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Semi-join Strategies for Total Cost Minimization in Distributed Query Processing

by
William T. Bealor

A Thesis
Submitted to the Faculty of Graduate Studies and Research through the School of Computer Science in Partial Fulfillment of the Requirements for the Degree of Master of Science at the University of Windsor

Windsor, Ontario, Canada
1995
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Abstract

A new static heuristic, called Algorithm W is presented as an efficient method for reducing the total volume of data transmitted over the network during distributed query processing. It uses the concepts of profit, marginal profit and gain to construct small, highly selective reducers using cost-effective semi-join sequences. In most cases the heuristic has a complexity of $O(nm)$. A limitation of static strategies, such as Algorithm W is that they rely on accurate estimates to perform properly. The presence of estimation errors may lead to sub-optimal solutions. A solution to this problem is the use of a dynamic strategy (Boderick, 1985; Boderick, Pyra et al., 1989) in which the schedule of operations is monitored and corrected if the performance deteriorates. A purely dynamic heuristic, Algorithm DW is proposed which uses up to date information eliminating the need for schedule monitoring. It is shown that the overheads incurred by using exact information are minimal with respect to the overall total cost. A benchmark database is proposed upon which the empirical performance of the heuristics can be measured. Algorithm W is evaluated against the AHY General (total time) algorithm (Apers, Hevner, Yao, 1983) to investigate whether improvements are possible. The performance of the proposed heuristics are evaluated to test the hypothesis that a dynamic strategy using better estimates will produce improved schedules.
To my mother and father...
Acknowledgements

This work could not have been accomplished without the help of so many people. I would like to thank Dr. Morrissey for the ideas behind the heuristics along with the concept of marginal profit and the related proofs. Thanks to Dr. Bandyopadhyay and Dr. Pinto for their comments on my thesis. I appreciated all of the comments and discussions with all of my colleagues in the database research group. I would also like to thank a couple of good friends, Mounia whose friendship and support helped me get through some tough times and Steve for all of his technical support as well as being a good friend. Lastly, I would like to thank my parents for all of their support and understanding over these last few years.
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DW. ................................................................. 88
With the proliferation and continued advancement of telecommunication technology, it is not surprising to see the development of decentralized information systems. Distributed Database Management Systems have certain advantages over traditional Centralized Database Management Systems in that they achieve the advantages of performance, reliability, availability and modularity that are inherent in distributed systems [CP84, OV91, Teo92]. By definition, a distributed database is a collection of multiple, logically interrelated databases distributed over a computer network. Each site within the network consists of an autonomous database capable of processing local applications as well as distributed applications which require access to data from several different sites via a communication network [CP84, OV91].

The use of a relational query enables users to specify a description of the required data without having to know the physical location of the data. The retrieval of data from various sites in a distributed database is referred to as distributed query processing. It is evident that the performance of a Distributed
Database Management System is critically dependent upon the capability of the query optimizer to derive efficient query processing strategies [ES80]. In addition to increasing the response time for a query, the use of an ineffective processing strategy may cause performance deterioration over the entire distributed database [OS88].

The most common approach to distributed query optimization has been the use of a static three phased approach that utilizes either join or semi-join operators as the primary reducing operator. Of those algorithms employing semi-joins as the primary reducing operator, the algorithms developed by Apcrs, Hevner and Yao [AHY83] are regarded as the best heuristics to date. Other less common methods are based on the use of improvement algorithms [CL84], the pipelining of the semi-join process [RK91], adaptive selection of execution strategies [TI90] as well as the use of one-shot fixed precision semi-joins [WLC91]. For specific types of distributed databases, the use of specialized semi-joins have been proposed as the primary reducing operator [PC90, CL90].

Clearly, in the case of static algorithms, any realistic query optimization hinges on the accurate estimation of the cardinality of intermediate results and final results of a query [Gra89, Loh89]. It is argued in [Loh89] that the two major assumptions (the uniform distribution of data and attribute independence) in the probabilistic models used by nearly every optimizer are flawed, resulting in estimation errors.

In addition, little work has been done in the validation of the optimization algorithms [Sel89]. In most cases algorithms are compared in theory without
Introduction

considering the effect of using real data. Previous work in benchmarking database systems [BDT83], suggests that it should not be unreasonable to validate an algorithm's performance against a realistic database.

While it commonly agreed upon that real world data does not conform to the uniform distribution and attribute independence assumptions, to our knowledge no one has examined whether or not these assumptions have an effect on the performance of distributed query processing. Clearly, validation would answer this question. In addition, it would also provide insight into the accuracy of the estimation techniques.

With respect to the development of new heuristics, citations indicate that the Apers-Hevner-Yao (AHY) Algorithms are considered to be the best heuristics proposed to handle general queries. Heuristics proposed after the AHY algorithms are typically designed around specific hybrid operators, architectures, network topologies, etc. Are the AHY algorithms the best that can be achieved?

In this thesis the following questions are examined:

□ Can improvements be made in semi-join based query optimization heuristics?

□ Are the assumptions of uniform data distribution and attribute independence valid for real world data?

□ Will the use of current information available to a dynamic heuristic provide better performance than its static counterpart?

To address these questions a benchmark database has been developed on which
the performance of the AHY General (total time) algorithm will be compared with two proposed heuristics namely, Algorithms W (static) and DW (dynamic).

1.1 THESIS ORGANIZATION

This work is organized into six chapters with chapter 1 constituting the introduction to this thesis. In chapter 2 the relevant background material for this thesis is reviewed. This review includes discussions on the goal of distributed query processing, estimation techniques as well as static and dynamic query processing strategies.

In Chapter 3 all of the notations and definitions that are used throughout this work are presented. In particular, theorems, proofs and lemmas for numerous concepts employed by the proposed heuristics are presented.

Chapter 4 presents detailed descriptions of the three heuristics. A comparative example between Algorithm W and AHY is provided to clarify how each heuristic is executed. This example also serves to illuminate the differences that exist between the two heuristics.

In Chapter 5 the evaluation methodology is discussed. Particular attention is paid to the design of the benchmark database and the queries with which the heuristics are evaluated with. The remainder of this chapter is used to present the experimental results along with a discussion of the conclusions that can be inferred from the results.

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Lastly, chapter 6 provides a summary of the conclusions attained from the work that this thesis represents along with some plans for future work.
In this chapter background information on the distributed query optimization problem is presented. In Section 1, the overall objectives of distributed query optimization are examined. Section 2, details the use of semi-joins as the primary reducing operation. Lastly, in Sections 3 and 4 respectively we present and discuss the use of static and dynamic strategies for distributed query optimization are discussed.

### 2.1 QUERY OPTIMIZATION OBJECTIVES

Most research with the exception of [ESW78] has concentrated on the optimization of a particular class of queries commonly known as Select-Project-Join queries\(^1\) [CP84, OV91]. The formulation of an optimized execution strategy is based on the minimization of some objective cost function or functions. Some commonly used objective functions [Bod85, BR88b] are the:

- dollar cost due to network usage

\(^1\) Also referred to as conjunctive normal form queries.
Background

- dollar cost due to local CPU usage
- combined dollar cost of both local CPU processing and network usage
- delay due to local CPU processing
- delay due to network data transfers
- combined delay due to local CPU processing and network data transfers
- volume of data processed by all information processors
- volume of data transferred over the network
- total size of partial results

Central to most optimization strategies is the use of either a total cost model or response time model. In the total cost model the objective is to minimize the overall costs that are incurred in processing the query. Most approaches assume the total cost to be the amount of data transferred. Due to the nature of distributed databases, it is possible that some or all of the processing required for a given query can be executed in parallel. The response time model is based on this supposition; seeking to minimize the elapsed time for query execution.

2.2 ESTIMATION

The fundamental goal of an optimization algorithm is the formulation of a query execution strategy that is optimal. Unfortunately, the formulation of an optimal solution can only be accomplished by performing an exhaustive search of all possible execution strategies. The complexity of such an enumeration has been

---

2 A partial result refers to the size of a relation after the application of a relational operation.

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shown to be NP-hard [WC93], making any such algorithms too computationally expensive to implement. Hence, heuristic algorithms are employed to quickly formulate near-optimal strategies.

The performance of static query optimization algorithms is heavily dependant upon the estimation technique used to evaluate the sizes of partial results. Some of the commonly used algorithms are as follows.

To estimate the expected number of tuples in a relation resulting from an arbitrary number of join operations, Chen and Yu [CY90] propose the following theorem.

**Theorem:** Let $G = (V,E)$ be a join query graph and $G_R = (V_R,E_R)$ is a connected subgraph of $G$. Let $R_1, R_2, \ldots, R_p$ be the relations corresponding to nodes $V_R$ and $A_1, A_2, \ldots, A_q$ be the distinct attributes associated with edges in $E_R$.

Let $n_i$ be the number of different nodes (relations) that edges with attribute $A_i$ are incident to. Suppose $R^*$ is the relation resulting from the join operations between $R_1, R_2, \ldots, R_p$ and $m$ is the expected number of tuples in $R^*$. Then

$$m = \prod_{i=1}^{p} |R_i| \prod_{j=1}^{q} |A_j|^{n_j-1}$$

For the query graph illustrated in Figure 2.1, the expected number of tuples in the resulting relation is estimated as

$$\frac{\prod_{i=1}^{4} |R_i|}{|A||B|^3|C||D|}$$
Estimating the size of partial results after the application of a semi-join operation is somewhat different than that of the join operation. The two most common algorithms, outlined in [Yu85] are as follows.

Suppose that we have two single attribute relations, $R_1$ and $R_2$. Suppose further that the values of the common join-attribute, say $A$ are uniformly and independently distributed on both relations. If the semi-join $R_2 \times_A R_1$ is executed, the size of $R'_1$ can be estimated as $S(R_1) \times \rho_{2a}$, where $\rho_{2a}$ is the selectivity of attribute $A$ of relation $R_2$. The selectivity of the reduced attribute $A$ of relation $R_1$ is estimated by $\rho'_{1a} = \rho_{1a} \times \rho_{2a}$.

If the reducing relation is the result of a sequence of semi-joins, the incoming selectivity for this schedule is the product of the selectivities of all of the attributes in the schedule. The only restriction is that if there are multiple occurrences of an attribute in the schedule then only one instance of its selectivity is used.

Estimation is somewhat different when dealing with multi-attribute relations. Suppose $R_2$ is defined as above but $R_1$ is now a relation with two join-attributes $A$ and $B$. After the application of the semi-join $R_2 \times_A R_1$, the cardinality of $R_1$
is easily estimated as $|R_1| \times \rho_{2\alpha}$. $R_1$ may subsequently be used to reduce some other relation, say $R_3$, by performing the semi-join $R_1 \bowtie_B R_3$ over attribute $B$.

To obtain an accurate estimate of the size of $R_3$ after the semi-join it is necessary to estimate the cardinality of attribute $B$ of $R_1$ after the execution of $R_2 \bowtie_A R_1$.

Yu [Yu85] shows that this estimation problem is related to the problem: "Given $n$ balls with $m$ different colours. What is the expected number of colours if $t$ balls are randomly selected from the $n$ balls". In the semi-join problem the correspondences are: $n$ balls being the cardinality of $R_1$ prior to reduction; $m$ colours being the cardinality of the $B$ values in $R_1$; the $t$ selected balls correspond to the cardinality of $R_1$ after the application of the semi-join. The expected number of colours of the $t$ select balls is

$$m \times \left[ 1 - \prod_{i=1}^{t} \left( \frac{n((m - 1/m)) - i + 1}{n - i + 1} \right) \right]$$

It is important to note that while $t$ is a parameter in the ball-colour problem, the cardinality of $R_1$ after the application of the semi-join needs to be estimated. For this reason the formula, if evaluated in its present form is expensive computationally and may cause overflow or underflow for large values of $t$. The following function presented in [BGW+81, Yu85] provides an estimation to the above formula after $t$ has been estimated.

$$\begin{cases} m, & \text{if } t > 2m \\ \frac{(t+m)}{3}, & \text{if } 2m > t > m/2 \\ t, & \text{if } (m/2 > t) \end{cases}$$

The following example illustrates the use of this estimation formula.

**Example:** Suppose that $R_1$ and $R_2$ are the same as above and $R_3$ is a single attribute relation with attribute $B$. If $R_1$ is reduced by $R_2$ and $R_3$ using semi-joins,
$R_2 \times_A R_1 \times_B R_3$, the cardinality of $R_1$ can be estimated as $|R_1| \times p_1 \times p_2$, where $p_3$ is the selectivity of $R_3$ under attribute $B$. Because attributes $A$ and $B$ are independent of each other, the expected number of distinct values of $A$ and $B$ are estimated using the approximation formula described above.

2.3 SEMI-JOINS AS REDUCERS

Initially, distributed query optimization focused on the use of the relational join as the primary reducing operation. While simplistic in its execution, there exists the possibility that the size of the relation resulting from a join may exceed the sizes of the relations that participated in the join. This particular condition is illustrated in Figure 2.2.

In contrast, the semi-join operation is guaranteed to monotonically reduce the size of a relation, with the worst case being no reduction. In addition, the properties of semi-joins permit their computation with less intersite data transfers than for joins. If required, the reduction effect of a relational join may be obtained through the application of one semi-join and one join as defined by the equivalence relation

$$R_i \bowtie R_j \equiv (R_i \bowtie R_j; R_j \bowtie R_i)$$

Based on the properties of semi-joins, the number of tuples in the result of the application of a semi-join, say $R_2 \bowtie R_1$ will be in the range $1 \leq |R_2'| \leq |R_1|$. Variance in the reduction effect of a semi-join is illustrated in the examples presented in Figure 2.3. Because the reduction effects of a semi-join
are asymmetric\(^3\), it is necessary to consider both applications of the semi-join in order to determine which application produces the greatest reduction. Clearly the use of a semi-join such that \( S(R_i) \approx S(R'_j) \) (as illustrated in Figure 2.3(b)), will not be \textit{cost effective}. In this respect, optimization strategies based on semi-joins consider the use of \textit{beneficial semi-joins} only.

A beneficial semi-join refers to a semi-join in which the benefit of performing the semi-join exceeds the cost of executing it. In practise the benefit is considered

\(^3\) The semi-join \( R_i \bowtie R_j \) is not equivalent to the semi-join \( R_j \bowtie R_i \).
Background

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(a) (b)

Figure 2.3 Illustration of semijoins.

The cost associated with a semi-join refers to the cost of projecting the joining attribute from the reducing relation and transmitting it to the relation to be reduced. In general (with the exception of [VV84, HWY85, CL87, YGC88],

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\[ \text{Benefit} = \text{Benefit of materialized join} - \text{Benefit of virtual join} \]

\[ = \text{Selectivity of join attribute} \times (1 - \text{Selectivity of join attribute}) \]
Background

PLH89, AM91), the cost of projecting the reducing attribute is considered to be negligible in comparison to the transmission cost. Assuming a fixed transmission cost between sites, the cost of a semi-join is computed using the following function:

\[ C(R_i \bowtie_n R_j) = C_0 + C_1 \times S(d_{in}) \]

where the coefficients \( C_0 \) and \( C_1 \) are fixed constants representing the start-up cost for a transmission and the fixed cost per unit of data transmitted respectively. \( S(d_{in}) \) represents the size of the projected attribute \( d_{in} \).

2.4 STATIC STRATEGIES

As previously stated the distributed query optimization is an NP-hard problem [WC93]. Hence, numerous heuristic algorithms have been proposed for constructing “near optimal” query execution schedules [BGW+81, AHY83, Yu85, KR87]. The term “near optimal” is used loosely in the sense that measuring the performance of a particular heuristic requires the optimal execution schedule to be known. In [Bod85] an A* tree is used to determine the optimal execution schedules for 30 different queries. Clearly if thousands of queries are being tested, it is unrealistic to attempt to compute the optimal solution for each query. For this reason the performance of a heuristic algorithm is typically described in terms of an improvement made over another existing algorithm. As a result, it is not evidently clear how “close to optimal” a solution for a particular strategy may be.
2.4.1 Two and Three Phased Approaches

The traditional approach to distributed query optimization has been the use of a three phased approach [BGW+81, AHY83, Yu85, KR87], consisting of the following three phases:

**Phase 1 Initial local processing.** Tuples and attributes which are irrelevant with respect to the query are filtered out by appropriate selection, projection, and join operations at the local site prior to any data transmission. This has the effect of reducing the amount of data transmitted over the network.

**Phase 2 Semi-join preprocessing.** After local processing, semi-joins are used to further reduce the size of relations. Based on the equi-join clauses in the query’s qualification, a semi-join schedule (or sequence) is constructed. This schedule is subsequently used for the semi-join preprocessing.

**Phase 3 Final processing.** The resulting relations after the semi-join pre-processing phase are transmitted to the assembly site (usually the query site) where all of the relations are joined to form the result of the query. If it is the case that the assembly site is not the query site, the final result must be subsequently transmitted to the query site.

While not explicitly stated, if redundant relations are permitted, the identification of the required sites is performed within the local processing phase.

Alternatively, there are a few heuristic algorithms that are based upon a two
Background

phased approach consisting of the following phases:

**Phase 1** Determine the sequence of relational operations which minimizes the total size of the partial results.

**Phase 2** Apply a polynomial time algorithm to find the optimal network site locations for executing the sequence of relational operations.

The rationale behind the two phased approach is that it essentially decomposes the optimization problem into two easier problems which may be solved more efficiently. Results in [BR88a] indicate that this approach yields beneficial results when both CPU and data transmission costs are incorporated into the objective cost function.

One of the first optimization algorithms (based on the use of semi-joins) to be proposed and implemented was the SDD-1 optimization algorithm, developed for the SDD-1 distributed database system [BGW+81]. Designed under the assumption that the transmission of data was the slowest component in query processing, the objective of the algorithm was to process a query with a minimum amount of intersite data transfers. It is important to point out that a reduction in the amount of intersite data transfers has the additional advantage of reducing the network load.

Being essentially an iterative hill-climbing algorithm, the SDD-1 algorithm always selects the most profitable reduction that is immediately at hand. The major disadvantage of this approach lies in its inability to backtrack and consider other execution strategies which may produce better solutions.
Another set of heuristics, proposed by Apers, Hevner and Yao [AHY83] was developed to handle simple as well as general types of queries. It is evident from citations in numerous articles that the Apers-Hevner-Yao (AHY) algorithms are considered to be milestones within the field of distributed query optimization.

Using the three phased framework that is common to many heuristics, a new static heuristic, Algorithm W is proposed. Using semi-joins and the concept of marginal profit, Algorithm W attempts to minimize the overall total cost of executing a query. A complete description of Algorithm W is presented in chapter 4.

2.5 DYNAMIC STRATEGIES

Static query optimizers rely heavily on various techniques for estimating the sizes of partial results, selectivities and other parameters pertaining to the distributed environment. It is recognized that a strategy based on inaccurate estimations may be far from optimal [ES80]. Any estimation errors in static strategies will be propagated and compounded during the execution of the schedule. Two alternative approaches exist for avoiding this problem.

The first approach relies on various dynamic query execution techniques to alleviate the problem. A dynamic query execution has the advantage that a strategy may be modified if it is found that it is not proceeding as planned. To determine whether a strategy is proceeding as planned requires information regarding the progress of the strategy to be gathered by one or more processors. The collection
of information on the current progress of a strategy is commonly referred to as monitoring. Based on this monitoring there is some decision making process which decides whether the current strategy being executed should be aborted and a new strategy proposed for the portion of the strategy that “has yet to be processed”. If the current strategy is to be aborted then some form of corrective action will be needed to form and initiate a new strategy in order to complete the query. Various methods of monitoring and corrective action are discussed in [BRJ89]

Irrespective of the method of monitoring, the decision to correct can be made using methods based on either frequent reformulation or the use of preestablished threshold values. A description of both approaches is outlined below.

Reformulation. Whenever a new partial result is formed, the unexecuted portion of the query is reformulated using the most up-to-date information available. A correction is appropriate if the new reformulation has a lower cost than that of the current strategy.

Threshold. When a strategy is formulated, additional information is included to support the decision making process. For each parameter used in the formulation, two threshold values, $V_{\text{low}}$ and $V_{\text{high}}$, are constructed. A strategy is corrected if the actual value of a parameter falls outside the range of the associated threshold values.

---

4 For total cost estimation the parameter is the size of partial results.
In any given query there exist some partial results whose estimates are more critical than others. A threshold method proposed in [BR88b] deals with this problem through the use of a Critical Path Network. In this situation, threshold values are only constructed for partial results that are considered to be critical to the overall execution of the query. If any critical threshold value is exceeded, it is known that the strategy will be delayed and should be subsequently aborted and corrected.

The second approach is to provide more accurate estimates. However, it is noted that applications supporting the computation of accurate estimates are typically expensive in terms of size and upkeep of the required statistical information [BRJ89].

In this thesis a purely dynamic heuristic called Algorithm DW is proposed, which computes the execution strategy for a query on the fly using up to date information on the participating relations. A dynamic execution of this form does not require any schedule monitoring. In addition, it is believed that the overhead associated with maintaining up to date information will not constitute a significant portion of the overall total cost. A detailed description of Algorithm DW is given in Chapter 4.
Assumptions and Definitions

For this thesis a distributed database management system is considered to be a collection of independent databases connected via a point-to-point network. Queries executed by the distributed database management system are taken from the select-project-join (SPJ) class of queries. Each relation is located at a different site and has at least one attribute, other than any join attributes, that is required at the query site. For each relation it is assumed that the attribute values are uniformly distributed and that attributes are independent of one another. The cost of executing a query is considered to be a linear function relative to the total amount of data that is transferred across the network. It is also assumed that the local processing costs are negligible with respect to the data transmission costs.

As semijoins are the basis for all of the algorithms discussed in this thesis, this operation is outlined first. Suppose a query requires two relations say $R_1$ and $R_2$ to be joined, that is execute $R_1 \bowtie R_2$. A straightforward approach is to ship both relations to the query site and perform the join there. Alternatively, semijoins

---

5 Alternately referred to as conjunctive normal form queries.
Assumptions and Definitions

may be used to reduce one or both of the relations prior to being shipped to the query site. A semi-join from relation $R_1$ to $R_2$, denoted $R_1 \bowtie R_2$, is executed in the following manner:

1. Project $R_1$ over the common join attribute to get $R_1[j]$.
2. Ship $R_1[j]$ to the site of $R_2$.
3. Execute $R_1[j] \bowtie R_2$.

Using the semi-join, the size of $R_2$ is reduced by eliminating those tuples which will not occur in the relation $R_1 \bowtie R_2$. A carefully chosen sequence of semi-joins can significantly reduce the sizes of the relations before they are shipped to the query site, thus reducing the total amount of data transferred across the network.

The following are defined for each relation $R_i$, $i = 1, 2, \ldots, m$:

- $A_i$ number of distinct attributes in relation $R_i$ where $A_i > 1$.
- $S(R_i)$ size (in bytes or any suitable measure) of $R_i$.
- $|R_i|$ the cardinality of relation $R_i$.

For each attribute$^6$, $d_{ij}$, $j = 1, 2, \ldots, A_i$ of $R_i$ the following are defined:

- $D(d_{ij})$ the domain of possible values for attribute $d_{ij}$.
- $|D(d_{ij})|$ the cardinality of $D(d_{ij})$, that is the number of distinct values that make up the domain for $d_{ij}$.

* The denotation $d_{ij}$ refers to the $j$th join-attribute of relation $R_i$.

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Assumptions and Definitions

\[ |d_{ij}| \] the cardinality of relation \( R_i \) projected over attribute \( d_{ij} \), that is
the number of distinct values in attribute \( d_{ij} \).

\[ S(d_{ij}) \] size of attribute \( d_{ij} \).

\[ \rho(d_{ij}) \] selectivity of attribute \( d_{ij} \), where selectivity is defined as

\[ \frac{|d_{ij}|}{|D(d_{ij})|} \]

With the execution of any semi-join there is some degree of overhead. The execution of the semi-join \( d_{ij} \bowtie d_{kj} \) incurs a cost that is proportional to the amount of data (size of \( d_{ij} \)) that is transmitted from the site of \( R_i \) to the site of relation \( R_k \). The cost is defined as

\[ C(d_{ij} \bowtie d_{kj}) = C_0 + [C_1 \times S(d_{ij})] \]

where \( C_0 \) and \( C_1 \) are fixed constants. In all of the following definitions and examples in this thesis it is assumed that \( C_0 = 0 \) and \( C_1 = 1 \).

The benefit associated with the execution of a semi-join is equal the amount of data that will not be needed in the final result and hence does not need to be transmitted to the final result site. The benefit is defined as

\[ B(d_{ij} \bowtie d_{kj}) = S(R_k) - (S(R_k) \times \rho(d_{ij})) \]

\[ = S(R_k) \times (1 - \rho(d_{ij})) \]

A semi-join is termed profitable if the benefit outweighs the cost. Profit is defined as

\[ P(d_{ij} \bowtie d_{kj}) = B(d_{ij} \bowtie d_{kj}) - C(d_{ij} \bowtie d_{kj}) \]
Assumptions and Definitions

A reducer is defined as any attribute which can be used to reduce any other attribute (or relation). For the distributed query optimization, the identification of those reducers which are inexpensive to use and are good at reducing other relations (i.e. small attributes with high selectivities) is of key interest. Each of the proposed heuristics presented in this thesis attempts to construct reducers for each attribute in a cost effective manner. Each reducer is built using a sequence of semijoins \( d_{a_j} \times d_{b_j} \times d_{c_j} \times \ldots \times d_{m_j} \) such that \( S(d_{a_j}) \leq S(d_{b_j}) \leq S(d_{c_j}) \leq \ldots \leq S(d_{m_j}) \). The final attribute to be reduced is considered to be the reducer and is denoted \( d^*_{m_j} \). To estimate the cost and benefit of using a reducer \( d^*_{m_j} \), some provision for estimating its selectivity is required. The selectivity of a reducer with respect to any relation occurring in its construction sequence is defined as

- \( \frac{1}{\prod_{i=1}^{n} S(R_i)} \) with respect to \( R_m \), since \( d^*_{m_j} \) has no reduction effect on the relation in which it is contained.
- the product of selectivities of all of the attributes which occur after \( d_{ij} \) in the sequence, since \( R_i \) has already been reduced by those attributes which precede it in the sequence.

In the case of relations which have a common-join attribute but do not appear in the construction sequence, the selectivity of the reducer with respect to the relation is simply the product of all of the selectivities of the attributes in the sequence. The selectivity of a reducer \( d^*_{m_j} \) w.r.t. the relation \( R_i \) is formally
Assumptions and Definitions

defined as

\[
\rho\left(d_{m_j}^*\right) = \begin{cases} 
1, & i = m \\
\prod_{x=i+1}^m \rho(d_{xj}). & i < m \\
\prod_{x=1}^m \rho(d_{xj}). & \text{otherwise}
\end{cases}
\]

The cost associated with the application a reducer is the cost of transmitting it to the site of the relation that is to be reduced, which is simply \(S\left(d_{m_j}^*\right)\). To estimate the benefit of applying the reducer it is necessary to estimate the reduction effects the reducer will have on the relation if the reducer were to be used. The estimated size of \(R_i\) after the semi-join \(d_{m_j}^* \times R_i\) is computed as

\[
S'(R_i) \times \rho\left(d_{m_j}^*\right)
\]

where \(S'(R_i)\) is the estimated size of \(R_i\) after all semi-joins preceding it in the sequence have been performed and \(\rho\left(d_{m_j}^*\right)\) is the estimated selectivity of the reducer w.r.t. \(R_i\) as defined above. The benefit of the semi-join \(d_{m_j}^* \times R_i\) is subsequently defined as

\[
B\left(d_{m_j}^* \times R_i\right) = S'(R_i) \times \left(1 - \rho\left(d_{m_j}^*\right)\right)
\]

In some cases semi-joins may not be profitable, however their use may increase the profitability of subsequent semi-joins. These semi-joins are identified by examining their estimated marginal profit. For example, consider the semi-join \(d_{xj}^* \times d_{yj}\). Put simply, the marginal profit is the “extra” profit we acquire by using \(d_{yj}^*\) as the reducer rather than \(d_{xj}^*\). For each relation that can be reduced using \(d_{xj}^*\) (and \(d_{yj}^*\)) there may exist some “extra” profit. The marginal profit is
Assumptions and Definitions

therefore considered to be the sum of these "extra" profits. However, the following facts must be considered when computing the marginal profit:

\[ \square \quad \text{There is no profit in the semi-join } d^*_y \times R_y \text{ since the attribute belongs to the relation.} \]

\[ \square \quad \text{There is no profit in the semi-join } d^*_y \times R_i, \text{ if the cost outweighs the benefit of the semi-join.} \]

\[ \square \quad \text{If the case where the semi-join } d^*_x \times R_i \text{ is not profitable but } d^*_y \times R_i \text{ is profitable, the marginal profit is simply the profit of the semi-join } d^*_y \times R_i. \]

\[ \square \quad \text{In the case of } R_x \text{ we have } P(d^*_x \times R_x) = 0, \text{ therefore the marginal profit is } P(d^*_y \times R_x). \]

For all other cases the marginal profit w.r.t. \( R_i \) is defined as

\[
MP_{R_i}(d^*_y \times d_{yj}) = P(d^*_y \times R_i) - P(d^*_x \times R_i)
\]

\[
= S(R_i) \times (\rho(d^*_y) - \rho(d^*_x)) + S(d^*_x) - S(d^*_y)
\]

The marginal profit with respect to \( R_i \) can be summarized as

\[
MP_{R_i} = \begin{cases} 
0, & \text{if } i = y \\
0, & \text{if } P(d^*_x \times R_i) \leq 0 \text{ and } P(d^*_y \times R_i) \leq 0 \\
P(d^*_x \times R_i), & \text{if } P(d^*_x \times R_i) \leq 0 \\
P(d^*_x \times R_i), & \text{if } i = x \\
P(d^*_y \times R_i) - P(d^*_x \times R_i), & \text{otherwise}
\end{cases}
\]

The total marginal profit is obtained by summing all positive marginal profits:

\[
MP(d^*_x \times d_{yj}) = \sum_{i=1}^{m} MP_{R_i}(d^*_x \times d_{yj}) \text{ s.t. } MP_{R_i} > 0
\]

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The gain of a semi-join is defined to be the sum of its profit and marginal profit:

\[ G(d_{x,j} \bowtie d_{y,j}) = P(d_{x,j} \bowtie d_{y,j}) + MP(d_{x,j} \bowtie d_{y,j}) \]

A semi-join is cost effective if its gain is positive. In the proposed heuristics, the construction of reducers is based solely on the use of cost effective semi-joins. In the case where a semi-join is profitable however, there is no marginal profit, the semi-join should not be executed since it will be at least as profitable to use the reducer to reduce the relation instead.

**Theorem 3.1.** If, as part of the schedule to construct the reducer \(d_{m,j}^*\), there occurs a semi-join \(d_{x,j}^* \bowtie d_{y,j}\) such that \(P(d_{x,j}^* \bowtie d_{y,j}) > 0\) and \(MP(d_{x,j}^* \bowtie d_{y,j}) = 0\) then it is at least as profitable to execute \(d_{x,j}^* \bowtie d_{y,j}\) instead, where \(d_{m,j}^*\) is the reducer.

**Proof.** When constructing the reducer \(d_{m,j}^*\) the semi-joins are executed in the following order

\[ d_{a,j} \bowtie d_{b,j} \bowtie d_{c,j} \bowtie \cdots \bowtie d_{x,j} \bowtie d_{y,j} \cdots \bowtie d_{m,j} \]

Therefore we have \(S(d_{x,j}^*) \geq S(d_{y,j}^*)\) and \(C(d_{x,j}^* \bowtie d_{y,j}) \geq C(d_{m,j}^* \bowtie d_{y,j})\). Because \(S(d_{x,j}^*) \geq S(d_{y,j}^*) \Rightarrow \rho(d_{x,j}^*) \geq \rho(d_{m,j}^*)\) it is clear that \(B(d_{x,j}^* \bowtie d_{y,j}) \leq B(d_{m,j}^* \bowtie d_{y,j})\).

Therefore \(P(d_{m,j}^* \bowtie d_{y,j}) \geq P(d_{x,j}^* \bowtie d_{y,j})\). \(\Box\)

**Corollary 3.1.** Profitability is not a sufficient condition for performing a semi-join during the construction of a reducer.
Corollary 3.2. Semi-joins with no marginal profit should not be performed.

Corollary 3.3. A semi-join should be performed if the marginal profit exceeds the cost. For example, consider the semi-join \( d_{xj}^* \times d_{yj} \) which is part of the reducer construction sequence. If there exists relations \( R_i \), \( i \neq y \) such that

\[
\sum_{i=a}^{m} S(R_i) \times (\rho(d_{xj}^*) - \rho(d_{yj}^*)) - S(d_{yj}^*) > 0
\]

then \( G(d_{xj}^* \times d_{yj}) > 0 \), therefore the semi-join should be performed.

### 3.1 Gainful Non-Profitable Semijoins

In this section it is shown that while a semi-join may not be immediately profitable, it may be gainful if the marginal profit is sufficiently large. Gainful semi-joins should therefore be executed because the overall goal is to maximize the reduction effect. In this particular case the reduction effect is due to the increased selectivity that is propagated from the non-profitable semi-join to later semi-joins. For example, the data in Table 3.1 represents a query after all local

<table>
<thead>
<tr>
<th>Relation</th>
<th>( S(R_i) )</th>
<th>( S(d_{ij}) )</th>
<th>( \rho(d_{ij}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>R1</td>
<td>1000</td>
<td>500</td>
<td>0.5</td>
</tr>
<tr>
<td>R2</td>
<td>800</td>
<td>600</td>
<td>0.6</td>
</tr>
<tr>
<td>R3</td>
<td>3000</td>
<td>700</td>
<td>0.7</td>
</tr>
<tr>
<td>R4</td>
<td>5000</td>
<td>800</td>
<td>0.8</td>
</tr>
</tbody>
</table>

**Table 3.1** A statistical representation of a query.

Note: for simplicity, in this example we assume that each tuple or attribute value constitutes one unit of data transmission cost.
Assumptions and Definitions

processing has been carried out. All that remains is to join the relations and ship them to some (other) result site.

The semi-join \( d_{11}^* \times d_{12} \) is clearly not profitable since the cost is 500 units and the benefit is only 400 units. However, this semi-join is gainful because the marginal profit is substantial:

\[
MP_{R_4}(d_{11}^* \times d_{21}) = S(R_4) \times (\rho(d_{11}^*) - \rho(d_{21}^*)) + S(d_{11}^*) - S(d_{21}^*)
= (5000 \times 0.2) + 500 - 300
= 1200
\]

Clearly, the marginal profit is greater than the cost of the semi-join, hence this is a gainful semi-join. Obviously, \( d_{21} \) should be used to reduce \( R_4 \) however, this fact needs to be identified when the semi-join \( d_{11}^* \times d_{12} \) is considered. The calculation of marginal profit and gain provides the information necessary to make an appropriate decision.

Lemma 3.1. The semi-join \( d_{xj}^* \times d_{yj} \) is gainful but not profitable if there exist relations \( R_i, i \notin \{x,y\} \) such that

a) \( S(d_{xj}^*) > S(R_4) \times (1 - \rho(d_{xj}^*)) \) and

b) \( \sum_{i=a}^m \left[ S(R_i) \times (\rho(d_{xj}^*) - \rho(d_{yj}^*)) \right] - S(d_{yj}^*) > 0 \)

Condition (a) follows from the definition of \( P(d_{xj}^* \times d_{yj}) \). If condition (b) holds then there exist one or more relations \( R_i, i \notin \{x,y\} \) for which

\[
\sum_{i=a}^m MP_{R_i}(d_{xj}^* \times d_{yj}) > C(d_{xj}^* \times d_{yj})
\]

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This implies that $G\left(d_{xj} \times d_{yj}\right) > 0$ hence, the cost of the semi-join outweighs any immediate benefit but the marginal profit is greater than the cost indicating that it must be gainful.

**Corollary 3.4.** A necessary condition for adding a semi-join to the schedule for reducer construction is that the marginal profit must be greater than the cost of the semi-join.

**Corollary 3.5.** If a relation can be found where the marginal profit of the semi-join exceeds its cost, it is not necessary to examine another relation.
In this chapter the details of the three heuristics implemented in this thesis namely, Algorithms AHY General (total time), W and DW are presented. For this thesis Algorithm AHY is used as a benchmark with upon which the performance of the proposed heuristics W and DW can be based. The reasoning behind this selection is twofold. First, the AHY algorithm is considered by many to be the best general query optimizer proposed. Secondly, there is extensive literature describing the execution of the heuristic.

In section 1 the details of the AHY algorithms are presented. In the following section the description of the proposed heuristic, Algorithm W is given. Section 3 presents a comparative example of the two heuristics to illustrate their respective use and relative differences. Lastly, the proposed dynamic heuristic, Algorithm W is described.

4.1 APERS-HEVNER-YAO (AHY) ALGORITHMS

A collect of algorithms for optimizing a special class of simple queries

---

A simple query refers to a query that has only one common join attribute.
has been introduced and investigated in [AHY83]. These algorithms namely Algorithm SERIAL and Algorithm PARALLEL attempt to minimize the total time and response time respectively. In each algorithm, semi-joins are used to reduce the size of relations by deleting those tuples which will not play a role in the final join.

Extending Algorithms SERIAL and PARALLEL, Apers, Hevner and Yao present Algorithm GENERAL which is capable of optimizing general queries. A general query is characterized by relations which contain more than one common join attribute.

As the focus of this thesis is query optimization with respect to total cost, discussions on the AHY algorithms will be limited to Algorithm SERIAL and Algorithm GENERAL (Total Cost).

4.1.1 Algorithm SERIAL

Algorithm SERIAL works as follows:

Step 1: Order relations \( R_i \) such that \( S(R_1) \leq S(R_2) \leq \cdots \leq S(R_n) \).

Step 2: If no relations are at the result node, then select strategy

\[ R_1 \rightarrow R_2 \rightarrow \cdots \rightarrow R_n \rightarrow \text{result node} \]

or else if \( R_r \) is a relation at the result node, then there are two strategies;

a) \[ R_1 \rightarrow R_2 \rightarrow \cdots \rightarrow R_r \rightarrow \cdots \rightarrow R_n \rightarrow R_r \]

b) \[ R_1 \rightarrow R_2 \rightarrow \cdots \rightarrow R_{r-1} \rightarrow R_{r+1} \rightarrow \cdots \rightarrow R_n \rightarrow R_r \]
After studying the literature it appears as though Algorithm SERIAL initially ranks the relations in terms of size under the assumption that the cost of transmitting a relation is directly proportional to the size of the relation. If this is indeed the case, it is obvious that the use of a non-linear cost model in conjunction with Algorithm SERIAL would result in sub-optimal schedules.

4.1.2 Algorithm GENERAL

The overall strategy employed by Algorithm GENERAL is to decompose a general query into a collection of simple queries. These simple queries are subsequently processed using Algorithm SERIAL for total cost optimization. The resulting schedules are examined and integrated to form an optimized schedule representing the general query. A detailed for Algorithm GENERAL is given as follows (summarized from [AHY83]):

**Step 1:** Do all initial local processing.

**Step 2:** Generate candidate schedules. Isolate each of the $\sigma$ common join attributes, and consider each to define a simple query with an undefined result node. Apply Algorithm SERIAL to each simple query. This results in one schedule per simple query. From these schedules, the candidate schedules for each common join attribute are extracted. Consider the common join attribute $d_{ij}$. Its candidate schedule is identical to the schedule produced by Algorithm SERIAL, applied to the simple query in which $d_{ij}$ occurs, up to the transmission of $d_{ij}$. All transmissions after that are deleted from the schedule.

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Step 3: Integrate the candidate schedules. For each relation $R_i$, the candidate schedules are integrated to form a processing schedule for $R_i$. To minimize total cost, schedule integration is performed using either procedure Total or procedure COLLECTIVE. Outlines for procedures TOTAL and COLLECTIVE follow. It should be pointed out that procedure TOTAL does not consider the existence of redundant data transmissions in separate relation schedules. Therefore, strategies derived using procedure TOTAL may not be optimal.

Step 4: Remove schedule redundancies. Eliminate relation schedules for relations which have been transmitted in the schedule for another relation.

The following are outlines for procedures TOTAL and COLLECTIVE.

Procedure TOTAL

Step 1: Adding candidate schedules. For each relation $R_i$ and each candidate schedule $CSCH_i$, perform the following. If a schedule contains a transmission of a joining attribute of $R_i$, say $d_{ij}$, then create another candidate schedule identical to $CSCH_i$ except that the transmission of $d_{ij}$ is deleted.

Step 2: Select the best candidate schedule. For each relation $R_i$ and each common join attribute $d_{ij}$, $j = 1, 2, \ldots, \sigma$, select the candidate schedule which minimizes the total time (cost) for transmitting $R_i$. Only joining attributes which can be joined with $d_{ij}$ are considered. $BEST_{ij}$ denotes the best candidate schedule for relation $R_i$ and joining attribute $d_{ij}$. 

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Step 3: Candidate schedule ordering. For each relation \( R_i \), candidate schedules \( BEST_{ij} \) are ordered on joining attributes \( d_{ij}, j = 1, 2, \ldots, \sigma \), so that

\[
ART_{i1} + C(S(R_1) \times SLT_{i1}) \leq \cdots \leq ART_{i\sigma} + C(S(R_i) \times SLT_{i\sigma})
\]

Schedules involving joining attributes not in \( R_i \) are disregarded. \( ART_{ij} \) denotes the arrival time (cost) of the \( BEST_{ij} \) schedule. \( SLT_{ij} \) denotes the accumulated selectivity of the \( BEST_{ij} \) schedule into \( R_i \).

Step 4: Schedule integration. For each \( BEST_{ij} \) in ascending order of \( j \), construct the integrated schedule to \( R_i \) which consists of the parallel transmissions of candidate schedule \( BEST_{ij} \) and all schedules \( BEST_{ik} \) where \( k < j \). Select the integrated schedule that results in the minimum total time (cost) value

\[
TOTT_i = \sum_{k=1}^{j} \left[ ART_{ik} + C\left(S(R_i) \times \prod_{k=1}^{j} SLT_{ik}\right)\right].
\]

Procedure COLLECTIVE

Step 1: Select candidate schedule. For each relation \( R_i \) and joining attribute \( d_{ij}, j = 1, 2, \ldots, \sigma \), select the minimum cost candidate schedule that contains the transmission of all components of attribute \( j \) with selectivities less than 1.

Step 2: Build processing strategy. For each relation \( R_i \), define the schedule to be the parallel transmissions of all \( d_{ij} \) candidate schedules to \( R_i \).

Step 3: Test strategy variations. Using a removal heuristic, construct new strategies by removing the most costly data transmission. The total time cost of the new strategy is compared with that of the old strategy, with the less costly
strategy being maintained. Testing continues until no further cost benefit can be obtained.

An illustrative example of AHY General (total time) is presented in section 4.3.

4.1.3 Complexity Analysis of Algorithm GENERAL (total time)

If it is assumed that a general query requires data from $m$ relations, and that all $m$ relations are joined on $\sigma$ joining attributes. In step 2, Algorithm SERIAL is applied to each simple query. Because the joining attributes must be ordered by size the complexity is $O(\sigma m \log_2 m)$.

The complexity of procedure TOTAL is $O(\sigma m^2)$. In step 1, no more than $O(\sigma m)$ candidate schedules are added. For each relation the procedure must subsequently determine the $BEST_{ij}$ schedule among the $O(\sigma m)$ candidate schedules. Hence, the complexity of step 2 is $O(\sigma m^2)$. Therefore, the complexity for an arbitrary general distributed query, Algorithm GENERAL (total time) has a processing complexity no worse than $O(\sigma m^2)$.

4.2 ALGORITHM W

In this section a proposed static heuristic (Algorithm W) that attempts to minimize total cost is described. The algorithm is characterized by two distinct phases; first, semi-join schedules for constructing each reducer are formed using a cost/benefit analysis which is based on the estimated attribute selectivities and the
sizes of partial results. In the second phase the schedule is executed. A detailed
description of Algorithm W follows.

**Step 1:** Determine schedules for the construction of reducers. For each join-
attribute \( j \), establish a schedule for the construction of reducer \( d_{mn_j}^* \).

a) Order the attributes by increasing size such that

\[
S(d_{aj}) \leq S(d_{bj}) \leq \cdots \leq S(d_{mj})
\]

b) Next, evaluate the semi-joins in order beginning with \( d_{aj} \bowtie d_{bj} \). The semi-join
is appended to the schedule for constructing the reducer if

i. It is both profitable and marginally profitable. In other words

\[
P(d_{aj} \bowtie d_{bj}) > 0 \quad \text{and} \quad MP\left(\left.d_{aj}^* \bowtie d_{bj}\right\}\right) > 0
\]

ii. It is not profitable but is gainful. That is, we have

\[
P(d_{aj} \bowtie d_{bj}) \leq 0 \quad \text{but} \quad G\left(\left.d_{aj}^* \bowtie d_{bj}\right\}\right) > 0.
\]

If the semi-join is appended the next semi-join for consideration is \( d_{bj}^* \bowtie d_{cj} \)
otherwise \( d_{aj}^* \bowtie d_{cj} \) is considered. This process is repeated until all attributes
have been considered. The final attribute to be reduced is the reducer.

**Step 2:** Reducer selection and application review of unused semi-joins. In
this step the reduction effects of the construction and use of each reducer on all
applicable relations are considered. That is,

a) The reducers are ordered by increasing size.

---

9 It is important to note that each schedule is constructed independently and no semi-joins are actually executed in
this step.

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b) For each reducer in turn, estimate the reduction effects of constructing and applying it. Profitable semi-joins are appended to the final schedule.

**Step 3:** Review of unused semi-joins. After Step 2 it may be the case that a number of reducers have not been used as they are not profitable. In this case, check to see if there are any remaining profitable semi-joins for that particular join-attribute. This reevaluation process is carried out as follows:

a) sort the attributes by increasing size
b) evaluate each semi-join in turn, appending profitable semi-joins to the final schedule. Note, the marginal profit is not considered in this step.

**Step 4:** Execute the schedule. In this step the reducers are constructed and shipped to the designated sites to be used as reducers. The reduced relations are subsequently shipped to the query site where the answer is assembled.

An illustrative example of Algorithm W is given in section 4.3.

4.2.1 Cost-effectiveness Analysis of Algorithm W

The term "cost-effective" in this sense refers to the construction of good reducers with a minimum cost overhead associated with their construction. Under this context, the heuristic constructs and applies the reducers in the most cost-effective manner.

**Theorem 4.1.** Given relations $R_1, R_2, \ldots, R_m$ ordered such that

$$S(R_1[j]) \leq S(R_2[j]) \leq \cdots \leq S(R_m[j])$$
then the sequence of semi-joins\(((d_{1j} \times d_{2j}) \times d_{3j})\ldots \times d_{mj}\) constructs a reducer (for the join-attribute \(j\)) with minimum cost. (Minimum in the sense that the data transferred between nodes to construct the reducer is kept to a minimum.)

**Proof.** Assume that the data is distributed such that after the application of the semi-join \(d_{ij} \times d_{kj}\) we have \(S(d_{kj}) = S(d_{ij}) \times \rho(d_{ij})\), where \(\rho(d_{ij})\) is the selectivity of the attribute \(d_{ij}\).

Consider any \(x\) and \(y\) in the sequence above. By definition, we have \(S(d_{xj}) \leq S(d_{yj})\) which implies \(\rho(d_{xy}) \leq \rho(d_{yj})\). If we switch the order of \(x\) and \(y\) in the sequence we will incur an increase in the total cost, \(Cost_I\) where

\[
Cost_I = S(d_{yi}) - \rho(d_{xi}) \times S(d_{yi})
\]

as we no longer have the reduction effects of \(d_{xj}\). In addition, there is a decrease in the total cost,

\[
Cost_D = S(d_{xj}) - \rho(d_{yj}) \times S(d_{xj})
\]

since we now have the reduction effects of \(d_{yj}\).

In the pathological case where \(S(d_{xj}) = S(d_{yj})\), by definition \(\rho(d_{xj}) = \rho(d_{yj})\). By inspection it is clear that \(Cost_I = Cost_D\), hence the sequence is minimal in any case. For the remaining cases we want to prove that \(Cost_I > Cost_D\). Let \(S(d_{xj}) < S(d_{yj})\), by definition \(\rho(d_{xj}) < \rho(d_{yj})\). Substituting for \(Cost_I\) and \(Cost_D\) gives

\[
S(d_{yj}) - \rho(d_{xj}) \times S(d_{yj}) > S(d_{xj}) - \rho(d_{yj}) \times S(d_{xj})
\]
Simplification reduces this equation to

\[
\frac{S(d_{yj})}{S(d_{xj})} > \frac{1 - \rho(d_{yj})}{1 - \rho(d_{xj})}
\]

By definition, \(S(d_{xj}) < S(d_{yj})\) therefore,

\[
\frac{S(d_{yj})}{S(d_{xj})} > 1
\]

Similarly, by definition \(\rho(d_{xj}) < \rho(d_{yj})\) therefore,

\[
1 < \frac{1 - \rho(d_{yj})}{1 - \rho(d_{xj})}
\]

Hence, \(Cost_I > Cost_D\). Therefore, except for the noted case, if the order of any two semi-joins is swapped there is an increase in the total cost of constructing the reducer. Therefore, the sequence

\[((d_{1j} \Join d_{2j}) \Join d_{3j}) \ldots \Join d_{mj}\]

constructs the reducer with minimal cost. □

**Theorem 4.2.** Given reducers \(d_{x_1}^*, d_{x_2}^*, \ldots, d_{x_n}^*\) ordered such that

\[S(d_{x_1}^*) \leq S(d_{x_2}^*) \leq \cdots \leq S(d_{x_n}^*)\]

then the cost of utilizing the reducers is minimized if they are applied in this order.

**Proof.** By definition the selectivity is assumed to be proportional to size. Consider using any two reducers \(d_{ix}^*\) and \(d_{iy}^*\) on any relation \(R_z\) where \(S(d_{ix}^*) \leq S(d_{iy}^*)\) and \(i = z\).
The following two cases must be considered:

(Case 1) The semi-join $d_{ix}^e \times R_z$ is executed first. Then execute the semi-join $d_{iy}^e \times R_z$ only if it is profitable. The cost will therefore be either $S(d_{ix}^e) + S(d_{iy}^e)$ or $S(d_{ix}^e)$.

(Case 2) The semi-join $d_{iz}^e \times R_z$ is executed first. Then execute the semi-join $d_{iz}^e \times R_z$ only if it is profitable. The cost will therefore be either $S(d_{iz}^e)$ or $S(d_{iz}^e)$.

The cost of case 1 will always be less than or equal to the cost of case 2 (and the benefit of case 1 will always be greater than or equal to the benefit of case 2). Clearly the cost is minimized if the reducers are utilized in order of increasing size. □

4.2.2 Complexity Analysis of Algorithm W

Algorithm W as outlined produces cost-effective schedules in an efficient manner. Assume that a query requires the joining of $m$ relations over $n$ common-join attributes. In step 1a at most $m$ attributes are sorted resulting in a complexity of $O(m \log m)$. This step is repeated for the $n$ common-join attributes giving a complexity of $O(nm \log m)$.

In step 1b the profit and marginal profit are computed for $m - 1$ semi-joins. The calculation of profit is always $O(1)$ however, marginal profit is computed with respect to a variable number of other relations. In the worst case the marginal profit must be computed with respect to $m - 1$ relations, resulting in a complexity
of $O(n^2)$. Step 1b is repeated for each attribute, giving a best case complexity of $O(nm)$ and a worst case complexity of $O(nm^2)$.

In step 2a the $n$ reducers are sorted, with complexity $O(n \log n)$. In step 2b the cost and benefit of at most $m-1$ are computed. This is repeated $n$ times, resulting in a complexity of $O(nm)$.

In step 3 the construction sequences of unused reducers are reviewed. If $\alpha$ is the number of unused reducers to be reconsidered, the complexity for this step will be $O(\alpha m \log m)$. At worst case $\alpha$ will be $n-1$.

Thus, Algorithm W will have a best case complexity of $O(mn)$ and a worst case complexity of $O(nm^2)$. It is important to note that in most cases a positive marginal profit can be found with respect to a single relation. A positive marginal profit can usually be found by examining the largest relation not participating in the semi-join. Therefore, in most cases the expected complexity of Algorithm W is $O(nm)$.

### 4.3 A COMPARATIVE EXAMPLE

To illustrate and compare Algorithm W to Algorithm AHY General (total time), the execution of each algorithm on the sample query given in Table 4.1 are outlined in detail.
Applying Algorithm AHY General (total time) to the example, three simple queries are formed on attributes $d_{i1}$, $d_{i2}$ and $d_{i3}$. In step 2 of Algorithm AHY General (total time), the following serial candidate schedules are formed.

For $d_{i1}$,

\[
\begin{align*}
\sigma_{d_{i1}}: & \quad 300 \\
\sigma_{d_{i1}}: & \quad 250
\end{align*}
\]

For $d_{i2}$,

\[
\begin{align*}
\sigma_{d_{i2}}: & \quad 800 \\
\sigma_{d_{i2}}: & \quad 530 \\
\sigma_{d_{i2}}: & \quad 38
\end{align*}
\]

<table>
<thead>
<tr>
<th>$R_i$</th>
<th>$S(R_i)$</th>
<th>$S(d_{i1})$</th>
<th>$\rho(d_{i1})$</th>
<th>$S(d_{i2})$</th>
<th>$\rho(d_{i2})$</th>
<th>$S(d_{i3})$</th>
<th>$\rho(d_{i3})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R_1$</td>
<td>2000</td>
<td>500</td>
<td>0.83</td>
<td>800</td>
<td>0.53</td>
<td>600</td>
<td>0.60</td>
</tr>
<tr>
<td>$R_2$</td>
<td>4500</td>
<td>300</td>
<td>0.50</td>
<td>1000</td>
<td>0.67</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>$R_3$</td>
<td>6000</td>
<td>—</td>
<td>—</td>
<td>1400</td>
<td>0.93</td>
<td>800</td>
<td>0.80</td>
</tr>
</tbody>
</table>

Table 4.1 Query statistics for the comparative example.
For $d_{i3}$,

\[
\begin{array}{c}
\text{d}_{i3}: \begin{array}{c}
\text{600}
\end{array}
\end{array}
\]

\[
\begin{array}{c}
\text{d}_{i3}: \begin{array}{c}
\text{600} \quad \text{d}_{i3} \quad \text{480}
\end{array}
\end{array}
\]

The construction of the schedule for $R_1$ will be discussed in detail. Each of the three attributes will be handled in turn.

**Attribute $d_{11}$** In step 1 of Procedure TOTAL, the simple serial schedules for $d_{11}$ are examined to determine if any new schedules can be formed or if any schedules are not applicable to the current relation. For $d_{11}$ the $d_{11}$ schedule is not considered as it cannot be used to reduce itself. With only one candidate schedule to consider, schedule $d_{12}$ is selected as the $BEST_{11}$ candidate schedule for $d_{11}$:

\[
\begin{array}{c}
\text{d}_{i1}: \begin{array}{c}
\text{300} \quad R_1 \quad \text{1000}
\end{array}
\end{array}
\]

Total time = $C(300) + C(0.5 \times 2000)$

= 1300.

**Attribute $d_{12}$** In step 2 of Procedure TOTAL, two schedules are added to the candidate schedules for attribute $d_{i2}$.

\[
\begin{array}{c}
\text{d}_{i2}: \begin{array}{c}
\text{1000}
\end{array}
\end{array}
\]

\[
\begin{array}{c}
\text{d}_{i2}: \begin{array}{c}
\text{1000} \quad \text{d}_{i2} \quad \text{938}
\end{array}
\end{array}
\]
The Heuristics

Each of the schedules for $d_{12}$ are applied to $R_1$. Obviously, the $d_{12}$ schedule is not considered, leaving four schedules to be evaluated.

\[
\begin{array}{c|c|c|c|c|c}
 d_{12} & 800 & d_{22} & 530 & R_1 & 1340 \\
\end{array}
\]

Total time = $C(800) + C(0.53 \times 1000) + C(0.67 \times 2000)$

= $800 + 530 + 1340$

= 2670.

\[
\begin{array}{c|c|c|c|c|c}
 d_{32} & d_{12} & 800 & d_{22} & 530 & 498 & R_1 & 1247 \\
\end{array}
\]

Total time = $C(800) + C(0.53 \times 1000) + C(0.36 \times 1400)$

+ $C(0.62 \times 2000)$

= $800 + 530 + 498 + 1247$

= 3075.

\[
\begin{array}{c|c|c|c|c|c}
 d_{32} & d_{22} & 1000 & d_{22} & 938 & 1340 \\
\end{array}
\]

Total time = $C(1000) + C(0.67 \times 2000)$

= $1000 + 1340$

= 2340.

\[
\begin{array}{c|c|c|c|c|c}
 d_{32} & d_{22} & 1000 & d_{22} & 938 & R_1 & 1247 \\
\end{array}
\]

Total time = $C(1000) + C(0.67 \times 1400) + C(0.62 \times 2000)$

= $1000 + 938 + 1247$

= 3185.

Because the schedule $d''_{22}$ has the smallest total time it is selected as the BEST$_{12}$ schedule.

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**Attribute $d_{13}$**  In step 2 of Procedure TOTAL only one schedule is added to the above schedules for attribute $d_{13}$.

\[
\begin{array}{c|c}
\hline
\text{d}_{33} & 800 \\
\hline
\end{array}
\]

Each of the schedules with the exception of $d_{13}$ are applied to $R_1$.

\[
\begin{array}{c|c|c|c}
\hline
\text{d}_{33} & \text{d}_{13} & 600 & \text{d}_{33} & 480 & R_1 & 1600 \\
\hline
\end{array}
\]

Total time = $C(600) + C(0.6 \times 800) + C(0.8 \times 2000)$

\[
= 600 + 480 + 1600 = 2680.
\]

\[
\begin{array}{c|c|c}
\hline
\text{d}_{33} & 800 & R_1 & 1600 \\
\hline
\end{array}
\]

Total time = $C(800) + C(0.8 \times 2000)$

\[
= 800 + 1600 = 2400.
\]

Because $d'_{33}$ has the smallest total time, it is chosen as the $BEST_{13}$ schedule.

In Steps 3 and 4 of Procedure TOTAL, the $BEST_{1i}$ schedules are ordered by smallest total time and integrated to construct the following three schedules:

\[
\begin{array}{c|c|c}
\hline
\text{d}_{21} & 300 & R_1 & 1000 \\
\hline
\end{array}
\]

\[
\begin{array}{c|c|c}
\hline
\text{d}_{21} & 300 & R_1 & 470 \\
\hline
\end{array}
\]

\[
\begin{array}{c|c|c}
\hline
\text{d}_{22} & 1000 & 670 \\
\hline
\end{array}
\]
Since the first of these schedules has the smallest total time; it is chosen as the solution of Algorithm AHY General (total time) for $R_1$.

The respective solutions for relations $R_2$ and $R_3$ are constructed in the same manner. The query processing strategy that is constructed by Algorithm AHY General (total time) for the example query is

![Diagram]

The application of Algorithm $W$ to the query is now examined. In step 1, the sequences for constructing reducers are determined. On inspection, it is clear that at most three reducer may be constructed: $d_{11}$, $d_{12}$ and $d_{13}$.

**Reducer for $d_{11}$** The first semi-join considered is $d_{21} \times d_{11}$, where the cost is 300 units and the benefit is 700 units. The marginal profit of the semi-join
with respect to $R_2$ is computed as

$$MP_{R_2} = (4500 \times 0.17) - 250$$

$$= 515.$$ Since the profit and marginal profit are positive, the semi-join is added to the schedule for constructing the $d_{i1}$ reducer. As there are no further semi-joins to consider, the reducer is therefore $d_{i1}$. For this reducer the construction schedule is simply the semi-join $d_{21} \bowtie d_{11}$.

**Reducer for $d_{i2}$** The first semi-join to consider is $d_{i2} \bowtie d_{22}$, where the cost is 800, the benefit is 2115 and the marginal profit with respect to $R_3$ is calculated as

$$MP_{R_3} = (4500 \times 0.17) + 800 - 530$$

$$= 1035.$$ This semi-join is added to the construction schedule for $d_{i2}$. Next we consider $d_{22} \bowtie d_{32}$. The cost is 530, the benefit is 3869 and the marginal profit with respect to $R_1$ is computed as

$$MP_{R_1} = (2000 \times 0.05) - 446 + 530$$

$$= 184.$$ This semi-join is added so $d_{32}$ is constructed by the semi-join sequence $d_{i2} \bowtie d_{22} \bowtie d_{32}$.

**Reducer for $d_{i3}$** The only semi-join to be considered is $d_{i3} \bowtie d_{33}$. The cost is 600, the benefit 1800 and the marginal profit with respect to $R_1$ is calculated as

$$MP_{R_1} = (2000 \times 0.2) - 480$$

$$= 400 - 480$$

$$= -80 \Rightarrow 0.$$
As there is no marginal profit in using $d^*_3$, no reducer is constructed for $d_{i3}$.

Therefore the construction sequences that will be considered consist of the following semi-joins:

\[
\begin{align*}
&d_{21} \rightarrow d_{11} \\
&d_{12} \rightarrow d_{22} \rightarrow d_{32}
\end{align*}
\]

The reducers produced are $d^*_{11}$ and $d^*_{32}$. The size of $d^*_{11}$ is estimated as

\[500 \times 0.5 = 250\]

and the size of $d^*_{32}$ is estimated as

\[1400 \times 0.53 \times 0.6 = 446.\]

In step 2 of Algorithm W, the use of each reducer is considered. Reducer $d^*_{11}$ is considered first, since it is the smallest. The effects of constructing the reducer; the relation sizes and the selectivity of $d^*_{11}$ with respect to each relation is given below. Next, the effects of using the reducer are considered. The cost

<table>
<thead>
<tr>
<th>$R_i$</th>
<th>$S(R_i)$</th>
<th>$\rho(d^*_{11})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1000</td>
<td>1.0</td>
</tr>
<tr>
<td>2</td>
<td>4500</td>
<td>0.83</td>
</tr>
<tr>
<td>3</td>
<td>6000</td>
<td>0.0</td>
</tr>
</tbody>
</table>

of $d^*_{11} \times d_{21}$ is 250 the benefit is 765, therefore this semi-join is profitable and should be appended to the final schedule. Consequently, the use of $d^*_{11}$ implies that the semi-join sequence for constructing $d^*_{11}$ should be appended to the final schedule prior to its use. Clearly, no other reductions are possible with $d^*_{11}$ as...
it cannot be used to reduce itself and relation $R_3$ does not have a common-join attribute for $d_{i1}$. After the use of the reducer, the reduction effects are estimated to be such that $|R_2| = 4500 \times 0.85 = 3735$.

Next, the use of reducer $d_{32}^*$ is considered. The effects of its construction on the relation sizes and its selectivity with respect to each relation is shown below. The cost of $d_{32}^* \bowtie R_1$ is 498, the benefit is 380; the cost of $d_{32}^* \bowtie R_3$ is 498, the benefit is only 138. Clearly, since neither semi-join is profitable, the reducer will not be constructed, leaving the following as the final schedule for the construction and application of reducers:

\[
d_{21} \rightarrow d_{11}^* \quad \text{and} \quad d_{11}^* \rightarrow R_2
\]

In step 3 of Algorithm W those reducers that were not used in steps 1 and 2 are reexamined, appending any profitable semi-joins to the final schedule. Taking into consideration the construction and use of the reducer $d_{11}^*$, the current relevant statistics are:

\[
\begin{array}{cccc}
R_i & S(R_i) & S(d_{i2}) & \rho(d_{i2}) \\
1 & 1000 & 800 & 0.53 \\
2 & 3735 & 1000 & 0.67 \\
3 & 6000 & 1400 & 0.93 \\
\end{array}
\]

\[
\begin{array}{cccc}
& S(d_{i3}) & \rho(d_{i3}) \\
& 600 & 0.60 \\
& 800 & 0.80 \\
\end{array}
\]
The first semi-join considered is $d_{13} \times d_{33}$. The cost is 600 and the benefit is 2400 so this semi-join is appended to the final schedule. The current relevant statistics subsequent become

<table>
<thead>
<tr>
<th>$R_i$</th>
<th>$S(R_i)$</th>
<th>$S(d_{i2})$</th>
<th>$\rho(d_{i2})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1000</td>
<td>800</td>
<td>0.53</td>
</tr>
<tr>
<td>2</td>
<td>3735</td>
<td>1000</td>
<td>0.67</td>
</tr>
<tr>
<td>3</td>
<td>3600</td>
<td>1400</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Reconsidering the semi-join $d_{12} \times d_{22}$ shows that it has a cost of 800 and a benefit of 1755. As a profitable semi-join it is appended to the final schedule. The final semi-join to consider is $d_{22} \times d_{32}$ which has as cost of 530 and a benefit of 2321, therefore it is also appended to the final schedule. As there are no more semi-joins to be considered the final schedule produced by Algorithm W is:

\[
\begin{align*}
&d_{21} \xrightarrow{300} d_{11} & d_{11} \xrightarrow{250} R_1 & d_{13} \xrightarrow{600} d_{33} & R_1 \xrightarrow{1000} QS \\
&d_{12} \xrightarrow{800} d_{22} & R_2 \xrightarrow{1980} QS & d_{22} \xrightarrow{530} d_{32} & R_1 \xrightarrow{1279} QS
\end{align*}
\]

Based on the sample query Algorithm AHY General (total time) produces a schedule with total cost of 7694 units. For the same data Algorithm W produces a schedule with a total cost of only 6739 units.

---

10 Note that it is not possible to correctly estimate the size for $d_{32}$ however, the maximum it can be is 1145. The selectivity is changed to reflect this modification.
The Heuristics

This example illustrates two problems associated with the AHY General (total time) algorithm.

1. Because the algorithm constructs reduction schedules for each relation independently of each other it does not take advantage of the possible use of highly effective reducers on other relations.

2. While the reduction schedules are executed in parallel, there is no synchronization mechanism in place to avoid redundant data transmissions\(^\text{11}\). For example, consider final schedules that were produced by the AHY algorithm for relations \(R_2\) and \(R_3\). Clearly, if these schedules were synchronized only one transmission of \(d_{12}\) would be required, reducing the total cost by 800 units.

4.4 ALGORITHM DW

Static strategies, such as Algorithm W rely on the accurate size estimation of intermediate results in order to produce good semi-join schedules. In static heuristics, small errors are propagated and typically compounded as the heuristic progresses, resulting in sub-optimal schedules [ES80]. In this section we propose a purely dynamic version of Algorithm W which we refer to as Algorithm DW. In this algorithm, only one semi-join is examined at a time and executed immediately if it is gainful. This heuristic requires minimal monitoring, and does not call for any modification of the execution schedule as the dynamic information eliminates

\(^{11}\) Some of these issues are addressed in the COLLECTIVE version of the algorithm however, insufficient details were available to permit a comparative performance evaluation.
any estimation errors. Being a dynamic version of Algorithm W, the complexity and cost-effectiveness of Algorithm DW are identical to those of Algorithm W.

In the dynamic heuristic the use of centralized control (the query site) is assumed. Information on the sizes of intermediate results are relayed to the control site which decides on the next operation to be performed. Clearly, we incur additional overhead (as discussed in [BRJ89]) but our primary concerns are:

1. The number of messages that are sent from the relation sites to the query site, reporting on the size of partial results. In particular, the number of messages required is the same as the number of partial results produced, and we can assume that these messages are relatively small since only information on the cardinality of the reduced relation (the number of tuples) and the cardinality of the attributes of that relation need to be sent to the central site (query site).

2. The possibility of increased response time, since all of the reducers are constructed in serial rather than in parallel as in Algorithm W.

4.4.1 Description of Algorithm DW

In the case of the dynamic algorithm, all assumptions and definitions remain the same as in the static cases except for a slight variation in the definition of the selectivity of one attribute with respect to another. Consider the dynamic execution of the following semi-join sequence: \( d_{aj} \bowtie d_{bj} \bowtie d_{ej} \). The selectivity of \( d_{aj} \) w.r.t. \( d_{bj} \) is estimated as

\[
\frac{|d_{aj}|}{|D(d_{ij})|}
\]
When the semi-join \( d_{aj} \times d_{bj} \) is executed, the cardinality of both the reduced \( R_h \) and \( d_{bj} \) is known exactly. The selectivity of \( d_{bj}^* \) with respect to \( d_{cj} \) is subsequently estimated as

\[
\frac{|d_{bj}^*|}{|D(d_{ij})|}
\]

### 4.4.2 Outline of Algorithm DW

Under the assumption that a query consists of \( m \) relations and \( n \) join-attributes and let \( J \) be the set of all unused join-attributes and \( N \) the set of join-attributes that have been found non-profitable. Initially \( J \) contains all join-attributes and \( N \) is empty.

Algorithm DW is executed as follows:

#### Step 1:
From the join-attribute set \( J \), select attribute \( d_{ij} \) such that

\[
\forall x, y \ S(d_{ij}) \leq S(d_{xy}), \quad x = 1, \ldots, m; \quad y = 1, \ldots, n.
\]

#### Step 2:
Order the attributes \( d_{xj} \) by size such that \( S(d_{aj}) \leq S(d_{bj}) \leq \cdots \leq S(d_{mj}) \).

#### Step 3:
Consider the semi-join \( d_{aj} \times d_{bj} \). The semi-join is executed if and only if \( MP(d_{aj} \times d_{bj}) > 0 \) or \( P(d_{aj} \times d_{bj}) < 0 \) but \( G(d_{aj} \times d_{bj}) > 0 \). If the semi-join is executed the next semi-join considered is \( d_{bj}^* \times d_{cj} \), otherwise \( d_{aj} \times d_{cj} \) is considered. This step is repeated until all applicable semi-joins are considered. Remove the common join-attribute \( j \) from \( J \). If no semi-joins were performed add \( j \) to \( N \) and return to Step 1, otherwise continue.

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Step 4: Perform all profitable semi-joins \( d_{x_j}^* \bowtie R_i \), where \( d_{x_j}^* \) is the reducer constructed in Step 3.

Step 5: Remove all common-join attributes from \( N \) and add them to \( J \). Repeat steps 1 to 5 while \( J \) is not empty.

When the set \( J \) becomes empty Algorithm DW will have applied all of the profitable reductions that it was capable of identifying. Finally the reduced relations are shipped to the query site.
As noted in [Sel89], little work has been carried out in the validation of optimization algorithms. In most cases only analytical comparisons are made between algorithms. The use of empirical studies not only provides comparisons between algorithms but also a means of evaluating the validity of assumptions made and the techniques used.

5.1 METHODOLOGY

The framework for evaluating the algorithms is based on the following objectives:

□ To Test Algorithm W with a wide variety of select-project-join (SPJ) type queries.

□ To compare Algorithm W with the Apers-Hevner-Yao (AHY) algorithm.

□ To compare the performance of Algorithm W with its dynamic version Algorithm DW.
Some would argue that using only SPJ queries is too restrictive with respect to the type of query tested. However, we do not consider this to be a limitation since it is possible to translate any query into SPJ form.

5.1.1 The Test Queries

For the evaluations a query is considered to be the statistical information on the relations and attributes that are participating in the query after all local site processing. While it is unrealistic to construct explicit queries as in [Bod85], this statistical representation facilitates the construction of a wide variety of test queries.

By varying a number of parameters it was possible to construct queries with the following characteristics:

- Each query consisted of between 1 and 6 relations and the number of join-attributes varied between 2 and 4. Overall, this gave us 12 different types of test queries (e.g. 3 relations – 2 attributes, 3 relations – 3 attributes, etc.)
- The cardinality of each join-attribute domain varied between 500 – 1500.
- Each relation had between 800 and 6000 tuples.
- To provide realistic queries, the number of join-attributes in each relation were varied between 1 and the maximum number of join-attributes with the restriction that the query remain “connected” in the sense that all relations must be joined to answer the query. For our evaluations we considered 3 levels of connectivity namely, 50%, 75% and 100%. A detailed outline of connectivity can be found in Appendix A.
Evaluation

- Each relation has one other (non-joining) attribute which is required at the query site.

Generating the query (statistics table) is accomplished in a 4 step process:

1. Given the number of relations and the maximum number of join-attributes, the cardinality of the domain for each join-attribute is randomly chosen.

2. Next, the occurrence of join attributes within each relation are randomly determined such that the desired connectivity is satisfied.

3. The cardinality for each join-attribute of each relation is randomly chosen such that it does not exceed the cardinality for its associated domain. In addition, the cardinality is restricted to guarantee that the selectivity will be in the range $0.5 \leq \rho(d_{ij}) \leq 1.0$.

4. Lastly, the cardinality for each relation is randomly chosen such that the cardinality of the relation exceeds the cardinality of any of its join-attributes.

The actual query construction is handled by the C program `create_query.c` (see Appendix B). Given the desired number of relations and the maximum number of join-attributes, the program will produce a query statistics table as well as the input parameters that are required for constructing the actual relations.

5.1.2 The Test Database

A major advantage in adopting the statistical representation of queries is that in order to execute a query we are only required to construct the relations that are
participating in the query (as opposed to having to construct an entire database).

The Wisconsin benchmark database proposed by Bitten, Dewitt and Turbyfill [BDT83] provided a good basis for developing the benchmark distributed database required for evaluating the queries. For simplicity, as in [BDT83], only integer values are considered. The primary difficulty with using the Wisconsin database as defined is that relations are populated with attribute values in an identical fashion. For example, suppose it is decided that the domain for some attribute say $A$ is 1000, hence the possible values will be in the integer range $0 - 999$. If for relation $R_1$ attribute $A$ is to have a selectivity value of 0.5, attribute $A$ will be populated with the integers $0 - 499$. Similarly, if for relation $R_2$, attribute $A$ is to have a selectivity of 0.8, attribute $A$ will be populated with values in the range $0 - 799$. Clearly, using this method of populating the attribute values results in the creation of key attributes only. As the use of non-key attributes is of concern this particular approach to populating attribute values is not appropriate.

The benchmark database employed for evaluation purposed is based essentially on the Wisconsin benchmark database [BDT83] with modifications to the attribute domain value selection and population methods. The modifications are outlined as follows:

1. To overcome the problem of key attributes, the values for a particular attribute are randomly selected from the domain pool of values for that attribute. For example, suppose the cardinality of the domain for attribute $A$ is 1000, which implies that the possible values are $0 - 999$. If attribute $A$ of relation $R_1$
Evaluation

is required to have a cardinality of 500 (or equivalently having a selectivity of 0.5). 500 different values will be randomly selected from domain, thus constituting the actual values for attribute A, \( D(d_{1a}) \).

2. When uniformly populating the relation with values, the values for attribute A are simply selected in a uniform manner from \( D(d_{1a}) \). Because the attribute domain is based on a random selection of values from the overall domain of values, the problem of attribute dependance is not encountered.

3. For non-uniform populations, each value in \( D(d_{1a}) \) is used once after which a beta function is used to select each subsequent value. Using each value at least once guarantees the correct initial selectivity for the attribute, after which the beta function provides a skewed distribution in the number of occurrences of each value.

In addition to the statistical information, create_query.c also produces input files corresponding to each relation in the query. These input files are subsequently used by the relbuilder.c program to construct the relations that are described in the statistical table. Details regarding relbuilder.c can be found in Appendix B.

5.2 EXPERIMENTAL RESULTS

The performance the heuristics was evaluated with 6 test runs, corresponding to each connectivity - distribution pair (e.g. 50% connectivity - uniform distribution, 50% connectivity - random distribution, etc.) Each run consisted of 1,200
queries. For each query, 100 semi-join schedules were constructed and executed using each of the heuristics, recording the costs incurred. Overall, a total of 7,200 queries were used to evaluate the performance of the algorithms.

Descriptions of each run can be found in Table 5.1. Summaries of the data collected for each run can be found in Appendix C.

<table>
<thead>
<tr>
<th>Run #</th>
<th>Distribution</th>
<th>Connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>uniform</td>
<td>100%</td>
</tr>
<tr>
<td>2</td>
<td>random</td>
<td>100%</td>
</tr>
<tr>
<td>3</td>
<td>uniform</td>
<td>75%</td>
</tr>
<tr>
<td>4</td>
<td>random</td>
<td>75%</td>
</tr>
<tr>
<td>5</td>
<td>uniform</td>
<td>50%</td>
</tr>
<tr>
<td>6</td>
<td>random</td>
<td>50%</td>
</tr>
</tbody>
</table>

Table 5.1 Descriptions of individual runs.

5.2.1 Relevance of Results

The application of t tests (see Appendix B) to the experimental results clearly indicate that for all six experimental runs, the differences observed in the percent reduction of Algorithm W to that of the AHY Algorithm are statistically significant. In particular, the probability that the results are due to chance under 198 degrees of freedom is approximately 1:10,000. This is not the case for the comparison of Algorithm DW to Algorithm W.

Given the relative similarity in results for Algorithms DW and W it is not surprising to find the difference in percent reduction was not found to be significant in all runs. In Table 5.2, the runs in which it was not possible to disprove the
null hypothesis (that the differences in the means arose by chance) are indicated by a square. Clearly for uniform distributions (runs 1, 3 and 5), the results are significant for queries 3–2 to 5–2. For random distributions (runs 2, 4 and 6), the results are only significant for queries 3–2 to 4–2. Additional experimentation with larger run sizes should be conducted to determine whether the questionable runs are in fact significant.

### 5.3 CONCLUSIONS

#### 5.3.1 Algorithm W versus AHY (total cost)

The following conclusions are made based on the results of the test runs:

<table>
<thead>
<tr>
<th>Query</th>
<th>Run 1</th>
<th>Run 2</th>
<th>Run 3</th>
<th>Run 4</th>
<th>Run 5</th>
<th>Run 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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</tr>
<tr>
<td>3-3</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3-4</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4-2</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4-3</td>
<td>-</td>
<td>■</td>
<td>-</td>
<td>■</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>4-4</td>
<td>-</td>
<td>■</td>
<td>-</td>
<td>■</td>
<td>-</td>
<td>■</td>
</tr>
<tr>
<td>5-2</td>
<td>-</td>
<td>■</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5-3</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>5-4</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>-</td>
</tr>
<tr>
<td>6-2</td>
<td>■</td>
<td>■</td>
<td>-</td>
<td>■</td>
<td>■</td>
<td>-</td>
</tr>
<tr>
<td>6-3</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
</tr>
<tr>
<td>6-4</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
<td>■</td>
</tr>
</tbody>
</table>

Table 5.2 Statistical relevance of differences between Algorithm DW and Algorithm W.
Overall Algorithm W performs satisfactory in reducing the volume of network data transfers during the query processing. On average it provides a reduction of between 32% and 97% (approximately) over the unoptimized total cost\textsuperscript{12}.

\textsuperscript{12} Note, the degree is reduction is dependent upon the number of join-attributes as well as the overall connectivity of the query.

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Algorithm W clearly outperforms AHY (as illustrated in Figures 5.1–5.3). On average Algorithm W outperforms AHY by approximately 18%. The greatest difference in performance is found in those queries involving only two join-attributes, with queries involving three relations being an exception.

Results indicate that Algorithm W performs well under both uniform and
null queries\textsuperscript{13} were a frequent occurrence in the 100% connectivity queries. In particular, the null queries occurred most frequently above the 4–2 query type. From Figure 5.3 and Tables C.1 and C.2 it is evident that the execution schedules produced by Algorithm W produce a null query very quickly due  

\textsuperscript{13} A null query simply refers to an empty solution.
Evaluation

to the manner in which the schedules are constructed. AHY by contrast, produces a null query late in its execution or not until all of the final relations are joined. Clearly, it is advantageous to identify null queries as early as possible, thus minimizing the amount of unnecessary network data transfers.

□ Algorithm W does not suffer from the synchronization and redundant transmission problems that arise from attempting to optimize the schedules produced by AHY General (total time).

5.3.2 Algorithm W versus Algorithm DW

A comparison of Algorithm W to Algorithm DW was undertaken to answer the following questions:

Will a purely dynamic heuristic outperform its static counterpart?

For the most part the answer is unequivocally "no" (see Figures 5.4–5.6) however, the relevance tests indicate that further experimentation is required for query types greater than 5–2 under uniform distributions (and for query types greater than 4–2 for random distributions). Overall, Algorithm W outperforms DW by 2% to 6% on average (approximately). In the case of the three relation, two attribute query type, the difference is quite significant. This is a result of the naive strategy adopted by Algorithm DW. Clearly, the availability of up to date information is not sufficient for the heuristic, hence some method must be provided to take into account any global conditions. Currently, the greedy approach used by DW considers the execution of a semi-join with no form of "look ahead" except...
for the calculation of marginal profit. In addition, the decision to begin with the cheapest semi-join may not lead to the construction of the best reducer. If for a particular semi-join the anticipated reduction does not occur, the execution of that semi-join has become an unneeded cost expenditure. In large queries these wasted transmissions are generally countered by improvements gained over the course of the execution of the query. However, in small queries the limited number of semi-joins does not allow DW to recover from “poor” semi-joins.

The problem is to design an improved algorithm which will construct the “best” reducer first while still attempting to minimize the overheads. The results clearly indicate that further research is required in this area.

*Will the response time of a dynamic heuristic (DW) increase due to the increased number of serially executed semi-joins?*

In most cases a significant increase in response time is experienced however, in some cases with large queries under 50% connectivity the response time is actually improved with respect to Algorithm W. (See Table C.7). However, the question of relevance along with the proposal of an improved heuristic requires that further testing be performed in order to fully answer this question.

*Does the transmission of the statistics regarding intermediate results back to the query site constitute a significant cost?*

Based on the results, the transmission of the statistics of intermediate results does not constitute a significant cost. In the significant cases, this overhead does not exceed 3% of the overall total volume of data transferred to process the
Figure 5.4 W vs DW cost comparisons for 100% connectivity.

(See Table C.8)
Figure 5.5 W vs DW cost comparisons for 75% connectivity.
Figure 5.6 $W - DW$ cost comparisons for 50% connectivity.
Chapter 6
Conclusions and Future Work

Two new semi-join based heuristics for minimizing the total volume of network data transfers in distributed query processing have been presented. Algorithm W is a static heuristic which uses the concepts of profit, marginal profit and gain to construct inexpensive and highly selective reducers. Algorithm W has been shown to be both efficient and cost effective with a worst case complexity of $O(nm^2)$ and a best case complexity of $O(nm)$. Algorithm DW is a purely dynamic version of Algorithm W which executes semi-joins in a greedy one at a time manner. Unlike other dynamic heuristics proposed, DW does not require schedule monitoring or reformulation during execution.

The experiments using random data distributions indicate that heuristics using a uniform data distribution assumption do not experience any noticeable drop in performance. Additional experimentation should be carried out on very large relations to see if this is still the case.

Extensive testing of the algorithms indicate that Algorithm W consistently outperforms the Apers-Hevner-Yao (AHY) General (total time) algorithm. Re-
Conclusions and Future Work

Suits seem to indicate that the Algorithm W outperforms Algorithm DW, even though the differences were not significant. It should be noted that the lack of relevant statistical results suggest that additional experimentation is required to form a definitive answer. It was also shown that the overheads associated with the dynamic heuristic were minimal with respect to the overall cost, thus illustrating that the use of up to date information does not require extensive overhead. Acknowledging that Algorithm DW is essentially a very naive and simple heuristic, it is clear that further research is required to determine whether it is possible to develop a dynamic heuristic which will provide any significant improvement over Algorithm W.

6.1 FUTURE WORK

Continued development of both static and dynamic heuristics. Some specific examples include:

- Modify algorithm W to use marginal profit as the selection criteria, as opposed to the current method based on minimum cost.
- Using the concept of marginal profit, develop a new dynamic heuristic which constructs reducers using more than one common-join attribute.
- Investigate the use of bloomfilters [Mul90, Mul93] in a dynamic heuristic. The characteristics of bloomfilters suggests that they can provide insight into the relative reduction capabilities of each of the join-attributes.

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Another key area of continued research is in the development of more sophisticated and flexible benchmark database. The desired database should allow for the use of primary keys, foreign keys, and composite keys. In addition, controls would be added to provide some degree of attribute distribution and attribute dependance in order to more closely model real world data. Lastly, the software for constructing the database should be flexible enough to allow for random database generation, based on predefined parameters or manual construction via a user interface.
Selected Bibliography


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The term "connectivity" is used to describe the general underlying presence of join-attributes within a query. For any query it is somewhat unrealistic to assume that every relation will have an occurrence of each join-attribute. To allow for varied occurrences of join-attributes within relations, the probability that a relation will have a specific join-attribute is based upon some probability. For the experiments conducted in this thesis, these probabilities were chosen to be 50%, 75% and 100%. It is important to note that the use of probabilistic selection alone will may not result in a valid query. For the heuristics presented in this thesis, the following conditions must be satisfied:

1. At least two relations must have an occurrence of the same join-attribute.
2. It must be possible to join every relation to form a single conjunctive normal form query.

To determine whether condition 2 holds, a graph is constructed with the relations as the nodes and the join-attributes as the edges. Condition 2 holds if it can be shown that the graph is fully connected, hence the term "connectivity."
Therefore, a query with connectivity of 50% refers to one in which approximately half of the join-attributes do not occur within the relations. It is important to note that these percentages are approximations with respect to the queries of 5 and 6 relations. The exact minimum coverage (%) is given by the formula

\[ \frac{2m - (n - 2)}{nm} \times 100. \quad n \geq 2; m \geq 1 \]

where \( m \) represents the number of join-attributes and \( n \) the number of relations.

**Proof.** Let \( n = 2 \) and \( m \) be some arbitrary positive integer. With only two relations, condition 1 requires that each relation must have an occurrence of each of the \( m \) join-attributes. This also guarantees that condition 2 holds as well. Therefore, for two relations the minimum coverage is 100%. Hence the formula holds for \( n = 2 \).

Clearly, for each additional relation that is added to the query, it only requires the presence of one join-attribute (i.e. \( n - 2 \)) in order to satisfy condition 2. Condition 1 will always be satisfied as the first two relations must have an occurrence of every join-attribute.

Hence, the formula computes the exact minimum coverage (%) of join-attributes for a query involving \( n \) relations and \( m \) join-attributes. □
Appendix B
WWW Availability

Copies of this thesis, the programs described within, and the raw statistical results are available via the World Wide Web at the following URL:

http://www.cs.uwindsor.ca/meta-index/research/dbrg/

The programs used in this thesis are given in the following table.

<table>
<thead>
<tr>
<th>File Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>create_query.h</td>
<td>The header file for the create_query.c program.</td>
</tr>
<tr>
<td>create_query.c</td>
<td>Program for creating the query statistics.</td>
</tr>
<tr>
<td>relbuilder.h</td>
<td>The header file for the relbuilder.c program.</td>
</tr>
<tr>
<td>relbuilder.c</td>
<td>This program uses the query statistics to construct actual relations that match the statistical characteristics. Note, this program allows for either uniform or random data distributions when generating the relations.</td>
</tr>
<tr>
<td>betaf.c</td>
<td>The function used to generate the random distributions.</td>
</tr>
<tr>
<td>ahy.h</td>
<td>The header file for the ahy.c program.</td>
</tr>
<tr>
<td>ahy.c</td>
<td>The main logic for the Apers-Hevner-Yao Algorithm General (total time).</td>
</tr>
<tr>
<td>w.h</td>
<td>The header file for the w.c program.</td>
</tr>
<tr>
<td>w.c</td>
<td>The main logic for Algorithm W heuristic.</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>File</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DW.h</td>
<td>The header file for the DW.c program</td>
</tr>
<tr>
<td>DW.c</td>
<td>The main logic for the Dynamic W heuristic.</td>
</tr>
<tr>
<td>dyn_sjoin.c</td>
<td>Program for executing semi-joins in the Dynamic W heuristic.</td>
</tr>
<tr>
<td>runAHY.c</td>
<td>Program for executing the schedules produced by the AHY algorithm on the physical database.</td>
</tr>
<tr>
<td>runW.c</td>
<td>Program for executing the schedules produced by the Algorithm W on the physical database.</td>
</tr>
<tr>
<td>sjoin.c</td>
<td>The function for executing semi-joins between the physical relations.</td>
</tr>
</tbody>
</table>
Appendix C

Result Summaries

C.1 TOTAL COST

The experimental results for total cost analysis have been summarized into the following tables. Query types are given in column 1. The entries in each row (query type) represent the average over 100 runs. Column 2 gives the percentage by which the AHY algorithm reduces the unoptimized total cost; similarly columns 3 and 4 represent the respective percent reductions obtained by Algorithm W and DW. Column 5 shows the percentage improvement of Algorithm W over AHY and column 6 gives the percentage improvement of Algorithm DW over W. The averages over all of the query types are given at the bottom of the table.
<table>
<thead>
<tr>
<th>Type</th>
<th>AHY</th>
<th>W</th>
<th>DW</th>
<th>W-AHY</th>
<th>DW-W</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-2</td>
<td>46.29</td>
<td>61.70</td>
<td>51.58</td>
<td>15.41</td>
<td>-10.12</td>
</tr>
<tr>
<td>3-3</td>
<td>59.93</td>
<td>77.48</td>
<td>70.83</td>
<td>17.54</td>
<td>-6.64</td>
</tr>
<tr>
<td>3-4</td>
<td>71.66</td>
<td>89.10</td>
<td>85.58</td>
<td>17.44</td>
<td>-3.53</td>
</tr>
<tr>
<td>4-2</td>
<td>57.65</td>
<td>78.43</td>
<td>69.96</td>
<td>20.78</td>
<td>-8.47</td>
</tr>
<tr>
<td>4-3</td>
<td>72.07</td>
<td>91.97</td>
<td>89.87</td>
<td>19.90</td>
<td>-2.11</td>
</tr>
<tr>
<td>4-4</td>
<td>79.14</td>
<td>95.50</td>
<td>94.96</td>
<td>16.36</td>
<td>-0.53</td>
</tr>
<tr>
<td>5-2</td>
<td>62.98</td>
<td>87.12</td>
<td>82.09</td>
<td>24.14</td>
<td>-5.03</td>
</tr>
<tr>
<td>5-3</td>
<td>76.83</td>
<td>95.67</td>
<td>94.90</td>
<td>18.84</td>
<td>-0.77</td>
</tr>
<tr>
<td>5-4</td>
<td>83.13</td>
<td>97.08</td>
<td>96.76</td>
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<td>-0.32</td>
</tr>
<tr>
<td>6-2</td>
<td>70.51</td>
<td>93.64</td>
<td>92.00</td>
<td>23.13</td>
<td>-1.63</td>
</tr>
<tr>
<td>6-3</td>
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<td>97.12</td>
<td>16.14</td>
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<tr>
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<td>83.97</td>
<td>97.71</td>
<td>97.47</td>
<td>13.74</td>
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</tr>
<tr>
<td>Averages:</td>
<td>70.43</td>
<td>88.54</td>
<td>85.26</td>
<td>18.12</td>
<td>-3.28</td>
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</tbody>
</table>

Table C.1 Uniform distribution with approx. 100% connectivity.
<table>
<thead>
<tr>
<th>Type</th>
<th>AHY</th>
<th>W</th>
<th>DW</th>
<th>W-AHY</th>
<th>DW-W</th>
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</thead>
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<tr>
<td>3-2</td>
<td>48.66</td>
<td>63.70</td>
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<td>61.15</td>
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<td>74.02</td>
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<td>-5.54</td>
</tr>
<tr>
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<td>71.70</td>
<td>89.78</td>
<td>85.53</td>
<td>18.08</td>
<td>-4.25</td>
</tr>
<tr>
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<td>79.72</td>
<td>74.02</td>
<td>19.10</td>
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<td>92.33</td>
<td>91.64</td>
<td>19.41</td>
<td>-0.70</td>
</tr>
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<td>79.32</td>
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<td>22.19</td>
<td>-0.65</td>
</tr>
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<td>95.21</td>
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<td>-0.56</td>
</tr>
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Table C.2 Random distribution with approx. 100% connectivity.
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<td>83.16</td>
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<td>22.75</td>
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<td>93.54</td>
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Table C.3 Uniform distribution with approx. 75% connectivity.

University of Windsor, 1995
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<td>-1.66</td>
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<td>68.72</td>
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<td>-2.57</td>
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<td>89.74</td>
<td>87.78</td>
<td>21.84</td>
<td>-1.96</td>
</tr>
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<td>95.11</td>
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Averages: 58.01  76.56  72.26  18.54  -4.29

Table C.4 Random distribution with approx. 75% connectivity.
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<td>-9.82</td>
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Averages: 42.60 60.43 53.70 17.83 -6.73

Table C.5 Uniform distribution with approx. 50% connectivity.
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Averages: 43.36 61.56 55.02 18.20 -6.54

Table C.6 Random distribution with approx. 50% connectivity.

C.2 RESPONSE TIME

The following Table summarizes the percent increase in response time that Algorithm DW incurs over Algorithm W. The columns correspond to the individual test runs which are described in chapter 5.
<table>
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<th>Run 3</th>
<th>Run 4</th>
<th>Run 5</th>
<th>Run 6</th>
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Table C.7 Percentage increase in the response time for Algorithm DW over W.

C.3 OVERHEAD COSTS

The following Table summarizes the costs incurred by overhead in Algorithm DW as a percentage of the overall total cost.

University of Windsor, 1995
<table>
<thead>
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Table C.8 Overhead as a percentage of the total cost in Algorithm DW.
## Vita Auctoris

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<th>William T. Bealor</th>
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University of Windsor, 1995