DATA WAREHOUSE DESIGN:
AN INVESTIGATION OF
STAR SCHEMA

By

WEIPING LI

Bachelor of Science
Nanjing University
Nanjing, Jiangsu
People's Republic of China
1989

Master of Arts in Economics
Nanjing University
Nanjing, Jiangsu
People's Republic of China
1992

Submitted to the Faculty of the
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Thesis Approved:

D. E. He

Thesis Adviser

H. Lu

J Chandler

Wayne B. Powell

Dean of the Graduate College

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Chapter 1

Introduction

A *data warehouse (DW)* is a stand-alone repository of integrated information available for decision support on-line analytical processing (OLAP) querying and analysis [1]. Unlike a traditional database that is mainly designed for online transaction processing (OLTP) applications, a data warehouse is designed for data analysis of knowledge management and decision support systems within a corporation. It is driven from business analysis needs. It also can be viewed as an evolution of management information systems.

Before the 1980s, two important technical developments--the Personal Computers and the relational database--during this period contributed to the emergence of end-users in a business as separate client [4]. Most business people had little exposure to technology and looked to "someone else" such as the Information Support (IS) experts to provide them with the information they needed as a basis for decision-making. By the mid-1980s, with the growth of PCs and the simplification of data processing technology, end users were provided with more tools to deal with both the business and technical aspects of data. With the increasing power and sophistication of computer technology, more complex processes within a business have been automated; for instance, bookkeeping functions for bankers were automated and moved toward a real-time ATM environment [4].

Since the competitive advantage gained from data automation trends in the same industry are very similar, the challenge has been to "identify areas where computing could support activities beyond the day-to-day production process [4]". This trend is often described as a move from a data processing approach to business-driven information technology strategy. Support for decision-making processes became a prime target after the mid-1980s.

1.1 Decision Support System

Usually, end users in a business have the following characteristics: they are familiar with business terms, driven by real business needs to solve existing problems or to find new opportunities; aware of the value of "real" information in decision making; at ease using technology to meet their goals; open to "do-it-yourself" solutions, but wanting to avoid repetition; and understand the meaning of data in current applications. Since the mid-1980s, the success of a business in the fast-changing, competitive environment depends on efficient decision-making, to guide either a long-term strategy or a short-term tactics. The best way to accelerate decision making is to build a Decision Support System (DSS), a system that can provide the right information at the right time and can be accessed easily by users to analyze a situation and to make decisions rapidly.

In most companies, there is no shortage of data to support decisions since their current OLTP systems designed to run the day-to-day business have been gathering detailed financial, operational and sales transaction data for decades. The real challenge for decision-makers is to sift through mountains of historical data intelligently to find answers to real world "what –if" questions [2]. According to J. Bischoff [2], these questions might be about:

(1) Product trends, for example,

- Over the past 3 years, what were the weekly sales for a selected brand for total U.S.?
- How does this compare to sales for the category and average number of products carried each week within the category for total U.S.?

(2) Competitive analysis, for example,

- What are the top 25 brands (products, styles, etc.) for this period for total U.S. based on sales dollars?

(3) Product mix analysis, for example,

- Within a product category, what is the percent mix, based unit sales, of each brand within the category?

There is a common theme to such questions: the use of data for marketing or competitive advantages. This has led to the concept of a partitioned view of the business data: one part is dedicated to running the business at a detailed level while the second part focuses on managing the business at a summary level.

1.2 The Introduction of Data Warehouse

To support those decision-related queries, a large amount of computing power is required to work and summarize millions of records. IS departments in corporations once made several attempts to deliver necessary decision making information to end users in companies to meet their strategic query demands[7]. One approach was to connect analysts directly to operational systems, primarily mainframes. This approach failed because mainframes are architected as excelling at capturing information rather than disseminating it. A second approach was to create and to deploy decision support systems based on specialized hardware and software. The cost of this technology is usually very high and far exceeds the means of most small companies. Finally, the problem of how to cope with the vast amount of operational market data in a cost-effective manner for use of DSS brought about the solution of building a data warehouse [7].

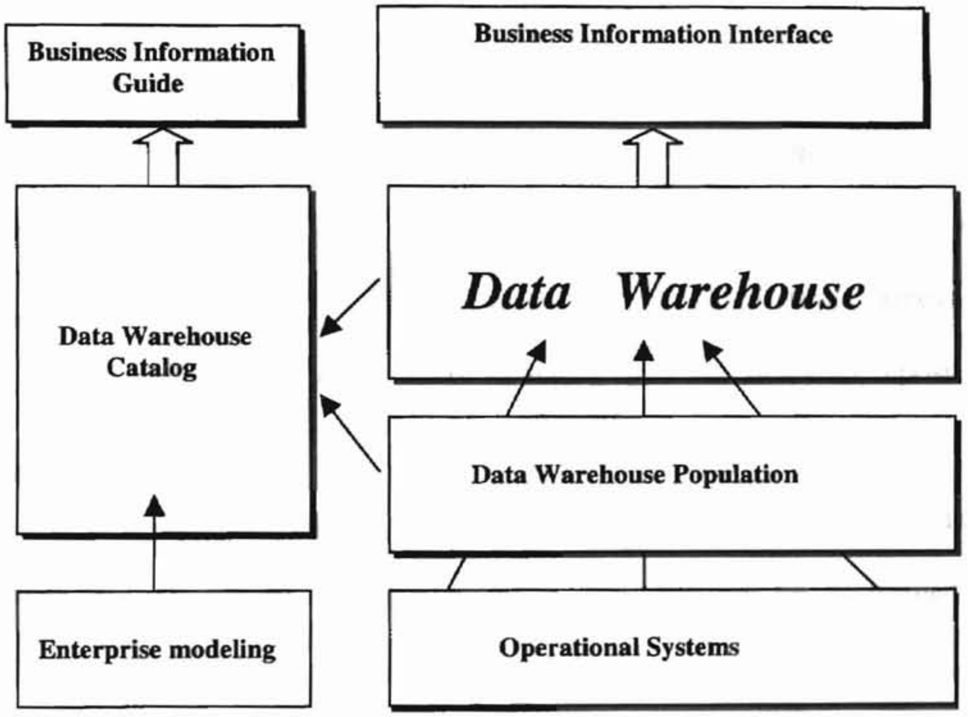

Business Information Guide
Business Information Interface
Data Warehouse Catalog
Data Warehouse
Data Warehouse Population
Enterprise modeling
Operational Systems

Figure 1. Data Warehouse
(Source: Barry Devlin ©1997)

To support those decision-related queries, a large amount of computing power is required to work and summarize millions of records. IS departments in corporations once made several attempts to deliver necessary decision making information to end users in companies to meet their strategic query demands[7]. One approach was to connect analysts directly to operational systems, primarily mainframes. This approach failed because mainframes are architected as excelling at capturing information rather than disseminating it. A second approach was to create and to deploy decision support systems based on specialized hardware and software. The cost of this technology is usually very high and far exceeds the means of most small companies. Finally, the problem of how to cope with the vast amount of operational market data in a cost-effective manner for use of DSS brought about the solution of building a data warehouse [7].

A data warehouse integrates operational and other data from a variety of internal and external sources, transforms that integrated data into consistent information, and provides easy, flexible and fast access for users [13]. Such a data warehouse break the barriers of existing database offerings by giving corporations access to all their information in any form and have consolidated them into one data repository separated from the original sources.

A remarkable advantage of using a data warehouse is, at the data warehouse, strategic queries can be answered and data analysis can be performed quickly and efficiently since the information is available directly, with model and semantic differences existing in original data sources previously resolved. Warehouse data can be accessed without seizing the information sources; e.g., holding locks or slowing down processing. Accessing data at the data warehouse does not incur costs that may be associated with accessing data sources [4].

1.3 Technology of Data Warehousing

Data warehousing refers to a collection of decision support technologies to assure the realization of the goal of decision support by Data Warehouse. A general data warehousing technology includes back-end tools for extracting, cleaning, and loading data into data warehouse, design and data modeling typical of OLAP in data warehouse, as well as the front-end client tools for online analytical query and data analysis. The following figure (Fig.2) represents the three levels of decision support tools based on a data warehouse and the development of intelligent techniques will be the highest goal.

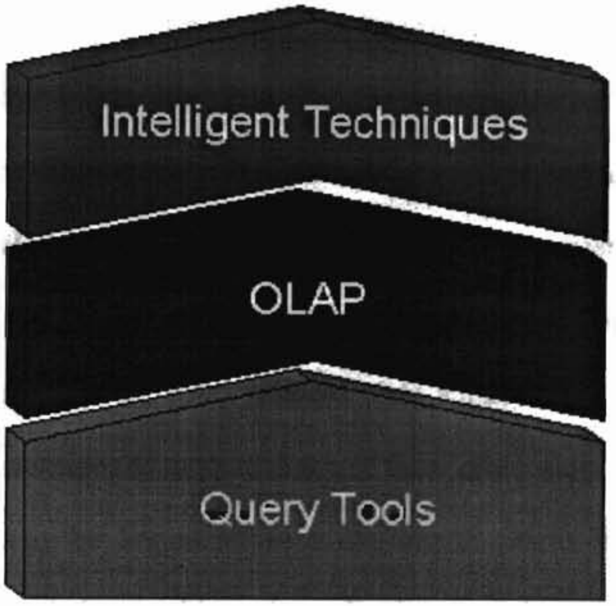


Figure 2. Decision Support Tools
(Source: McLaren I. , http://home.clren.net/imclaren)

With a business-driven implementation, a Data Warehouse allows for the use of data in new and innovative ways. The warehouse became a vehicle for enterprise-wide business view and changes.

1.4 Data Warehouse Design and Modeling

Data warehouse design and modeling methodology are the core problem that will make all objectives of Data Warehouse possible. Researchers have been involved in many of its theoretical aspects, but it is still a hot topic influencing the performance of a data warehouse.

In an organization, a typical data warehouse is maintained separately from its operational databases as a new kind of database. Since a data warehouse serves the specific goal of OLAP query and decision support systems, the functional and performance requirements of its data modeling and design methodology is different from traditional operational databases that serves the need of on-line transaction processing (OLTP).

By using a data model in the star schema, data in redundant dimensions are allowed and the dimensional information is pre-joined and aggregated for the users; thus simplify the relationships that must be analyzed by the users. This is different from the usual operational database that usually is normalized. For instance, for a sales data warehouse, the time of sale, sale district, salesperson, and product can be some meaningful dimensions of interest. Each of these dimensions is hierarchical. For example, time of sale may be organized as a day-month-quarter-year hierarchy, product as a product-category-industry hierarchy, district as city-state-region-country hierarchy. Typical OLAP operations on data warehouse include rollup (increasing the level of aggregation), and drill-down (decreasing the level of aggregation or increasing detail) along one or more dimensions, a slice-and-dice (selection and projection), and pivot (re-orienting the multidimensional view of data). A more detailed discussion about star schema is found in chapters 4 and 5.

To explore the use of star schema in data warehouse design, this thesis models the retail sales problem using the star schema to determine how and why a star schema is used for business OLAP. Due to the complexity of building a complete data warehouse, this thesis does not show the implementation of a complete data warehouse design except the database modeling, analysis query and related problems from star schema.

While this thesis shows the fundamental theoretical aspects of a data warehouse: its concept, its characteristics, relationship with traditional database, and major steps of building a data warehouse, the star schema for data warehousing design is the emphasis of investigation in this thesis.

In the following chapters of this thesis, Chapter 2 presents a review of literature on data warehouse, including its concepts and characteristics, technical architecture of data warehouse, methodology of design, management of data warehouse, etc. Chapter 3 will talk about the relationships between a data warehouse and the usual operational databases. Chapter 4 investigates the use of star schema in the design of data warehouse. Chapter 5 presents an implementation case using star schema. A summary and conclusion are included in the last chapter.

Chapter 2

Literature Review

Today's industry is moving toward powerful hardware and software technologies to process vast volumes of information analytically. Any business in the information age, if not wanting to run the risk of having insufficient information needs to use new technology to help it catch the power of information. Building a data warehouse as a repository for storing information of interest to each organization is an important start for success of a business [4].

Many commercial products for data warehousing technology have been developed to satisfy a rapidly expanding market. At the same time, there has been a significant amount of research about the data warehouse with its related technology. Research on data warehousing covers all its basic aspects: the general concept of a data warehouse; its applications, architecture and components; its design methodology, data warehouse building, and the management. Representative literature is in the bibliography of this thesis.

Concepts and Characteristics of Data Warehouse

Although the concept of data warehouse was introduced in mid-1980's [13], the development and use of the data warehouse experienced a slow period for almost ten years since there were many different definitions of what is meant by a data warehouse [15]. However, interest in the data warehouse peaked over the last two years, and understandings of data warehouses increased [16]. In addition to the definition of data warehouse presented at the beginning of this thesis, there are also two other definitions of data warehouse popular among data warehouse workers.

Bill Inmon, who is also referred to as "the father of data warehouse" [15] defined data warehouse as a "subject-oriented, integrated, non-volatile, time-invariant collection of data in support of management decisions." In their book of *Developing the Data Warehouse,* Inmon and C. Kelly used this definition to analyze the advantages of the data warehousing approaches, and to investigate the general architecture and suggested functionality of data warehouses. Many data warehouse researchers follow this definition to emphasize that the four characteristics, subject-oriented, integration, non-volatile, time-variant are required for a data warehouse.

The other definition comes from Joseph Fong in his article *Data Warehouse for Decision Support* [19]. He defined the data warehouse as an analytical database that is designed for large volumes of read-only data, providing intuitive access to information that will be useful in making decisions.

No definition excludes the key indicator that a collection of data is a data warehouse, but each has a different perspective and emphasizes different points. For example, Inmon's definition emphasizes the characteristics of data in data warehouse while Fong's definition focuses on the analytical function of data warehouse. All recognize the following characteristics of a data warehouse.

--- Data warehouse is the single information source for the enterprise. It is built by extracting and integrating data from any source and in any form.

--- Data warehouse can be comprised of a collection of subjected-oriented databases by collecting data based on subjects instead of processes.

--- Data warehouse provides the widespread, distributed availability of information by integrating and disseminating all kinds of data

--- Data warehouse provides end users with information in a business context.

---The delivery of information throughout the business is automated by the data warehouse approach

---Data warehouse improves end users' confidence of the quality of information they use since they have ownership of their business information that provide non-volatile, validated historical data.

The Application Trends in Data Warehousing

The data warehouse helps corporations to increase the "intelligence" of a business process and the knowledge of users involved in decision-making process. Increasingly, corporations are realizing the great potential of the data warehouse in decision support. The market scale of the data warehouse therefore is expanding rapidly and is expected to increase more in the next few years. Following numbers indicate that from 1995 to 1998, the sales of the data warehouse related hardware, database management systems, software, and total market has experienced very rapid development

	1995	1998
Hardware	$ 1 billion	$ 3.5 billion
DBMS	$ 700 million	$ 3 billion
Other Software	$ 300 million	$ 1.5 billion
Total Market	$ 2 billion	$ 8 billion

Facing the era of widely using electronic technology, organizations require different levels of analysis and information granularity, that is, different data, different subsets, different summarization levels and different time periods. The cost effectiveness of data warehouse applications in satisfying these needs have made it a good choice for many companies. On the other hand, the rapid expansion of network technology also helps the proliferation of shared data in data warehouse and brings about the evolvement into networked warehouse.

As more and more organizations realize the data warehouse is critical to success in competition, the application fields for the data warehouse have involved almost all industries. Fields having relative mature usage of data warehouses are listed in the following table.

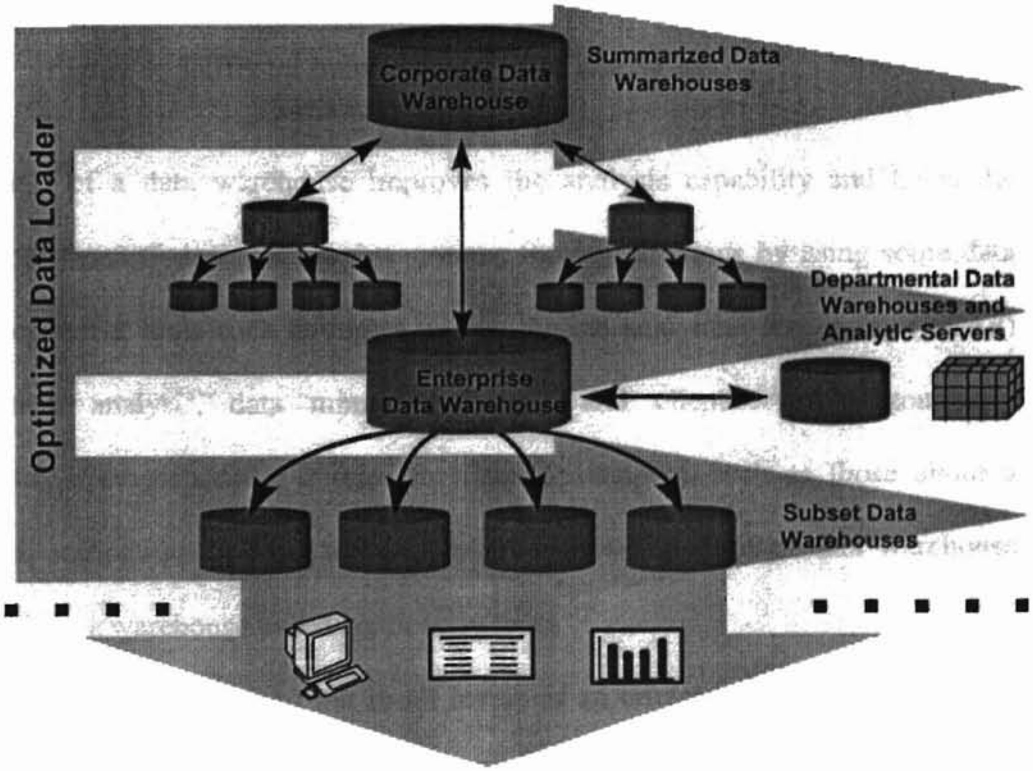

Optimized Data Loader
Corporate Data Warehouse
Summarized Data Warehouses
Departmental Data Warehouses and Analytic Servers
Enterprise Data Warehouse
Subset Data Warehouses

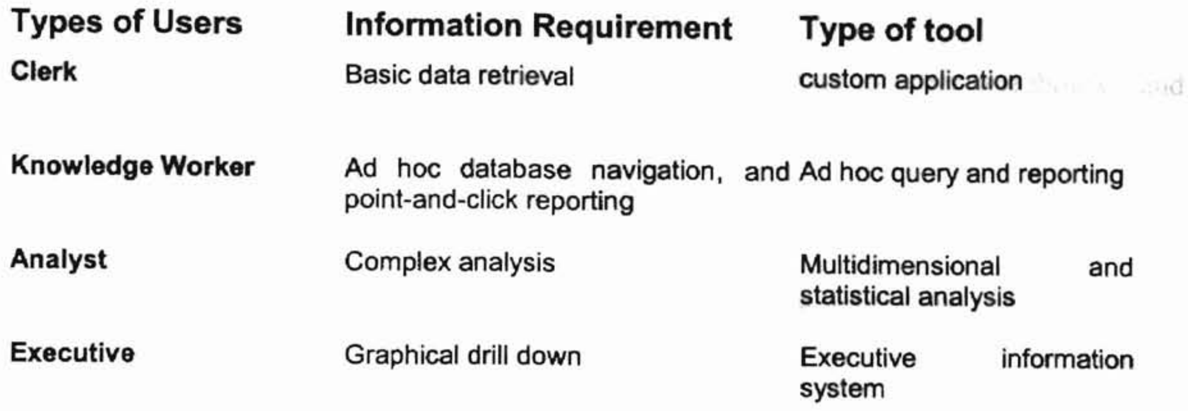
Figure 3. Networked Warehouse, Local and Shared Data
(Source: Ins & outs at http://www.redbrick.com)

Industries	**Applications**
Customer Packaged Goods	Promotion analysis
Retail	Category management
Telecommunications	Call/rate usage analysis
Healthcare	Claims analysis
Transportation/Distribution	Logistics management
Financial Services	Consumer credit analysis
Data Service Providers	Value-added data analysis

Figure 4. Different Industries and Data Warehouse
(Source: P. Gray ©1997)

The use of a data warehouse improves the analysis capability and helps the development of "smart" decision support systems for organizations by using some data warehouse dependent tools such as report writers, online analytical processing (OLAP) tools, statistical analysis, data mining packages, and client/server programming languages, etc. Comprehensive queries for decision support, such as those about a product trend, competition market analysis, can be answered through data warehouse combined with data warehouse based application tools.

Decision-making is carried out in all levels of an organization by people at any level. Different users may use a data warehouse in different ways for their own purposes. The following figure summarizes the users of data warehouse and the way they use data warehouses. Correspondingly, different companies may purchase different product tools for different users.



Types of Users	Information Requirement	Type of tool
Clerk	Basic data retrieval	custom application
Knowledge Worker	Ad hoc database navigation, and point-and-click reporting	Ad hoc query and reporting
Analyst	Complex analysis	Multidimensional and statistical analysis
Executive	Graphical drill down	Executive information system

Figure 5. Different Users of Data Warehouse
(Source: Oracle White Paper, http://www.oracle.com)

Technical Architecture of Data Warehouse

The architecture of a data warehouse can be described in two ways. The first is based on different function components of data warehouse. According to V. Poe [19], the various components of a data warehouse and their functions should be:

- Design component, for designing warehouse databases
- Data acquisition component, for capturing data from source files and databases, and for cleaning, transporting, and applying it to data warehouse databases
- Data manger component, for creating, managing, and accessing warehouse data
- Management component, for administering data warehouse operations
- Information directory component, for providing administers and users with information about the contents and meaning of data stored in warehouse databases

- Data access component, for providing business end users with the tools they need for accessing and analyzing warehouse data
- Middleware component, for providing end-users tools with access to warehouse databases
- Data delivery component, for distributing warehouse data to other warehouses and external systems

The other way describes the data warehouse architecture as based on the three basic operation areas comprising the data warehouse. A data warehouse consists of three functional areas: acquisition of data from legacy systems and other sources, storage in a relational database, and the access area for analytical tools. In the first functional area, the data are identified, copied, formatted and prepared for loading in the warehouse. In the second area, a vendor database management system such as Oracle, SQL Server7 may be used to house the data. In the third area, different types of decision support tools can be used to manipulate data in data warehouse. We usually refer to the data storage part when defining a data warehouse; however, the other two parts also are included in the general concept of a data warehouse.

In a general sense, data warehouses are data stores together with operations that can extract, integrate, manage, and analyze data from various operational systems and then make them available for decision making. Data warehouse possesses such a comprehensive architecture that they have great power for decision support systems. As the Oracle white paper on data warehouses states: "in reality, a data warehouse is simply a new approach to gathering data and generating reports from corporate information systems" [16].

Methodology of Data Warehouse Design

According to W. Inmon [11], data warehouse design normally goes through the following several steps:

(1) Planning: the creation of a project plan, including data requirement analysis and data modeling.

(2) Analytical database design: This step will focus database design and denormalization. In the database design, logical data model resulted from last step will be transformed into database schema. Then denormalization is to combine tables in a careful manner, by breaking rules normalization and reducing number of joins. Identifying keys and creating indexing strategies will also be done in this period. Chapter Four and Five will investigate this aspect in detail.

(3) Data mapping and transformation: The main task of this step is to determine what data is captured. It will cover: defining the source systems, determining file layout, developing written transformation specifications for sophisticated transformation, mapping source to target data, and managing operational metadata.

(4) Data extraction and load: Developing procedures and choose data transformation tools to transform and integrate data, load and move data into data warehouse.

(5) Automating data management procedures: This step is concerned with automating the extraction, transformation, and the load of the data warehouse.

(6) DSS application and tool development: At this step, with goals of providing information to users, to guarantee front end data access to the data warehouse and develop structured navigation paths to access predefined reports become important.

(7) Data validation and testing: At this step, a total systematic validation and testing is required.

Management of Data Warehouse

A data warehouse usually has heavy usage during daytime. Most data warehouses stay on-line between 16 and 22 hours per day in read-only mode. In the early morning, it then goes off-line for 2 to 8 hours for data loading, data indexing, data quality assurance and data release. As mentioned before, the management of data warehouse will include following tasks:

- Automating and scheduling the data extraction process.
- Automating and scheduling the data transformation process.
- Automating and scheduling the data load process.
- Creating backup and recovery procedures.
- Conducting a full test of all of automated procedures.

For a data warehouse that needs to be on line all the time, a back-up version in separate memory should be managed for extracting, transformation and loading updated data periodically.

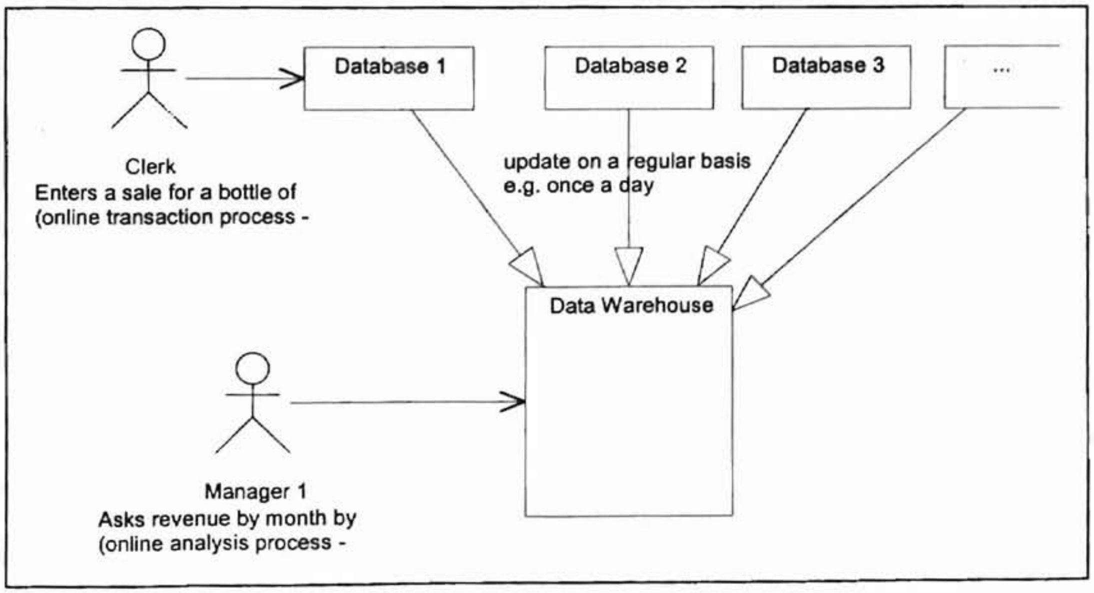
Chapter 3

Data Warehouse vs. Operational Database Design

Early attempts to support decision making were based upon automation traditional reporting. It usually is fragmented application-oriented development. With the maturation of Data Warehouse technology, distinctions evolved between the traditional database system the and new concept of data warehouse.

3.1 Relationship between DW and Operational Database

As we have seen, data warehouses and traditional operational databases are two related database concepts. Operational databases usually are in the form of a normalized relational database. In a general sense, data warehouses are data stores that extract, integrate, manage, and analyze data from various operational database systems then make them available for decision making. Different kinds of operational databases, as shown in



Database 1
Database 2
Database 3
...
Clerk
Enters a sale for a bottle of
(online transaction process -
update on a regular basis
e.g. once a day
Data Warehouse
Manager 1
Asks revenue by month by
(online analysis process -

Figure 6. From Operational Database to Data Warehouse

Figure 6, might be data sources or legacy systems for a data warehouse. that are designed

Figure 6 shows the relationship between a data warehouse and a normal database system. In this figure, the groups of databases at the top are *operational databases* used by clerks to perform data entries of daily transactions, such as the sale of a bottle of wine. The data warehouse at the bottom is the managerial database –a data warehouse used by managers for decision support queries. The operational databases feed data into the data warehouse on a regular basis. Because operational databases serve as the original data sources for a data warehouse, we use the terms operational database and traditional database interchangeably.

Both kinds of databases can use a relational database management system (RDBMS) to store and manage the data. Figure 7 below also explains the relationship between data warehouses and operational systems. However, a data warehouse mainly serves the goal of building decision support systems, but an operational database originally is used in on-line transaction processing (OLTP). Diverging requirements in meeting business needs have resulted in a functional gap between the two, and therefore they have different characteristics [15].

3.2 Functional Differences

Typically, the differences in two types of databases can be abstracted as follows:

First, a data warehouse is critical to management decisions that may affect company competitiveness while an operational database is critical for daily business operations.

Second, data warehouses are analytical databases that are designed to provide analytical information to assist in making tactical and strategic decisions, and are used as the foundations of DSS. Operational databases are processing systems that are designed to handle the day-to-day business affairs.

Third, data warehouses are read-only databases, but operational databases are read/write database since data in an operational database may be changing continually as business progresses. Data in an analytical database stays consistent and cannot be updated on-line by users. The data only is updated according to a predefined schedule. This is because analytical processing is done primarily through comparisons, and comparisons require stable data. Read-only data makes sense for analytical processing.

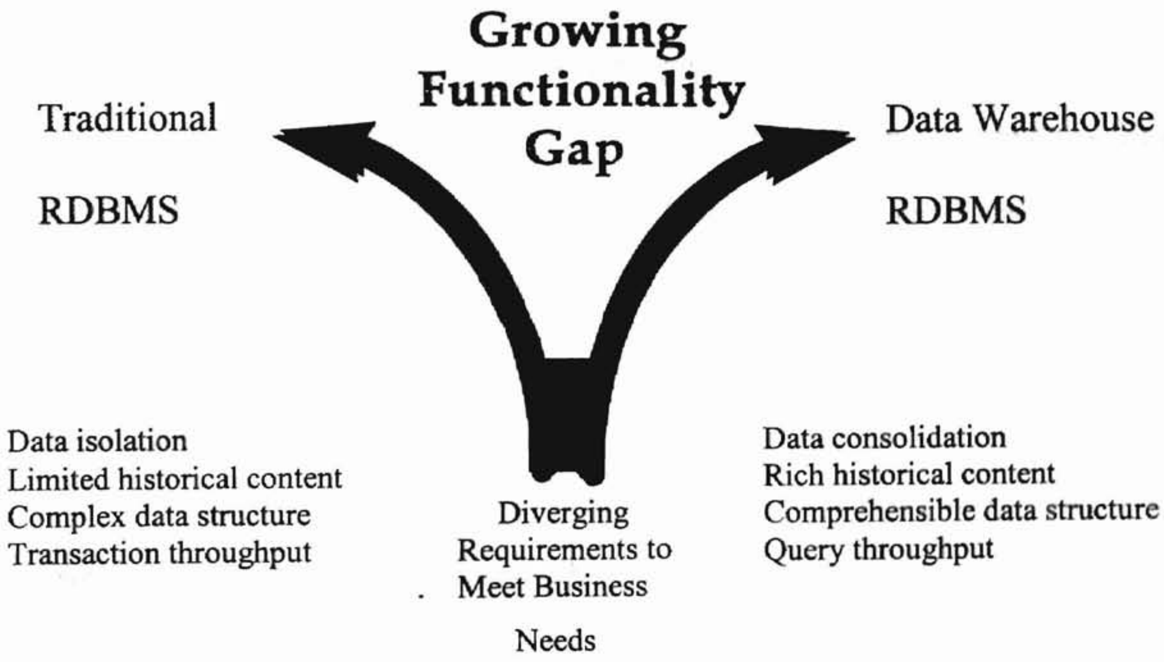


Figure 7. DW vs. Operational Database
(Source: Ins&outs, http://www.redbrick.com)

Fourth, data warehouses are historical databases, but traditional databases hold up-to-the-minute information. Though data warehouses may hold information as of a specific time, also called a snapshot of data, analyzing data patterns and trends over time often requires large volumes of historical data.

Fifth, a data warehouse uses data consolidation technology to integrate data into it, but an operational database may use isolated data as its source.

Finally, a data warehouse produces decision-related query throughput, but an operational database produces transaction throughput.

From a functional perspective, a data warehouse differs from an operational database in two ways. One, it gives end users direct access to corporate data with powerful graphical query and reporting tools. The other, it calls for the creation of a separate decision support database extracted from one or more operational systems. Data warehouses alter the way business users interact with corporate data, and the way how companies leverage that data. End users in managing level can access data directly with a data warehouse. They free IS departments to focus on tasks such as building various applications by executing strategic queries and build reports on-line themselves. Use of a data warehouse also allows end users to navigate large corporate data stores in an ad hoc, interactive fashion without impacting critical operations.

3.3 Design Differences

One of the purposes of a database design must be to minimize the resources required to run applications on the database. Traditional transaction processing systems, such as bank teller machines, generate a set of simple queries of the database to return small result sets. An example query is, "what is my current account balance?" OLTP systems must do this while supporting a large number of concurrent users, many requesting changes to the data held in the database, for instance, a withdrawal of money from a bank account. These characteristics have lead to designs that minimize the time to do updates. The most notable solution is the normalization process that removes all duplicated data from a data set, resulting in each datum being held just once. This means that each update must change only the data in a single location.

Similarly, the data warehouses targeted for decision support requires the database design methodology to minimize resources used in running complex analysis and visualization of OLAP applications. As previous figure 2 shows, decision support applications range from simple query tools, to OLAP multidimensional analysis systems which enable different aggregated views of data, to intelligent data mining solutions. The bottom level may include database vendors or specialist query tool suppliers such as Crystal and Brio, the second level may include MicroStrategy and Arbor Software, and the third are like IBM and Integral Solutions[17]. These query tools are characterized by generating much more complex queries than queries used in transaction processing systems, which rather than returning small result sets have to examine large sets of data in order to return their results. In addition, the queries that are generated by managerial people are largely unpredictable. Also, decision support applications tend to have fewer users than transaction processing systems, and updates tend to be done in overnight batch processes rather than online. These several new characteristics have lead to the development of new database design techniques to try to minimize the amount of data that must be transferred from hardware disks to answer a query. To realize this, data warehouse is typically modeled multi-dimensionally, and the star schema is just a simplified representation of the multidimensionality in business world.

Chapter 4

Database Design in Warehouse: Star Schema

A data warehouse is a consolidated database. To build a data warehouse involves comprehensive work and several steps, as stated in Chapter 2.

The first step, in the planning stage, a team of data warehouse workers is chosen from people who know the business and the technology; the requirements for the data warehouse of the specific business should be analyzed; then the conceptual model of this specific business can be determined.

The second step is the database design stage: a logical model of the data warehouse is formed, then transformed into a database schema based on the preceding step, so that the basic structure of the data warehouse repository is determined to facilitate business query.

Third, data mapping and transformation: in this step we decide what data to be captured and build the mapping relationship between source and target data in the data warehouse.

Fourth is data extraction and loading. This is a procedure to choose tools to extract and load actual data from source data to the data warehouse.

Fifth step is to implement programs, procedures, or purchased tools to automate the periodic data extraction and loading.

The sixth step is to develop DSS and query tools over the data warehouse; to develop an uniform interface for end users to access data warehouse and to generate reports.

In the final step, a test of the performance of the data warehouse is carried out.

This chapter will focus on step 2 to discuss the problems during DW design procedure and identify the basic components of star schema.

4.1 Requirement for DW design

A data warehouse should be designed to satisfy the strategic needs of a corporation; that is, a data warehouse should be able to answer strategic queries and to provide fast, accurate reports with graphic results for decision-making. The functionality or design of the data warehouse should not constraint the capabilities of strategic planners and analysts.

End users of data warehouses are designed to be business experts instead of computer professionals, thus the structure of data warehouse should be a good representation of the multidimensionality of real business, easily to be understood by business people. Output of data warehouse also needs to be in business-aware format.

A successful design of a data warehouse needs to combine business knowledge and technological knowledge. Considering each business is different and data warehouse ad hoc queries often require viewing summary information from the underlying database and scanning large amounts of data, business analysis is usually necessary in data warehouse design. There are some common strategic concern areas for business, such as budgeting, sales, marketing, financial reporting, profitability analysis, intellectual capital, etc.; thus, data warehouse design will usually abstract several finance related measures like price, cost, investment, return of investment (ROI) as main analysis objects. These entities are major attributes in fact tables.

4.2 The essence of analytical processing

The objects for analysis can be one of those measures above of that is of interest to business operation. It can be defined as a function (or mapping) of its corresponding variables, and each variable represents a dimension of the domain space [21]. For instance, suppose *w* is denoted as sales, and let *x* be the products, y be the regions, and *z* the time. Then for a certain instance of (x_0, y_0, z_0), i.e., for product x_0, in region y_0, at time z_0, we have the sales w_0, denoted by $w_0 = f(x_0,y_0,z_0)$. Along each dimension, hierarchies can be defined.

Figure below shows a hierarchy defined under x. Suppose that the domain of the variable x is {1, 2, 3, 4, …12}, representing the months of a year. For the hierarchy in Figure 6, we define $x' \in \{\alpha,\beta,\chi, \delta\}$as quarters, $x'' \in \{\theta, \phi\}$ as half-years, and $x''' \in \{\zeta\}$ as year, where α=[1,2,3], β=[4,5,6],χ=[7,8,9],δ=[10,11,12], θ=[1,…6], ϕ=[7,..12], and ζ=[1,…12].

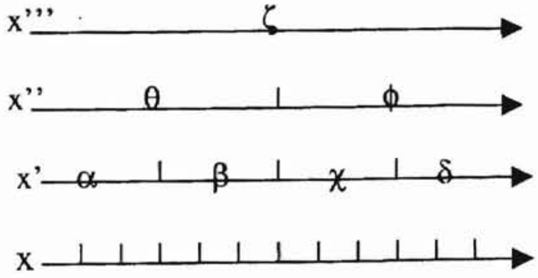


Figure 8. Dimension hierarchies of x
(Source: Ming-chuan Wu ©1997)

The aspects of analytical processing consist of the analytical activities, such as forecasting, comparing, ranking, rolling up, drilling down, growth analysis, etc. The primitive operations for these activities are data consolidation.

Data consolidation is the process of aggregating detailed data into single blocks of summarized information [16]. For instance, if we want to aggregate w along the dimension x to the level x', it can be represented as

$$W' = F(x', y,z) = \Sigma f(x,y,z), \text{ where } x \ni x'$$

This equation aggregates the monthly sales data to a quarterly sales summary. It is also possible to consolidate data along multiple dimensions simultaneously, which is referred to as multidimensional analysis [16].

4.3 Database design and modeling in DW

Any database design consists of conceptual, logical and physical designs. In the conceptual design stage, the requirements and goals for the database, the subject of the database and the external view of the database should be defined. In the logical design phase, a data store schema is selected suitable for the specific conceptual needs. In the physical design phase, the actual storage way of the data in system will be planned.

Because of the independent character of the three designs, the data model used in the conceptual design phase need not necessarily be the data model used chosen in the logical design phase. For example, choosing the multidimensional model for conceptual modeling does not imply that the data warehouse should be built on a multidimensional database system. In fact, it is common in data warehouse design that to use the multidimensional model for the conceptual design of a data warehouse, but choose a relational database server as the data store [16].

In general, a data warehouse's design point is to consolidate data from multiple, often heterogeneous, sources into a query database. This is also one of the reason why data warehouse is rather difficult to build. The main factors include:

(1) Heterogeneity of data sources, which affects data conversion, quality, timeliness

(2) Use of historical data, which implies that data might be "old"

(3) Tendency of databases to grow very large.

The data model of a data warehouse is the template that describes how information will be organized within the integrated warehouse framework. It will reflect the content and structure of the data warehouse, identifies major subjects and relationships of the model, including keys, attributes, and attributes groupings. The data model of data warehouse must consider its effect on the analytical query performance, data storage requirement, and data loading performance.

4.4 Star Schema

The data warehouse needs multidimensional data for analytical processing. The model for data warehouse should be capable of expressing multidimensionality. The two basic data constructs provided by the multidimensional model are facts and dimensions. These two constructs let the analysts view the data in the way they perform the actual analysis.

A star schema is a simplified data model derived from multidimensional model and good for representing most business application cases. It uses relational database semantics provided by all kinds of OLTP systems, which makes it easily compatible with legacy databases. Figure 9 below shows an example of star schema for business model.

A star schema contains one very large table, often referred to as the FACT table, and multiple smaller tables, called the DIMENSION tables. Using this approach can satisfy the requirements for business aggregated queries as aggregate queries tend to involve *facts* and *dimensions*.

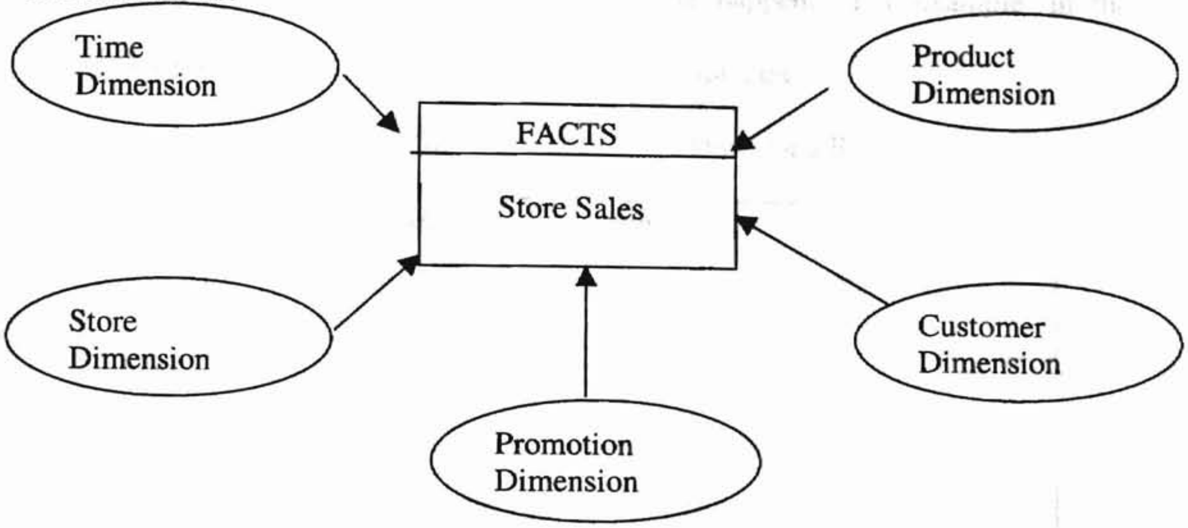


Figure 9. Example of a Star Schema
(Source: Joseph Fong ©1997)

Business usually needs to look up specific facts (units or amounts) though a set of dimensions (markets, products, period). Facts are things like revenue, net income, and cost. Typical dimensions are time, location, and product. For example, a query might ask for the total monthly revenue for each store. The fact involved in the query is "total revenue." The dimensions are "month"(time) and "store"(location). Because facts and dimensions are important elements in a data warehouse, most implementations of data warehouses use a similar scheme in that information is stored in a *fact table* and several *dimension tables*. It is important to notice that, in the typical star schema, the fact table is usually much larger than any of its dimension tables. This becomes an important consideration of the performance issues associated with star schema at last.

Table 1 below shows an example of a fact table. Table 2 and Table 3 are examples of the corresponding dimension tables. A fact table describes the facts for each record, which also contains the foreign keys from dimension tables. Dimension tables describe the dimension hierarchies where an aggregation can happen. For example, in the time dimension we can have year, quarter, month, week, day, etc.

Table 1. Fact Table of a Data Warehouse for a Retailer Store

Daily Sales	Product Key	Location Key	Time Key
$10000	P001	L101	T010
$40000	P110	L102	T010
…	…	…	…

Table 2. Product Dimension Table

Product ID (Primary Key)	Brand	Color	Size
P001	Sony	White	5'
…	…	…	…

Table 3. Location Dimension Table

Store ID (Primary Key)	City	State	Region
L101	Tulsa	OK	Midwest
…	…	…	…

Table 4. Time Dimension Table

Time ID (Primary Key)	Year	Month	Day
L101	1995	January	1
…	…	…	…

4.4 Advantages of star schema

A star schema consists of a central data table with the metrics you're measuring, surrounded by descriptive dimension tables. The idea is that a dimension table should "group all the interesting elements about that business dimension, such as customer or product, into one table." [17]. Such a design maximizes decision support and analysis.

Star schemas are simpler, and if there's no protective layer in between the user and data, a star schema is the best design techniques should be used in data warehouse design for the following five reasons [5].

(1). They're easier to understand and navigate. With a star schema there are fewer tables, so it's easier to understand relatively. Since there are fewer choices, such as fewer tables and fewer joins, it's less likely that the users will make mistakes in their queries. Most of all, it lets the companies "use business descriptions to name the tables, columns and contents of the columns. Avoid cryptic, eight-character, underscored-type naming conventions." [17]

(2) It gives better performance. It does this by minimizing the number of joins, since the number of joins is limited to the number of business dimensions. The fewer joins, hence the better performance. The dimension tables, much smaller than fact tables, can be heavily indexed without space ramifications. On the other hand, as all of the constraints

are made on the dimension tables, the fact table is efficiently accessed via the index built from all of the dimension table foreign keys—the configuration commonly referred to as a "star join."

(3). Star schemas support multidimensional analysis. This is that "slicing and dicing" of data required for the iterative analytical process. Star schemas retain the history for comparative analysis, and identify all the business dimensions used in analysis.

(4). Extensible design supports changing business requirements. In other words, star schemas are much easier to change and scale than other schemas, like snowflake schema. Star schemas can easily add attributes to the dimension tables or new fact columns without reloading tables. Such a dimension restructuring doesn't affect fact tables, as long as the appropriate level of detail, or granularity was selected for the initial design. In another word, with a star schema, users can easily add new "stars" to the "constellation."

(5). Star schemas are recommended for most DSS user tools. Most tools work best with a dimensional design, while a few even require it. Typically, the more sophisticated the tool, the more particular it will be about the design it needs.

Chapter 5

A Design Case Using Star Schema

In this part, a database design using the star schema is explored using a general retail business example. Due to the limitations of time and tools, a full cycle design of data warehouse is not included. Only data requirements analysis, data modeling, schema design, simple table joining and query tests are presented here. Implementation uses C++ language.

5.1 Data Requirement Analyzing and Modeling

The sales' results affect pricing decisions, marketing plans, and the stock price of public companies[1]. Retail sale is an important part of business since each business depends upon product movement. Building a data warehouse to support the retail sales' subject areas requires an understanding of the type of business, the sales cycle, and how the sales process relates to the marketing and pricing decisions.

Retail sellers usually are concerned with effective utilization of the resources like space, labor, and marketing dollars. Their profit comes from the maximized sales volumes and margin profit of each unit sold. By capturing extensive, detailed sales data, merchants can "stock the best-selling products, gain an upper hand in dealings with producers, and optimize promotional efforts" [1].

Generally, retail sellers, including departmental stores, grocery stores, or single commodity sellers, need to know what sells, where it sells, when it sells, and how much it will sell. A sales data warehouse for retail should be the foundation for profitability analysis. The pace of competition drives large retailers to create sophisticated data warehouses to track sales.

The initial data warehouse design for this retail sales example contains the time, location, product dimensions, and one fact table using facts like the units of sale, and the total dollar sales. It can be considered as a basic design for all retailers, and dimensions such as the customer information can be added if necessary for a specific industry. Each dimension table can grow in size.

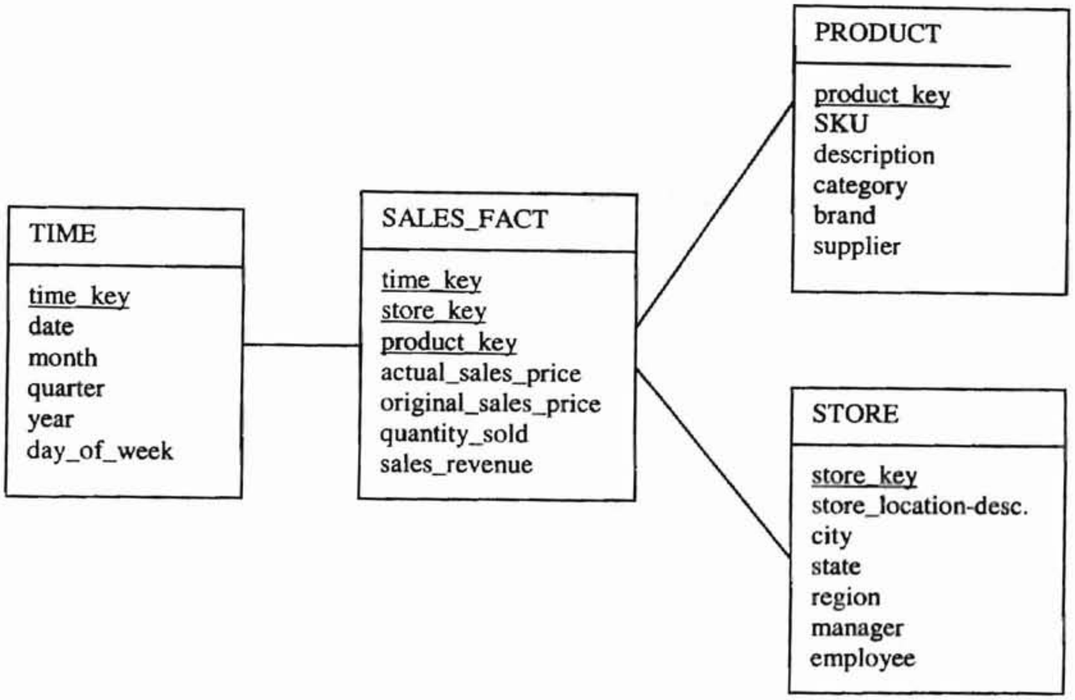


Figure 10. The Sales Schema for a Retail Super Store

The simple model here used to demonstrate the various design alternatives is composed of three dimensions, the Store and Product and Time. The third one, time, is composed of the following attribute hierarchy: date -> month -> quarter-> year-> day_of_week. The Store dimension has an attribute hierarchy of store -> district ->

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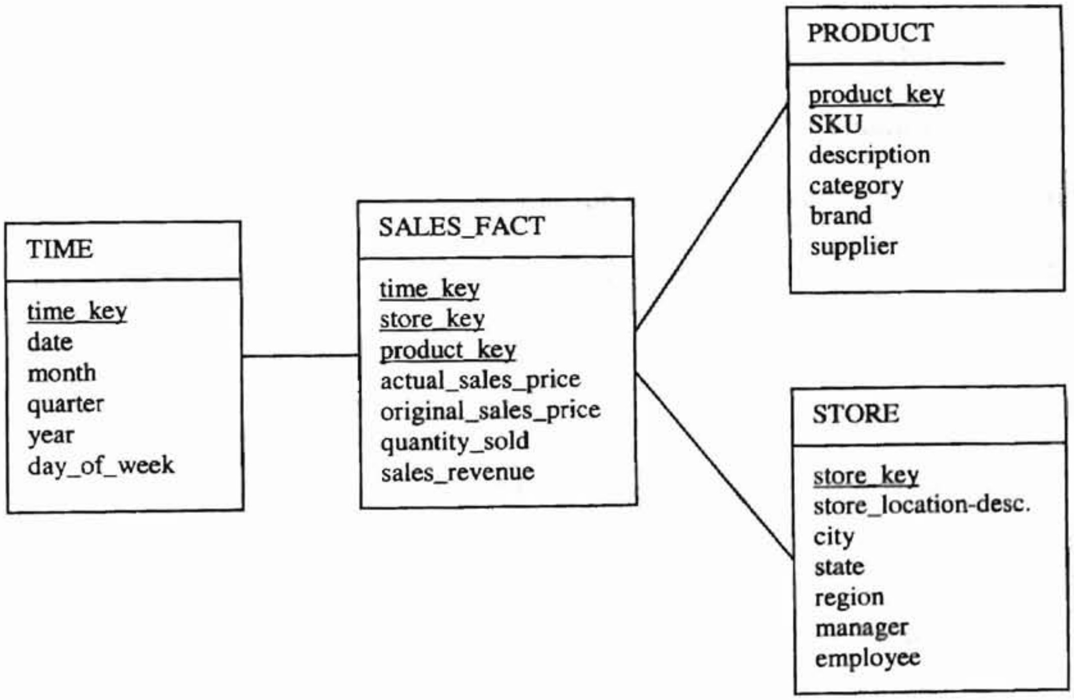

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region. Products is composed of products -> brand -> manufacturer. Based on this simple model, we can say that the granularity of data is products sold in stores by day.

5.2 Query Features

One of the queries that motivate the design maybe like: how much revenue did the new product generate by month, in the northeastern division compared with the plan. Obviously, it is a four-dimensional question, and therefore need a database with four-dimensional information. By comparison, the more complex a query is, the more dimensions may be included into the design. As this thesis is just a sample demonstration of star schema, schema is relatively simplified from actual considerations.

With a simpler design for retail sales, reports can be generated to track how much each products was sold in a specific location and time. Comparable results can be used to decide what factor like time, location or product variation, has brought about the difference of sales in each store. Consequently, corrections can be made in forecasting, marketing, and promotion activities.

A star query strategy is used corresponding to the star schema model. In a star query, each of the dimension tables is joined to the fact table using the primary key/foreign key relationship. Thus, in this thesis, the product, location and the time table would be joined with sales. Star queries only work in this simple model and in the real world it is not an optimal choice because the Cartesian-product joins would be slow and use too much memory. A compromise is to join relatively small dimension tables first and then to join them with the large fact table.

To speed the queries of very large fact tables in the design, tables can be aggregated in advance. That is, they only use the necessary granularity for queries, if needed, summarizing data before queries are performed.

Query performance can be improved by deploying hardware upgrades or an aggregation navigator in data summarization. Many data warehouse software vendors provide such products [17].

5.3 Implementation

This thesis used C++ to implement a simplified retail star schema after considering its convenience.

The major interface for this simulation is shown as in the following menu:

```
*******************************************************
*              1. Open Database                       *
*              2. Table View                          *
*              3. Table Join Query                    *
*              4. Close                               *
*              5. Exit                                *
*******************************************************
 Please make a choice:
```

Figure 11. The Main Menu

Each of these choices has a logic consequence to its following choice. Given the choice number 1, the database name for this simulation, which should exist already need to be input by the user, and the database will be opened. When choice number 2 made, a list of tables' names contained in the existent database will be displayed, so that we can see the table components of the opened database and further more can specify any one of them to show its contents. Choice number 3 will carry out the table joining after asking users to specify the tables they hope to have a joining query. The result from this choice will be a simple concatenation like "when in which-store sells how-much product A", which is a query of typical business interest usually. Prompts number 4 and 5 will let users to close the opened database and exit current program.

Data of each table for this program will be stored in file format instead of from standard input as this is closer to the actual situation in a real data warehouse. For simplification, data correspond to each table field is only in one string format with no allowing of multi-string in this program.

This program built one class called DBclass to carry out all related processing of tables in a database. The class has the following prototype:

```
class DBclass {
      char TableName[10][51], TableKey[10][20][51], TableData[10][50][20][51];
      int TableKeyNum[10], TableRecNum[10];
      int TableNum;
public:
      DBclass();
      ~DBclass();
      void open(ifstream &in);
      void close();
      void tableList();
      void getTableKey();
      void getTableData();
      void tableView(char *tbname);
      void tableJoinQuery(char *query);
};
```

As this simulation is mainly for the purpose of displaying star schema and its related query, a fixed size of database and its tables are used. For instance, tables are assumed to have no more than twenty fields and fifty records and database contains at most than ten tables. Functions in this class handle all database related behavior, such as function open(ifstream&) will be in charge of open a database file; close() will close an opened database; tableList() show the list of tables in the database. The function getTablekey() will open the files that store the information of keys for tables. Keys are in separate files that make changes easier. Similarly, the getTableData() function open the files for storing table contents and fetch them for processing. The tableView(char*) function will show contents of a table.

The tableJoinQuery(char*) does the major work of this simulation by implementing the table joins and output join results for a query. This method first identifies that each of the user-input table names for joining do exist in the database and then pick out these tables from the database. Joining start if the input joined table number is more than two and joins go on pair by pair. For any join, first will confirm the two tables have at least one common key and then obtain the record for joined result by joining those with same key value into one table. To set the keyNum, keyName and keyValue for each join is the key of this method.

The table joining method uses the naïve joining algorithms with traditional star query strategy. In this way, tables can be joined pair after pair using nested loops. That is, to join the first tables together and then joins the third to the result of the first join. But for the real world data warehousing, it is possible to use the star schema aware processor for speeding implementation.

5.4 Sample Inputs and Results

With the simple design and model, we can generate reports that track like: how much are selling in Monday in one of chain store. Sample inputs I used for testing the program is as follows.

Sales_fact table:

time_key	store_key	product_key	actual_sales_price	original_sales_price	quantity
1123	6421	569	6.00	7.50	14
1126	7431	588	31.00	33.00	10

Product table:

product_key	SKU	description	category	brand	supplier
124	817444-432	Spatula	Kitchen	Chef	Chef_Inc.
482	582031-901	DEET_Fresh	Camping	Monostar	Monostar
563	718201-440	Tefla_Sock	Men's_Sock	Sock_Woks	Tasmanian
569	673109-311	Golden_feet	Children's_Shoe	Torch	Weyley
588	989901-762	Russ_Coat	Children's_Coat	Russ	Hatchley

Store table:

store_key	store_location_desc.	city	state	region	manager	employee
6421	1211_Taylor_Avenu	New Bruswick	NJ	Northeast	R.S.	Mary
7431	1310 Cantwell	Moore	OK	Mid_US	W.H	Lisa

Time table:

time_key	date	month	quarter	year	day_of_week
1123	4	8	3	1997	Monday
1126	1	9	3	1997	Monday
1028	17	9	3	1997	Wednesday

Figure 12. Series of Sample Input Tables

Reports after query should lists the quantity sold by store and product at a specific time or period, depending on the queried tables' order and input in tables. Here is a sample output report by picking some meaningful fields to business only.

Brand Sales By Region

Products: Winter Coats Dept: Children

Period: from 8/4/97 to 9/1/97

Store_Region	Brand	Quantity	Sales Revenue
Northeast	Torch	14	$84
	WeKids	0	$0
Northeast Total		14	$84
Mid-us	Russ	10	$310
Mid-us Total		10	$310

Figure 13. A Sample Query Report

Chapter 6

Summary, Conclusions and Suggested Future Work

6.1 A General Summary

The functions of traditional databases aim at data processing rather than data analysis. For this reason, in the decision making environment, a single or even multiple traditional databases hardly could meet the application requirements. However, data warehouses can be viewed only as a complement to traditional databases even in this sense. They cannot be a total replacement.

The methodology of building a data warehouse is different from that of a traditional database. In its life cycle, data warehouse has some completely new steps, such as data mapping, and data transformation, data extraction, and loading. Even in the same steps they may have different goals and methods, for example, in the database design step, traditional databases emphasize normalization while data warehouses emphasize denormalization to gain fast response time and easy access.

The modeling of retail sales problem using star schema in this thesis explores the mechanism of basic database design in warehouse, such as how the query works in star schema, and how it makes the OLAP easier, although there are still some more problems to be answered.

6.2 Potential performance problems and solutions with star schema

Although the star schema is a preferred modeling for data warehousing, there are still a number of problems associated with star schema implementation, especially if a query-centered star schema is hosted on a traditional RDBMS optimized for OLTP. One problem is, as the star schema typically contains the entire hierarchy of attributes, index technology is used to improve the performance. However, carrying all the segments of the compound dimension key in the fact table increase the size of the index, and impacting both performance and scalability eventually.

The other is the pair-wise join problem. That is, the RDBMS needs to break the query into series of pair-wise joins and needs an optimizer to choose more efficient order to join. But generating large intermediate result sets severely affects query performance.

Potential solutions to these problems include: using a star join that is a high-speed, single-pass, parellizable and multi-table join. The Red Brick company has provided such products. Another is star index, that is, use indexes that are defined on selected columns of a table and query selectivity is limited to those columns. Star index is considered as an improved technology compared to traditional B-tree or bitmap indexes.

6.3 Future Research

The use of a data warehouse broadens the database's application area, and bringing about some new advanced research issues, such as the interoperability of data warehouses and operational databases as well as other sources and automation of data analysis and integration. Data warehousing technology should mature with the development of new database technology. Those areas that need further explorations include cubic operator implementation, materialized views, multi-way join algorithms, etc.

Design methodologies and design tools for DWs are need with the appropriate support for aggregation hierarchies. Future efficient operators like cubic operators will include a better mapping between the multidimensional and the relational worlds. Future operators should also take advantage of DW characteristics for allowing large table scanning. In the future joins will support multi-way joining which is parallelized in an optimized manner and partial results can be usable by multiple queries. As many queries over data warehouses require summary data, and therefore use aggregates, hence, materializing summary data or called materialized view technology can help to accelerate common queries at last. All such problems are still open for research and need more efforts in the future [31].

Acronym Table

DB	Database
DW	Data Warehouse
DSS	Decision Support System
ODS	Operational Database System
OLAP	On-line Analytical Processing
OLTP	On-line Transaction Processing
RDBMS	Relational Database Management System
ROI	Return of Investment

Glossary

Ad Hoc Query A query that has not been anticipated, usually run just once. It consists of dynamic SQL that has been prepared by a query tool.

Administrative data Data that will be used by a warehouse administrator in managing all aspects of the warehouse, for instance, date that a particular table was last updated, name of the job used for incrementally refreshing a particular table or set of tables.

Aggregation A process that is applied to combine data elements so that data is in the collective or in the summary form.

Architecture A framework for organizing the planning and implementation of data resources. The set of data, processes, and technologies that an enterprise has selected for the creation and operation of information systems.

Centralized Data Warehouse A style of data warehousing in which all warehouse data is located and managed from a single, central location.

Client/Server Computing A distributed approach to building applications in the result to the client. The server may manage communications, provide database services, etc. The client handles individual user functions, such as the desktop interface, help functions, etc.

Data A fact and its meaning. It is the "raw material" of information and a fundamental element in any organization.

Data Analysis The systematic study of data so that its meaning, structure, relationships, representation, validity, controls, volume, and origins are understood.

Data Administration (DA) The organization that has the overall responsibility for the enterprise's data resources and for the administration, control and coordination of all data related activities. The DA has the responsibility for planning, and defining the conceptual framework for the overall data environment. The functions of the DA typically include requirements definition, logical design, logical to physical mapping, maintenance of inventory of the current system, data analysis, administration of the corporate data dictionary, support of the application data dictionary, and business planning support.

Database (1) A repository for stored data that is integrated and shared. (2) A data collection that is organized for computer processing so as to optimize storage and increase the independence of the stored data structure from the processing programs.

(3) A formal, computerized method for storing details of interest to a business so that it may be accessed and manipulated.

Database Management System(DBMS) A computerized software system for creating, maintaining, protecting databases.

Data Driven An approach to design that begins with the data. The data becomes the central node of the design, and the process is derived from this model. The approach should produce subject database.

Data Flow Diagram A diagram that shows the flow of data between data stores and business processes.

Data Integrity The ability to preserve the accuracy, currency, and completeness of the data; the ability to produce results that are correct to a predefined level.

Data Loading The process of populating a data warehouse. It may be accomplished by utilities, user-written programs, or specialized software from independent vendors.

Data Management The function of organizing, cataloging, locating, storing, retrieving,, and maintaining data. Data management attempts to optimize the use of the data asset.

Data Mapping The process of identifying a source data element for each data element in the target environment.

Data Mart A collection of related data designed to meet the needs of a specific group of users. It is often a subset of the data warehouse. Although it often consists of highly summarized data, it also may contain detail data, depending on the needs of the specific group of users. It may or may not have been designed with corporate standards in mind.

Data Mining A process of analyzing large amount of data to identify patterns, trends, activities, and data content relationships.

Data Model A data model is a set of diagrams and definitions that represents the enterprise data and their interrelationships in a specific and consistent way. The data model contains entities, attributes, relationships, primary and foreign keys, and rules Governing the data.

Data Pivot A process of rotating the view of data.

Data Scrubbing The process of filtering, merging, decoding, and translating source data to create validated data for the data warehouse.

Data Sharing The ability to share information, rather than requiring identical data items to be entered or stored multiple times in the system.

Data Store A place in which data views are temporarily or permanently kept.

Data Transformation Creating "information" from data. This includes decoding production data and merging of records from multiple DBMS formats. It is also known as data scrubbing or data cleansing.

Data Warehouse A data warehouse is a collection of integrated, subject-oriented databases designed to support the DSS(decision support systems) function, where each unit of data is relevant to some moment of time.

Data Warehouse Technology A set of methods, techniques, and tools that may be leveraged together to produce a vehicle that delivers data to end users and integrated platforms.

Decision Support System A database designed to meet the needs of end users for information and analysis to facilitate decision making by enterprise management.

Denormalized Data Data that does not conform to the rules of normalization.

Distributed Data Processing The dispersion of computing functions and data at nodes electronically interconnected on a coordinated basis, geographical dispersion not being a requirement in every case.

Distributed Relational Database (DRDB) A collection off relational data that is stored in more than one system in a network and is accessible as though it were in a local system.

Enterprise Data Operational plus informational data. All nonprivate data in the enterprise.

4GL Fourth-generation Language.

Front End An application that runs on a workstation, usually for query purposes that can access a back-end processor that holds the server data.

Information Warehouse A set of DBMSs, interfaces, processes, tools and facilities to manage and deliver complete, timely, accurate and understandable business information to authorized individuals for effective decision making.

Join A cross match of any two columns in two or more tables.

Legacy Can refer to either systems, applications, or data. Those old production systems, applications, or data on which the business depends.

Metadata Data about data.

Normalization The process of reducing a complex data structure into its simplest, most stable structure. In general, the process entails the removal of redundant attributes, keys, and relationships from a conceptual data model.

Operational Database The database-of-record, consisting of system-specific reference data and event data belonging to a transaction-update system. It may also contain system control data such as indicators, flags, and counters. The operational database is the source of data for the data warehouse. It contains detailed data used to run the day-to-day operations of the business. The data continually changes as updates are made, and reflect the current value of the last transaction.

Operational Data Store A database to provide an interim step for near-real-time data to informational and operational queries. It minimizes the impact on production or operational systems while providing as current live data as possible. Can also serve as a data staging area for processing data into the data warehouse.

OLAP A common use of a data warehouse that involves real time access and analysis of multidimensional data such as order information.

Scalability The ability to scale to support larger or smaller volumes of data and more or less users. The ability to increase or decrease size or capability in cost-effective increments with minimal impact on the unit cost of business and the procurement of additional services.

Schema The logical and physical definition of data elements, physical characteristics and inter-relationships.

Snapshot An image of a database or file at a specific point in time. Generally used for reporting purposes.

Source Database A production operational database that feeds data warehouse.

Star Schema(or Star Join Schema) A specific organization of a database in which a fact table with a composite key is joined to a number of single-level dimension table, each with a single, primary key.

Subject-oriented Database A database that contains data that related to one or more logical subjects.

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VITA

Weiping Li

Candidate for the Degree of

Master of Science

Thesis: DATA WAREHOUSE DESIGN: AN INVESTIGATION OF STAR SCHEMA

Major Field: Computer Science

Biographical:

Personal Data: Born in Jiangsu, China, the daughter of Liuqun Li and Chunfeng Ye.

Education: Graduated from Taixing Middle School, Taixing, Jiangsu, P.R. China in June 1985. Received Bachelor of Science degree in Economic Geography and Urban Planning and a Master of Arts degree in Economic Management from Nanjing University, Nanjing, P.R. China in June 1989 and July 1992 respectively. Completed the requirements for the Master of Science degree with a major in Computer Science at Oklahoma State University in May, 2000.

Experience: Employed by the Finance and Economics Institute of Jiangsu Province as a researcher, Nanjing, Jiangsu, P.R. China, 1992 - 1996. Employed by the School of Public Affairs at Portland State University as a Computer Assistant and Graduate Research Assistant, 1996-1997. Employed by the Computer and Information Services at Oklahoma State University as a Computer Assistant, Jan. 1998-Dec. 1998. Employed by the Nutrition Lab at Oklahoma University as a database programmer, May 1998-May 1999. Employed by Department of Computer Science of Oklahoma State University as a Teaching Assistant, August 1999 to December.