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Optimising Data Modeling Approaches for Scalable Data Warehousing Systems

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ABSTRACT

Data warehousing has become a cornerstone of modern decision-support systems, enabling organizations to consolidate, store, and analyze large volumes of data for informed decision-making. With the exponential growth of data and increasing complexity in data sources, traditional approaches to data modeling and warehousing face challenges in scalability, real-time processing, and integration of diverse data types. This paper provides a comprehensive overview of data warehousing, highlighting its key components, traditional and modern approaches, and the evolving challenges in handling big data's volume, variety, and velocity. It emphasizes the importance of data modeling techniques, such as normalization, denormalization, and schema design strategies, to enhance scalability and performance. Furthermore, the paper identifies the critical need for innovative solutions to optimize data modeling for modern data warehouses, ensuring robust, adaptable, and efficient systems capable of supporting advanced analytics in diverse business environments.

Keywords : Data Warehousing, Scalability, Data Modeling, Schema Optimization, Data Partitioning, Hybrid Approaches, ETL.

I. INTRODUCTION

Data Warehousing is a cornerstone of decision-support technologies, enabling knowledge workers such as executives, managers, and analysts to make faster, data-driven decisions. Data warehouses help organizations make better strategic decisions by offering a structured architecture and powerful tools for organizing, understanding, and using data. Unlike operational databases, data warehouses are maintained as separate systems designed specifically for reporting and analysis. These systems consolidate historical data from diverse operational sources, creating a unified platform for information processing and in-depth analysis[1].

Modern data warehousing technologies have evolved to meet the demands of various industries, including manufacturing, retail, financial services, utilities, and healthcare. These systems not only handle structured data but also integrate semi-structured and unstructured data, addressing the challenges posed by the exponential growth in data volumes. Key features such as scalability, real-time data processing, cloud-based architectures, and advanced data visualization have transformed data warehouses into essential tools for business intelligence and analytics[2]. Scalability, in particular, is achieved through horizontal and vertical expansion, enabling data warehouses to accommodate increasing data volumes and support multiple users simultaneously[3].

At the heart of scalable data warehousing lies the optimization of data modeling approaches. Effective data modeling is crucial for ensuring system performance, flexibility, and scalability[4]. It involves designing data structures that comply with the scope of diverse business functions, maintaining ACID (Atomicity, Consistency, Isolation, Durability) properties during data transformation and storage, and defining appropriate levels of data granularity for filtering, aggregation, slicing, and dicing. Contemporary data warehouses emphasize logical modeling to support multiple platforms, improve performance at scale, and provide deployment flexibility[5]. They also focus on data governance, integration with master data management (MDM) systems, tracking data lineage, and processing high-velocity data in both batch and real-time modes.

Despite these advancements, optimizing data modeling approaches remains a critical challenge. With the growing complexity of modern data warehousing systems, there is a need for innovative techniques to enhance logical modeling [6], improve scalability, and ensure seamless integration with diverse data sources and cloud services.

Motivation of the paper

The rapid growth of data and the increasing complexity of modern data warehousing systems have highlighted the critical need for scalable and efficient solutions. Data modeling, a foundational aspect of data warehousing, directly impacts system performance, integration, and analytical capabilities. Traditional approaches often fall short in addressing the demands of real-time processing, cloud-based architectures, and diverse data types. This paper is driven by the need to optimize data modeling techniques to ensure modern data warehouses are robust, adaptable, and capable of supporting high-velocity data environments, enabling organizations to derive actionable insights effectively.

Overview Of Data Warehousing

In order to facilitate analytical reporting and decision-making, data warehousing involves integrating data from several sources into a single repository. It enables organizations to store both current and historical data in a structured manner, optimized for running complex queries and generating insights. By leveraging ETL (Extract, Transform, Load) processes and organized schemas, data warehouses ensure consistency, reliability, and accessibility of data[7]. Over time, data warehousing has evolved to address growing data volumes, diverse data sources, and the need for real-time analytics, making it an essential component of modern business intelligence and decision-making

Definition and key components of a data warehouse

Data that is organized and made available to aid in decision-making is known as a data warehouse. It has the following characteristics: It is not volatile, subject-oriented, integrated, consistent, and evolutionary [8]. A data warehouse, in layman's terms, is a facility that stores data for the purposes of archiving, security, and analysis. It is common practice to connect many computers to form a massive computer system[9]. There could include raw or structured data pertaining to a variety of subjects, such as firm sales, operations, summary, report, HR, inventory, and external data for modeling and analysis, among many others[10].

1) Components of a Data Warehouse

Data Warehouse Database:

The data warehouse infrastructure is based on the central database. The RDBMS technology is used to implement the database. Traditionally, these are standard relational databases running locally or in the cloud[11].

ETL Tools (Extract, Transform, Load)

- Used for sourcing, acquisition, clean-up, and transformation of data into a unified format.
- Functions include:
  - ➢ Eliminating unnecessary data from operational databases.
  - ➢ Standardizing names and definitions for data from various sources.
  - ➢ Populating missing data with defaults and calculating summaries and derived data.
  - ➢ De-duplicating repeated data from multiple sources[12].
- ETL tools generate corn jobs, shell scripts, or other automated processes to regularly update the data warehouse and maintain metadata.

MetaData

Data warehouse creation, management, and maintenance all make use of metadata, which is information about the data that constitutes the data warehouse. Metadata is an integral part of data warehouse design; it describes the data's origin, usage, value, and qualities and specifies how to work with the data[13]. Metadata is mainly classified into two types:

- **Technical Metadata:** Designers and managers of data warehouses rely on this metadata type, which includes details on the warehouse itself.
- **Business Metadata:** Metadata of this kind includes details that make the data warehouse's contents understandable to the end user [14].

Query Tools (Access Tools)

Classify the many ways in which users may engage with the data warehouse:

- Query and Reporting Tools: Includes production reporting tools for operational reports and report writers for simpler tasks.
- Managed Query Tools: Provide a meta-layer to shield users from SQL and database structure complexities.
- Application Development Tools: Used when custom reports are required beyond built-in analytical tools.
- Data Mining Tools: Discover correlations, patterns, and trends by extracting large datasets[15].
- OLAP Tools: Enable analysis through complex multidimensional views.

Data Mart

A records warehouse subset is a records mart. The records may be without delay gathered from the assets in an unbiased records mart. It is designed for commercial enterprises together with income and finance[16][17].

Traditional data warehousing approaches

- **Definition of Data Warehouse (DWH):** Inmon (1997): Management decision-makers may benefit from a DWH's subject-oriented, integrated, non-temporal, time-variant data collecting.
- **Kimball and Ross (2013):** A DWH is the integration of all Data Marts (DMs) in a company as the data contained is stored in the dimensional model[18].

2) Development Approaches:

- Top-Down Approach (Inmon): Then, a centralized DWH integrated construct occurs first.
- Subsidiary Data Marts (DMs) are established at a later date for individual departments[19].

3) Bottom-Up Approach (Kimball):

DMs are built first. The DWH is created by integrating these DMs.

Distinction Between DWH and Data Warehousing:

- **DWH:** Emphasizes on tertiary storage of data that has features such as being subject-oriented, integrated, non-volatile, time-variant data[20].
- **Data Warehousing:** Stresses out on putting into practice procedures, structures, and frameworks for organizing the algorithms, components and data for constructing DWH projects.

4) ETL and Data Extraction:

- The process of copying data in large files from source systems to the DWH environment[21].
- Usually obtained from Transaction Processing Systems such as order entry systems.
- DWH needs to be updated periodically thereby requiring extractions from time to time.

5) Logical Extraction Approaches:

Full Extraction:

- Then extracts all the data accessible in the source system at the time of data extraction.
- There is no need to track changes; it offers up the source data as it is.

Incremental Extraction:

- Takes only the refreshed figures that have occurred after the occurrence of any event at all, including extraction or any fiscal period closure.
- Needs some hand-like application columns (example, Last modified timestamp) or Change tables[22].

6) Physical Extraction Methods:

Online Extraction:

Data is read from the source system or other source system called as master slav or anchor-master-slave system (e.g. snap log table, change table)[23].

Offline Extraction:

Data is extracted and moved to a location disjoint from the source system through structures to its existing or created (flat files, dump files, redo log files, archive log files)[24].

Data Modeling Basics

7) Importance of data modeling in data warehousing

Organizes Data: Data modeling is a method for organizing and logically structuring data in a way that facilitates understanding and management [25].

- **Improves Data Quality:** Improving data quality is possible via data modeling, which helps in spotting and fixing data mistakes and inconsistencies.
- **Ensures Data Integrity:** Constraints and linkages enforced by data modeling safeguard data integrity and forestall data abnormalities [26].
- **Supports Decision Making:** Data models that are well-designed help to shed light on important topics and facilitate well-informed decision-making.
- **Facilitates Database Design:** Database efficiency and optimization are greatly enhanced by data modeling, an essential component of database architecture [27].
- **Reduces Redundancy:** Data modeling helps reduce data duplication by identifying and removing unneeded records.
- **Simplifies Data Retrieval:** Quick and easy data retrieval is made possible by a well-designed data model, which in turn improves system performance.
- **Enhances Application Development:** Data models facilitate the incorporation of data into software solutions by providing a framework for application development.
- **Enables Scalability:** Scalability and future expansion are both facilitated by a solid data model that can absorb more data with little to no impact on current operations [28].

Data Modeling Techniques For Scalability

Normalization vs. Denormalization

8) Normalization

Database normalization involves breaking down huge tables into smaller ones and establishing linkages between them in order to decrease reliance and duplication. The goal is to ensure data integrity and minimize the chances of anomalies during data operations like insertions, deletions, and updates[29].

9) Denormalization:

Denormalization is the process of combining normalized tables in order to achieve fast query response and short response time. It is beneficial for:

- Concerning conceptual questions which include more than one entity[30].
- Reflecting an increased incidence of requests for internet searches that need immediate response.
- One where Absolute Cell References are suitable for calculation-intensive scenarios, in particular across columns.
- Denormalization does improve performance but increases access efficiency at the cost of redundancy[31].

Schema Design Strategies

Overview of schema designs: star schema, snowflake schema, and galaxy schema are discussed below:

10) Star schema

This is the framework of a dimensional model. At its core is a series of dimension tables linked to a fact table. Included in it is: One big table in the middle (the fact table) Each dimension has its own collection of tiny tables that serve as attendants, called a "dimension table" [32].

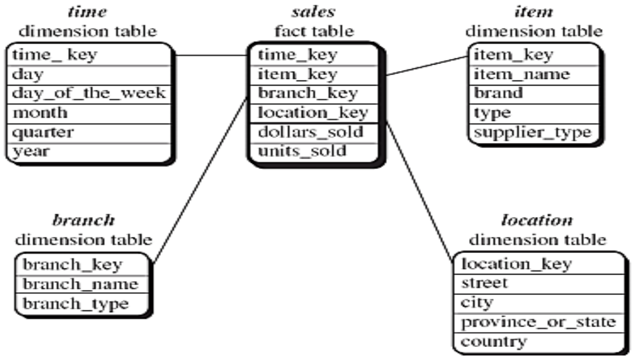

Fig. 1. Star Schema

11) Snowflake schema

Analogous to a snowflake, this schema is an improvement on the star schema that involves additional breaking (normalization) of a dimensional hierarchy into a series of smaller dimension tables.

On the other hand, more joins are required by the snowflake structure, which might make browsing less successful. Although it has certain characteristics with star schema, snowflake schema excels at dealing with enormous dimension tables, setting it apart from star[33]. The focal focus of a star schema is a fact table that links to several dimension tables in a linear fashion. Figure 2 depicts the snowflake schema mentioned below.

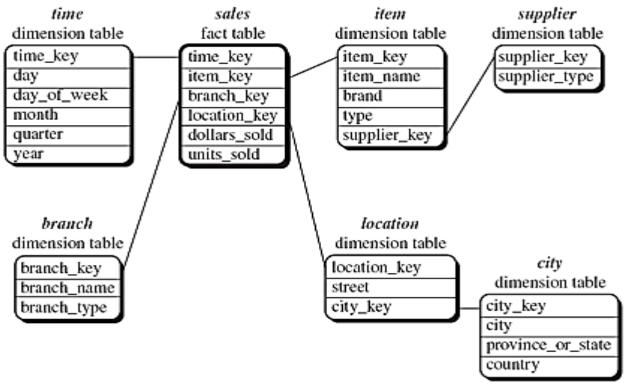

Fig. 2. Snowflake Schema

12) Galaxy schema:

A galaxy schema is one in which the dimension tables of many fact tables are shared. The fact tables inside a galaxy are not required to have any kind of direct relationship, unlike in a fact constellation schema

[34][35]. Figure 3 shows an example of a galactic framework.

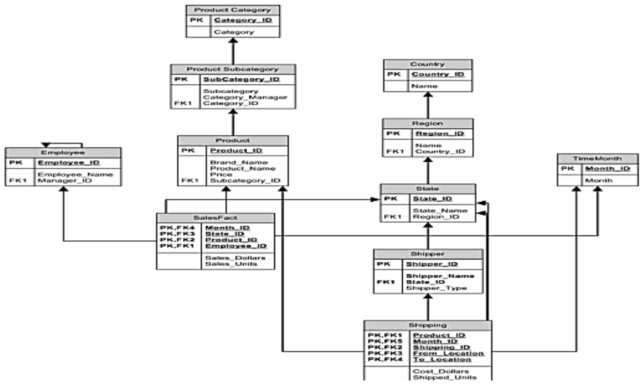

Fig. 3. Galaxy Schema

Indexing and Partitioning

13) Index based techniques

There are a number of indexing techniques that can handle multi-dimensional data sets. The fact that indexing structures can often include both point and geographic data is a major selling advantage when it comes to organizing big data sets; in particular, spatial data structures don't need modification to enhance data storage by means of greater spatial clustering[36]. Consequently, indexing structures like as the R-tree, R*-tree, and X-tree were found to potentially accommodate multi-dimensional data sets without changing the underlying data set [37][38][39].

R-tree

For effective management of geographical data, the R-tree is a dynamic index structure [38]. The operations of searching, adding, removing, dividing nodes, and updating have all been addressed by various algorithms. The algorithms in question are the following: Search, ChooseLeaf, Insert, SplitNode, FindLeaf, CondenseTree, Delete, and AdjustTree. Two critical procedures are invoked to guarantee optimal performance during the index record insert for new data tuples.

R-tree*

For effective support of multi-dimensional points and geographic data simultaneously, a variation of the R-tree called the R*-tree has shown to be very desirable [37]. This structure is fully dynamic, with no need for periodic global reorganization, and it is very resilient to ugly data distributions. Query operations may be coupled with insert and delete actions. Finding, inserting, removing, separating, updating, and forceful reinserting are all tasks for which several algorithms have been developed[40]. Select Subtree, InsertData, Insert, ReInsert, Overflow Treatment, Select SplitAxis, Split, and Select Splitindex are all algorithms that fall under this category. When adding a new entry to the tree, the determine Subtree method—which is identical to the Choose Leaf algorithm in the R-tree—is used to determine the best insertion route [41].

X-tree

For indexing and facilitating query processing of massive volumes of point and geographical data in high-dimensional environments, the X-tree (eXtended node tree) is suggested. It is a combination of a hierarchical R-tree directory and a linear array-like structure [38]. The X-tree, similar to the R*-tree, uses ReInsert and Choose Subtree algorithms in addition to Insertion and Split. To prevent splits that might result in overlap, the Insertion algorithm is the most crucial algorithm[42].

14) Partition-based techniques

Horizontal Partitioning

Divides dataset rows into disjoint subsets, where each subset contains the same columns as the full dataset. Techniques include:

- Range Partitioning: Segments data based on value ranges, ideal for range queries.
- Hash Partitioning: Uses hash functions to distribute data evenly, suitable for point queries.

- Random Partitioning: Distributes data randomly, ensuring balanced partitions but without maintaining order[43].
- Round-Robin Partitioning: Assigns records sequentially to partitions, ensuring balanced distribution but complicating range queries[44].

Vertical Partitioning

Divides columns into subsets based on usage patterns, with key columns shared across subsets. Techniques include:

- **Optimal Partitioning:** Minimizes redundancy under restrictive assumptions.
- **Heuristic Partitioning:** Practical methods used in real-world applications, based on column access patterns[45].

Hybrid Partitioning

Combines horizontal and vertical partitioning, dividing data by both rows and columns. This is often referred to as functional partitioning, used to optimize performance for specific queries or applications, such as separating transactional and reference data[46][47].

Partitioning on Hadoop Clusters

Techniques designed for distributed data systems like Hadoop:

- **Sequential Partitioning:** Divides data into fixed-size blocks, commonly used in Hadoop Distributed File System (HDFS)[48].
- **Random Sample Partitioning (RSP):** Creates random samples of the dataset, preserving statistical properties and reducing bias during analysis.

Key Challenges In Scalable Data Warehousing

Scalable data warehousing involves designing systems capable of handling increasing data volumes, velocity, and complexity while maintaining performance and reliability. However, achieving scalability presents several challenges:

Volume Growth

Challenge:

Exponential growth in data volume leads to longer query times and slower report generation.

Solutions:

- Use data partitioning to break large tables into smaller pieces for better query performance[49].
- Archive infrequently accessed data to keep the warehouse lean.
- Leverage cloud-based data warehouses for elastic scalability and data lake architectures for flexibility in storing raw data[50].

Complex Queries

Challenge:

Large datasets and intricate calculations strain resources and degrade performance.

Solutions:

- Optimize SQL queries and create indexes for faster data retrieval.
- Use materialized views to precompute joins and aggregations[51].
- Adopt parallel processing frameworks like Apache Spark or Databricks.
- Implement query caching and acceleration platforms for frequently accessed data[52].

Concurrency Issues

Challenge:

Simultaneous access by multiple users or applications can lead to bottlenecks.

Solutions:

- Scale horizontally by adding nodes or clusters. Use load balancing techniques to distribute query loads efficiently[53].
- Optimize data warehouse structures for better resource utilization.

Hardware Limitations

Challenge:

Physical infrastructure often cannot keep up with increasing demand.

Solutions:

- Upgrade hardware (memory, CPUs, storage) as a temporary fix.
- Transition to cloud-based solutions that offer automatic scaling and reduce infrastructure management complexities.

Data Integration

Challenge:

Increasing the number of data sources complicates integration processes.

Solutions:

- Automate data ingestion with scalable ETL/ELT tools.
- Use schema-on-read approaches for flexibility in querying diverse data sources.
- Partition and index data for faster integration and processing.

Cost Management

Challenge:

Scaling introduces financial challenges, including rising storage and computational costs.

Solutions:

- Implement cost audits and regular optimizations
- Use storage tiering to move infrequently accessed
- data to cheaper storage.
- Tune query performance to reduce unnecessary computational expenses[54][55].

Literature Review

This section presents a literature review on Energy-Efficient Open Radio Access Networks (ORAN) Ecosystems for Enabling Sustainable 5G Networks. A summary of the reviewed studies is provided in Table I for a comprehensive overview.

Feng (2021) conducted an analysis on the fundamental framework and analytical models of privacy data management in light of the advent of big data analytics. The shortcomings of existing models, issues with faulty management mechanisms, and the growing danger of information leakage are all examined. The privacy data management issues constitute the basis for the suggested optimized schemes, which aim to improve privacy data management methods, construct safe data platforms, and optimize the structure of data usage[56].

Banerjee and Davis (2009), provide a formal framework for data warehouse schema representation and schema evolution operator validity determination. They detail a program that, with the use of stored procedures and triggers, can show the effects of schema development. There have been models for data warehouse schema conceptual design, but academics have seldom taken a formal approach to schema evolution, and even fewer have offered software tools to ensure that operators for multidimensional schema development are valid[57].

Khan et al. (2022), give a one-size-fits-all solution for integrating StaaS with data pipelines, meaning computation on an on-premise server or a specific cloud, but integration with SaaS, and creation a ranking system for storage options using five important criteria: cost, proximity, network performance, the effect of server-side encryption, and user weights. The results show that the suggested method works well for data transfer performance and that it is possible to dynamically choose a storage solution depending on four main user situations[58].

Du, He and Huang (2021), solve the clustering issues with large datasets. The three main steps of the RSP-CE method are as follows: first, using RSP data blocks to generate base clustering results; second, aligning these results with the maximum mean discrepancy

(MMD) criteria; and finally, improving the RSP clustering results. With RSP data blocks, you may get a good idea of how to cluster distinct subsets of data to fit the total large data since the sample distributions are consistent throughout all of the data[59].

Ali (2018) offers a framework for handling and analyzing very big and complicated datasets with ease. The framework has the potential to be very useful for the communication business, which is required by regulators to keep detailed call records for its customers. Each subscriber activity results in a packet with over 500 characteristics. When service providers analyze transactional data, they get a better understanding of their customer's behavior. For instance, in order to explain subscribers' data consumption behavior, deep packet inspection uses transactional internet usage data[60].

TABLE I. PRESENTS THE SUMMARY OF LITERATURE REVIEW BASED ON DATA MODELING APPROACHES FOR SCALABLE DATA WAREHOUSING SYSTEMS

References	Focus On	Key Findings	Challenges	Limitations	Future Work
[56]	Privacy data management and big data analysis.	Identified issues like imperfect management mechanisms, information disclosure risks, and deficiencies in current models.	Increasing risks of information disclosure and deficiencies in privacy management mechanisms.	Limited to theoretical optimization schemes without real-world implementation validation.	Proposes optimizing privacy management mechanisms, building secure platforms, and improving data use structures.
[57]	Schema evolution in data warehouses.	Formalism for schema evolution validation and a software tool for visualizing schema evolution impacts.	Addressing the correctness of multidimensional schema evolution operators.	Limited focus on schema evolution without broader applicability to all data warehouse processes.	Further development of tools to enforce correctness and enhance visualization of schema evolution.
[58]	Integration of StaaS with data pipelines.	Developed a ranking method for storage options based on cost, proximity, network performance, and encryption impact.	Balancing cost-effectiveness with performance and security.	Evaluation scenarios are limited to specific use cases and parameters.	Expanding the ranking method for additional parameters and scenarios, integrating with broader cloud services.
[59]	Big data clustering using	Harmonized clustering results	Handling large-scale data	Limited to RSP data blocks,	Extending the algorithm for

	RSP-CE algorithm.	using MMD criterion, refining results for consistent sample distributions.	clustering with consistent results.	which may not generalize to all big data scenarios.	broader data distributions and refining clustering techniques further.
[60]	Framework for managing and analyzing large, complex datasets in the communication industry.	Framework effectively analyses transactional data for customer behavior insights.	Managing massive datasets with regulatory constraints and ensuring data accuracy.	Framework is specific to the communication industry and lacks cross-industry applicability.	Expanding the framework for cross-industry applications and improving scalability for even larger datasets.

Conclusion And Future Work

Data warehousing has become a cornerstone for organizations seeking to leverage data-driven decision-making by integrating, storing, and analyzing vast amounts of structured and unstructured data. This study reviewed the evolution of data warehousing systems, focusing on modern methodologies, schema design techniques, and performance optimization strategies. While these advancements have significantly improved efficiency and scalability, challenges such as real-time data processing, handling unstructured data, and ensuring data security and governance remain critical areas of concern.

Future research should delve into the integration of AI and ML techniques to improve data modeling, query optimization, and real-time analytics in data warehousing systems. Additionally, exploring hybrid architectures that combine cloud and on-premises solutions can address scalability and adaptability challenges. Addressing data governance and security in increasingly complex environments will also be essential for the next generation of data warehousing solutions.

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