiment Results on Oracle**



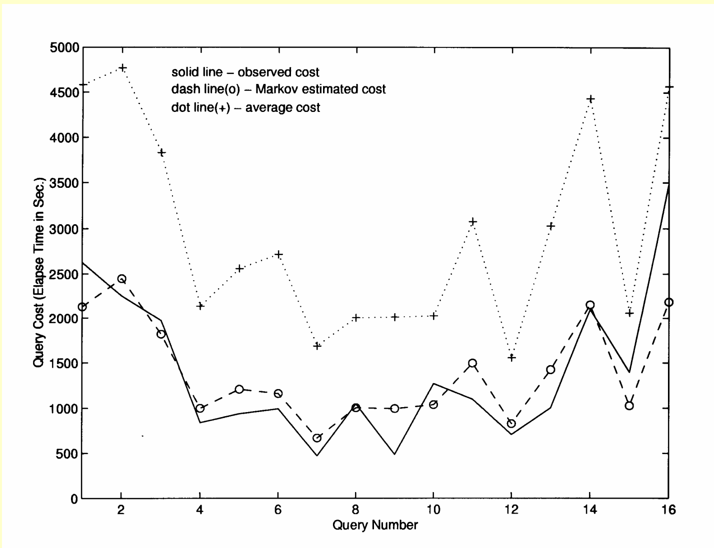
- **Probabilistic Approach**
  - **Motivation:** how to deal with a **rapidly** and **randomly** changing environment?
  - **Observations**
    - Occurrence of a contention state is a **random phenomenon** and governed by **laws of probability**
    - The sequence of occurrences of contention states can be considered as a **Markov chain**
    - Transition probability *Pij* for state *Si* changing to state *Sj* in the next step is **inversely proportional** to the distance between *Si* and *Sj*
  - **Limit probability**
    - $p_j = \underset{n\to\infty}{\text{limit}}\ P_{ij}(n)$ — the **limit probability**, where *Pij(n)* is the probability for *Si* changing to *Sj* after *n* steps

- **Properties**
  - **Independent of** initial state Si
  - Represent the **long-run portion** of time for the Markov chain being in the state
- **Satisfy the system of linear equations:**

$$p_j = \sum_{i=1}^{M} p_i P_{ij} \quad \text{for } j = 1,2,\ldots, M \quad \text{subject to } \sum_{j=1}^{M} p_j = 1$$

- **Cost formula**
  - Cost incurred in state Si: $p_i * C(Q)$
  - Fraction of work in state Si: $(p_i * C(Q)) / C(Q, S_i)$
  - Identity: $\sum_{i=1}^{M} (p_i * C(Q)) / C(Q, S_i) = 1$
  - **Cost formula:** $C(Q) = 1/[\sum_{i=1}^{M} p_i / C(Q, S_i)]$

– **Experiment results on Oracle**



- For more details:

Q. Zhu, S. Motheramgari, Y. Sun:

- “Cost Estimation for Queries Experiencing Multiple Contention States in Dynamic Multidatabase Environments”, ***Knowledge and Information Systems,*** Springer Verlag, 2001 (to appear)
- “Cost estimation for large queries via fractional analysis and probabilistic approach in dynamic multidatabase environments”, ***Lecture Notes in Computer Science (DEXA2000),*** Vol. 1873, 2000

6. Conclusions

- A **crucial challenge** for global query optimization in an MDBS is that some local cost information may not be available at the global level
- **A number of techniques** have been proposed to estimate local cost parameters at the global level in an MDBS
- **Query sampling method** is useful in estimating query costs in a static MDBS environment

- **Qualitative approach** is useful in estimating costs of queries experiencing one contention state in a dynamic environment
- **Fractional analysis approach** is useful in estimating costs of queries experiencing multiple contention states in a gradually changing dynamic environment
- **Probabilistic approach** is useful in estimating costs of queries experiencing multiple contention states in a rapidly changing dynamic environment
- **Further research** needs to done in future

For more information:

http://www.engin.umd.umich.edu/~qzhu