Lappeenranta University of Technology

School of Business and Management

Degree Program in Computer Science

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EVALUATING A MODERN IN-MEMORY COLUMNAR DATA MANAGEMENT SYSTEM WITH A CONTEMPORARY OLTP WORKLOAD

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ABSTRACT

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Evaluating a modern in-memory columnar data management system with a contemporary OLTP workload

Master's Thesis

93 pages, 34 figures, 7 tables

Examiner: Professor Ajantha Dahanayake

Keywords: Column-oriented DBMS, column store, HTAP, IMDB, performance, SAP HANA, SQLScript, TPC-E, workload breakdown

Due to the considerable differences between transactional and analytical workloads, a "one size does not fit all" paradigm is typically applied to isolate transactional and analytical data into separate database management systems. Even though the separation has its advantages, it compromises real-time analytics. To blur boundaries between analytical and transactional data management systems, hybrid transactional/analytical processing (HTAP) systems are turned into reality. HTAP systems mostly rely on in-memory computation to present profound performance. Also, columnar data layout has become popular specifically for analytical use-cases.

In this thesis, a quantitative empirical research is conducted with the goal of evaluating the performance of an HTAP system with a transactional workload. HANA (High-Performance Analytic Appliance), an in-memory HTAP system, is used as the underlying data management system for the research; HANA comes with two data stores: a columnar and a row data store. Firstly, the performance of HANA’s columnar store is compared with the row store. To generate the required workload, an industry-grade transactional benchmark (TPC-E) is implemented. Secondly, a profiling tool is employed to analyze primary cost drivers of the HTAP system while running the benchmark. Finally, it is investigated how optimal an HTAP-oriented stored procedure language (SQLScript) is for the transactional workload. To investigate this matter, several transactions are designed on top of TPC-E schema; the transactions then are implemented with and without using SQLScript iterative constructs. The transactions are studied regarding the response time and growth rate.

The experiment shows that the row data store achieves 26% higher throughput compared to its counterpart for the transactional workload. Furthermore, the profiling results demonstrate that the transactional workload mainly breaks down into eight components of HANA including query compilation and validation, data store access and predicate evaluation, index access and join processing, memory management, sorting operation, data manipulation language (DML) operations, network transfer and communication, and SQLScript execution. Lastly, the experiment reveals that the native SQL set-based operations outperform the iterative paradigm offered by SQLScript.

ACKNOWLEDGEMENTS

First of all, I am deeply grateful toward my supervisors. I would like to show my greatest appreciation to Prof. Ajantha Dahanayake for the invaluable guidance and advice she provided me. I also cannot find the words to express my gratitude enough for Dr. Alexander Böhm; I believe I have been fortunate to have such a patient, knowledgeable, and supportive supervisor who extremely cared about my work.

I also want to thank all members of HANA performance team at SAP for their wonderful help and collaboration. I owe many thanks to Mr. Lars Hoemke, Mr. Joachim Puhr, and Mr. Hassan Hatefi.

Last but not the least, I would like to dedicate this thesis to my exceptional father Ahmad, caring mother Ashraf, and beloved sister Yalda for their endless love, support, and encouragement throughout my life. I love them with all my heart.

TABLE OF CONTENTS

LIST OF SYMBOLS AND ABBREVIATIONS

ACID	Atomicity, Consistency, Isolation, Durability
BI	Business Intelligence
BCNF	Boyce-Codd Normal Form
CE	Customer Emulator
CPU	Central Processing Unit
DB	Database
DBMS	Database Management System
DM	Data Maintenance
DML	Data Manipulation Language
DRAM	Dynamic RAM
DRDB	Disk-resident Database
DW	Data Warehouse
DWH	Data Warehouse
ETL	Extract, Transform, Load
ER	Entity Relationship
ERP	Enterprise Resource Planning
GB	Gigabyte
HANA	High-Performance Analytic Appliance
HTAP	Hybrid Analytical/Transactional Processing
IMDB	In-memory Database
ITD	Initial Trade Days
KB	Kilobyte
MEE	Market Exchange Emulator
MMDB	Main-memory Database
MOLAP	Multidimensional Online Analytical Processing
MVCC	Multi-Version Concurrency Control
ODBC	Open Database Connectivity
OLAP	Online Analytical Processing
OLTP	Online Transactional Processing
OS	Operating System

NUMA	Non-Uniform Memory Access
NVRAM	Non-volatile RAM
PP	Production Planning
PL/SQL	Procedural Language/Structured Query Language
QPI	Quick Path Interconnect
RAM	Random Access Memory
RLE	Run Length Encoding
ROLAP	Relational Online Analytical Processing
SD	Sales and Distribution
SF	Scale Factor
SIMD	Single Instruction/Multiple Data
SMP	Symmetric Multiprocessing
SQL	Structured Query Language
SRAM	Static RAM
SUT	System Under Test
T-SQL	Transact-Structured Query Language
TB	Terabyte
TCO	Total Cost of Ownership
TPC	Transaction Processing Performance Council
TSX	Transactional Synchronization Extensions
VM	Virtual Memory

1 INTRODUCTION

1.1 Problem Description

Nowadays data is at the heart of organizations; in fact, data is crucial for businesses not only to operate their businesses but also to make sound decisions in a competitive market. Consequently, regardless of their sizes and business domains companies are exploiting database management systems (DBMSs) as the backbone to store and manage their data. Data-intensive applications can be classified into two broad categories: online transactional processing (OLTP) and online analytical processing (OLAP), and each one exhibit specific characteristics and requirements [1]. In OLTP systems, such as enterprise resource planning (ERP), DBMSs have to cope with a massive number of concurrent, short-lived transactions, which are usually simple (e.g., displaying a sale order for a single customer) while demanding milli-seconds response times. On the other hand, OLAP workloads are characterized by comparatively low volumes of yet complex and long-running queries.

Due to substantial differences between OLTP and OLAP workloads, different optimizations are applied in database management systems. To put it another way, the architecture of some database systems has been highly optimized for transaction processing like Microsoft SQL Server Hekaton [2] and H-Store [3] ; that of the others has been calibrated in conformity with analytical workload requirements (i.e., data warehouses) such as MonetDB [4] and HP Vertica [5]. Besides the optimizations, the data management systems have utilized disparate data layouts for OLTP and OLAP data. For instance, analytical data are traditionally consolidated into multi-dimensional data models such as star and snowflake, whereas the transactional data is mostly modeled using highly normalized relations [6]. One approach to serving the different requirements is separating the systems and running extract, transform, load (ETL) process to load operational data from OLTP systems to the OLAP ones. The periodical ETL process brings about four significant disadvantages [7]. Firstly, the ETL process is time-consuming and of high complexity. Secondly, the process compromises real-time analytics by relying on historical data. Also, acquiring two separate solutions increases the total cost of ownership (TCO). Last but not the least, keeping data inside two distinct systems leads to data redundancy.

In a conventional relational DBMS, data is stored in a row-wise manner meaning that records are stored sequentially. Copeland and Khoshafian [8] introduced an alternative approach to store the relations in the 1980s; the proposed data storage named columnar (also called column-oriented), keeps relations by columns as opposed to rows of data. Advantages of the columnar storage are fourfold compared to the row-oriented layout [9]. To start with, uniformity of the data stored as columns will pave the way for far better compression rates and space efficiency. Secondly, the columnar storage architecture enables extensive data parallelism. Moreover, it provides better performance for aggregations; aggregation is an essential operation for analytical queries. Finally, fewer data should be scanned in the columnar storage if queries access a few attributes. Recently, using columnar databases is a prominent approach for analytics gradually replacing the multi-dimensional data models [7]. However, it is lively discussed that the storage does not meet OLTP requirements due to two main reasons [10, 11]:

- OLTP queries mostly operate upon more than one relation field. Thus, accessing multiple fields is more scan-friendly in the row-oriented approach.
- Maintaining columnar storage in an update-intensive environment is expensive.

Besides the popularity of the columnar storage, in-memory database systems (IMDBs, also called main-memory database systems or MMDBs) are becoming more widespread. In the past decade, we have experienced a plummeting cost of dynamic ram (DRAM) modules and an ever-growing DRAMs' capacities Hence, in-memory database systems have turned into reality. The in-memory data management systems eliminate disk latencies and operate upon the data loaded into main memory. The systems present profound performance improvements as well as a foundation to satisfy new business requirements. [6]

To blur boundaries between analytical and transactional data management systems, some disruptive approaches have been taken toward building a single data management system capable of processing a mixture of both analytical and transactional workloads. The systems are so-called hybrid transactional/analytical processing (HTAP). Presently, a number of HTAP systems are available in the market including SAP HANA [12], HyPer [13], and VoltDB [14]. For instance, SAP (a multinational software company headquartered in Germany) has embraced the advantages of the columnar storage plus the strengths of in-memory data management into a single solution, HANA (HANA stands for High-Performance Analytics Appliance). SAP HANA, an in-memory DBMS initially designed for purely analytical workloads, has evolved to a system which supports mixed workloads on a columnar representation; the system can serve enormous enterprise resource planning (ERP) installations with 5 million queries per hour and more than 50K concurrent users [12].

1.2 Research Questions

There is no consensus on the efficiency of having a single data management system which can serve both analytical and transactional workloads. On the one hand, the approach has been overtly questioned by several studies [11, 10]. For instance, M. Stonebraker and U. Çetintemel [11] have argued that the hybrid approach is a marketing fiction. On the other hand, some HTAP systems such as SAP HANA are widely used as explained in the previous section. In fact, HANA has been designed to combine OLAP and OLTP workloads and the underlying data set based on columnar representation [9].

This study aims to answer the following research questions using SAP HANA as the underlying system.

- RQ1) How does an in-memory columnar HTAP perform with OLTP workload?
- RQ2) How does OLTP workloads breakdown into major components of an HTAP system?
- RQ3) How optimal an HTAP-oriented stored procedure language like HANA SQLScript is (see section 2.4.4) for OLTP workloads?

1.3 Research Methodology

This research consists of two central actions: a systematic literature study and a quantitative empirical research. The literature study covers:

- In-memory databases
- HTAP systems
- OLTP benchmarks
- SAP HANA.

The empirical study demands two major requirements.

1. An enterprise HTAP system supporting both row and columnar stores: SAP HANA is the data management system used in the thesis.
2. Implementing an industry-grade OLTP benchmark: TPC-E benchmark, an OLTP benchmark published by Transaction Processing Performance Council (TPC), is used for in the thesis. The benchmark is open source; it is designed to represent requirements of a contemporary OLTP system, and widely recognized by the database community.

After the implementation of the benchmark, it is run against both the data-storages to understand to what extent they differ regarding throughput. Then, profiling tools are used to understand how the OLTP workload decomposes into different components in SAP HANA. Finally, the study drills down into the mechanics of SQLScript language to analyze its efficiency for OLTP workloads.

1.4 Structure of the thesis

This subsection contains a short description of the structure of this thesis. The thesis is divided into six chapters. Chapter 2 of the thesis incorporate the literature study. Section 2.1 explores in-memory databases. The purpose of this section is to understand what are enablers, inner mechanics, and challenges with in-memory databases. Then, HTAP systems are investigated in section 2.2. The section 2.2 aims first to understand the main requirements of OLTP and OLAP systems. It is then explained how columnar and row-oriented databases correspond to the requirements. The section 2.2.5 finally wraps how a hybrid system can break the gap between transactional and analytical processing.

Afterwards, OLTP benchmarks are studied in section 2.3. A proprietary and an open-source benchmark have been reviewed in this chapter. The chapter presents how the benchmarks portray activities of OLTP systems.

Section 2.4 studies SAP HANA to understand how an HTAP system is designed. Understanding internal mechanisms of HANA then aids analyzing the experiment results.

An overview of SQLScript, a stored procedure language provided by SAP, is also provided since in the experiment transactions are implemented using the scripting language.

The TPC-E benchmark is inspected in section 2.5. The study helps the implementation and the analyzing stages. It also depicts how OLTP requirements have changed over the course of time by comparing the benchmark with its predecessor (i.e., TPC-C).

Chapter 3 explains the implementation of the benchmark used for the experiment. Technologies and the architectural designs applied to the implementation are also discussed in the section.

Finally, Chapters 4 and 5 demonstrate the results of the experiment and the main findings. The chapters also point out the limitations of the current work and the opportunities for future research.

2 RELATED WORK

2.1 Database Management System

A database (DB) is a set of data being organized in a meaningful way and accessible in different logical orders [15]. Furthermore, a database management system is a combination of a DB and a management system (MS). The primary objective of the management system is to aid data store and retrieval with efficiency and convenience [1]. DBMS can be regarded as an intermediary between entities who desire accessing a database (i.e., applications or end-users), and the actual physical data.

Database systems have been widely used over the course of the last five decades in multitudes of different applications including enterprise information systems, banking, education, telecommunication, and many more. Before database management systems are introduced, organizations mostly stored their organizational information in so-called flat files. Leveraging the database management systems is advantageous in several aspects compared to the file-processing systems. To begin with, the central data management system circumvents problems related to data redundancy and inconsistency. Moreover, the DBMS offers data independence by applying different levels of abstraction. What's more, using systems ensures ACID (Atomicity, Consistency, Isolation, and Durability) properties in transaction level. Finally, the systems enable data security by applying access control constraints. [1]

Databases utilize a collection of conceptual tools for describing data, relationships among them, data semantics, and consistency constraints. The collection is called data model and is the underlying structure of a database. The data models can be classified into several different categories such as relational and object-based as well as some semi-structured and unstructured data models. Among the data models, the relational is the most widely used. The relational model takes advantage of a collection of tables to represent data and the relationships between the data. The tables in the model are known as relations, and each relation consists of multiple columns with unique names. IBM developed the first experimental prototype for a relational DBMS as "System R" in the late 1970s. The focus of this paper is on Relational DBMS (RDBMS) which is referred as DBMS for the sake of consistency. [1]

2.1.1 Memory Hierarchy

As can be seen in Figure 1, a memory system is a hierarchy of storage devices. Each device has different costs, capacities, and access times. There is one specific characteristic in the hierarchy: the higher in the pyramid, the higher performance will be achieved. It is worth mentioning that the higher performance compromises the costs. [7]

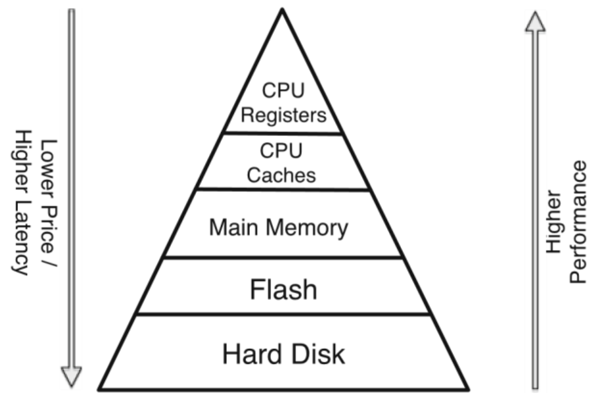


Figure 1 Conceptual view of memory hierarchy [7]

The CPU caches are made from static ram (SRAM) cells which provide data remanence as long as power supplied and are usually built out of four to six transistors [7]. In contrast, main memory is typically built of dynamic ram (DRAM) cells that are constructed using much simpler structure (i.e., a transistor and a capacitor). The more straightforward structure of DRAM cells makes it more economical compared to SRAM. However, the capacitor discharges over time; hence, DRAM chips should be refreshed periodically [16]. The charging and discharging of the capacitor limits the speed of DRAM cells. The hard disk is at the very bottom of the view. Even though hard disks offer massive capacities at economical prices, they are attributed to high access and read times.

Latency is a measurement to grasp how different storage media act in terms of performance. The latency is the time delay to load the data from the storage device until it is available in one of CPU registers [6]. While an L1 CPU cache reference (modern processors have multiple levels of cache including L1, L2, and L3) takes 0.5 ns, accessing the main memory reference takes 100 ns and a simple disk access takes 10 ms [7]. In the next section, it is explained how the significant difference in latency between the hard disk and main memory has led to building a new generation of database management systems.

2.1.2 Evolution Toward In-Memory Databases

Enterprise applications today demand more stringent throughput and response time requirements than ever before. Also, companies have become more data-driven and require to process ever-growing enormous data volumes to support their management decisions. Consequently, it is a must that data management systems meet the imposed requirements and constraints. Conventional disk-resident database systems (DRDBs) use disks as the primary storage and bring data into main memory as needed. This frequent disk access introduces a main bottleneck for the systems since disk input/output (I/O) could cause orders of magnitudes higher latency compared to main memory [6].

To address the disk I/O bottleneck, in-memory database systems (IMDBs, also called main memory database systems or MMDBs) are adapted as a new breed of database management systems. The database systems place data inside main memory and operate upon the data kept in the memory. The approach not only provides a profound performance improvement but also presents a foundation to satisfy new business requirements. Figure 2 depicts the advantage of using an in-memory database engine for a single primary key fetch and single row update based on the primary key in solidDB, an in-memory solution offered by IBM. In IMDBs, the role of disks could be left as persistent storage [6, 17].

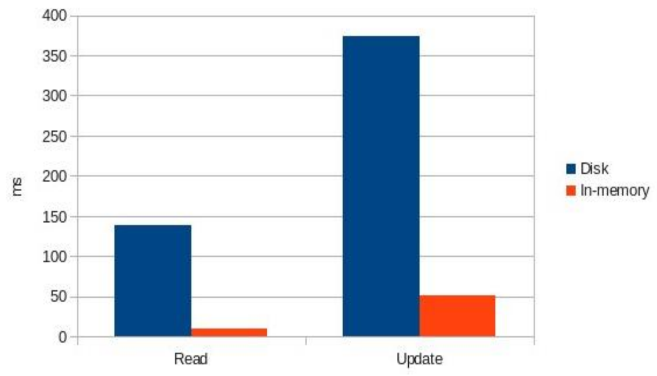


Figure 2 Advantage of using in-memory data management for a single fetch and a single row update [18]

To alleviate the disk I/O barrier, disk-resident database systems have extensively applied caching mechanisms to keep frequently accessed data in main memory. According to [17, 19], there are three primary differences between an IMDB and a DRDB with a huge cache. First, a DRDB still needs a buffer pool manager even when the data being accessed is already cached in main memory; accessing data through a buffer manager brings about overhead. A study by Lehman et al. [19] suggests that using the buffer manager increases execution times up to 40% even the database is cached in memory. Secondly, the related techniques developed for DRDBs are optimized under the assumption of disk I/O as the main cost of the system [20]. On the other hand, in designing and optimizing in-memory database systems achieving high performance on memory-bound data is of concern. Thirdly, using a main memory cache strategy still requires a buffer manager to compute the corresponding disk address of each requested tuple and check the existence of the computed address data in main memory while in IMDB data are accessed directly by referring to their memory address [17]. In other words, logical addressing will be replaced by memory-based addressing.

2.1.3 Key Enablers of In-Memory databases

IMDB is not a brand-new notion and has been studied as early as the 1980s [17, 21]; however, there are two dominant reasons that a wide range of IMDB solutions have turned into reality. The reasons are studied in the two next subsections.

2.1.3.1 Main Memory Cost Development

The past decade has witnessed a plummeting cost of main memory by a factor of 10 every five years; in addition, the main memory storage capacity and bandwidth have been developed strikingly [6]. Figure 3 demonstrates an overview of the decreasing price trend of main memory, flash drives, and disk drives over the course of time. At the time, systems with terabytes of memory are becoming common. Considering the increasing main memory densities, it can be believed that many applications' data can fit into main memory. Hence, the main memory developments might be considered as one of the major reasons that a range of IMDBs are offered by a variety of vendors. At present, an array of both proprietary and open source in-memory database systems are offered such as SAP HANA [22], Oracle TimesTen [23], Microsoft SQL Server Hekaton [2], IBM solidDB [18], VoltDB [14], HyPer [13] and so on.

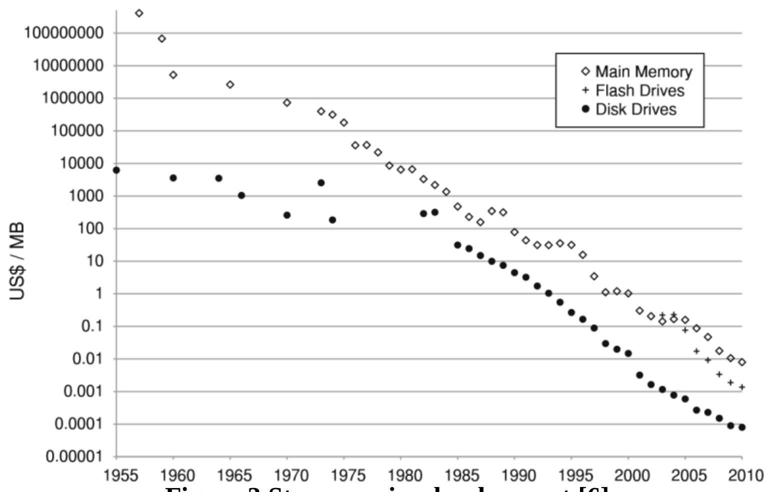
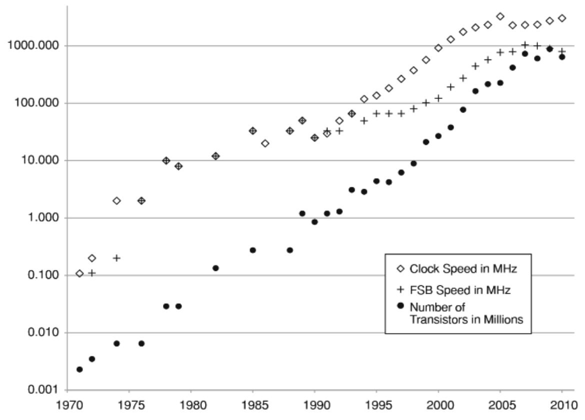
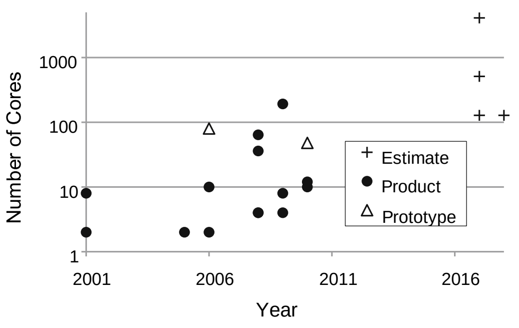


Figure 3 Storage price development [6]

2.1.3.2 Shift Toward Multi-Core Paradigm

Besides the availability of main memory as discussed, there is another trend in hardware realm which has been converged toward the in-memory revolution. This trend is the advent of multi-core central processing units (CPUs) [6]. In the past, single-core processors led the home and business computer domains and increasing clock speed was the dominant paradigm in CPU development. Since 2001, a paradigm shift from the increasing clock rate to increasing number of cores per CPU has taken place [24]. The transformation is illustrated in Figure 4 (b). The multi-core paradigm can pave the way for a massive parallelism in IMDBs which is not achievable in DRDBs since disk access latency could skew the processing time among parallelized steps. By harnessing the multi-core computation power, in-memory database systems are able to process more and more data per time interval and achieve excellent levels of performance and scalability.





(a) (b)

Figure 4 (a) Clock speed, FSB speed, and transistor development, (b) Development of number of cores. [1]

2.1.3.3 Impact of memory resident data

As explained in Section 2.1.2, IMDBs provide a profound implication on performance comparing to DRDBs. However, such an excellent performance cannot be gained merely by placing data in the memory. Indeed, it demands specific optimizations to maximize the performance. In this section, the critical issues and optimizations required while building a main-memory database system are briefly introduced. The challenges and choices are discussed based on the following concepts.

1. **Data storage:** Unlike the disk-resident DBMSs in which on-disk formats constrain data layout, in-memory database management systems are more flexible in leveraging formats that could gain better performance and design goals [17]. To illustrate, clustering records per a primary key index is often used for storing data in the disk-resident systems [25]. However, in main memory databases, sets of pointers to data values could represent relational tuples [17]. As it is discussed in [17], taking advantage of the pointer following sequences for the data representation is twofold. First, in cases there are variables appeared multiple times in the database, pointers could refer to a single stored value and save space [26, 27]. Secondly, it streamlines handing variable-length fields because the fields are represented as a pointer into a heap [28, 29].
2. **Buffer Management:** DRDBs traditionally exploit buffer managers to hide disk access latency. Upon receiving a block access, the buffer manager seeks inside an array of page objects (called buffer pool) and returns the corresponding main memory address providing that the block is found in the buffer pool. Otherwise, it reads the block from disk into the buffer pool. The buffer manager should use a replacement strategy like Least Recently Used (LRU) in cases that the pool is full. In addition, using the buffer manager requires synchronization techniques to synchronize data between disk and the buffer pool. Even though the buffering could provide a performance gain, it has some expenses like calculating the addresses and high paging overheads. On the other hand, IMDBs are free from the buffer management overheads since all operating data is kept inside main memory. [19]
3. **Indexing structure:** It has been discussed that traditional data structures like balanced binary search trees are not efficient for main memory databases running on

a modern hardware [30, 17, 31]. Firstly, the traditional data structures do not optimally exploit on-CPU caches (are not cache-efficient) [30]. Secondly, main memory trees do not require short bushy structures because traversing deeper trees is much faster in main memory comparing to disk [17]. Hence, several new indexing structures have been designed and proposed for use in main memory like Bw-Tree [32], T-Tree [31] and ART [30]. According to [25], multi-core scalability and NUMA-awareness (NUMA stands for Non-Uniform Memory Access) are also of high importance in designing indexing methods since indexing structures could provide a foundation for parallelism.

4. **Concurrency control:** It is argued that in an IMDB, lock contention may not be as significant as in a DRDB since transactions are likely to be completed more quickly and locks will not be held as long [17]. Hence, choosing small locking granules such as fields or records might not be effective in reducing lock contentions; it is suggested that large lock granules (e.g., relations) are more efficient for memory resident data [28]. It is also proposed that the objects in memory can contain lock information to represent their lock status instead of using hash tables containing entries for the locked objects [17]. Besides the mentioned concurrency control optimizations, most modern systems are shifting from pessimistic two-phase locking mechanism to the optimistic ones that ideally never block readers while still supporting high ANSI isolation levels like serializability [25]. Also, using latch-free data structures is another approach that has been adapted for achieving high levels of concurrency [2].
5. **Query processing and compilation:** Most conventional database systems translate a given query into algebraic expressions. The iterator (also called Volcano-style processing) is a traditional method for executing the algebraic expressions and producing query results; each plan operator yields tuple streams that are iterable by using the **next** function of the operator [33]. While the iterator model is acceptable in disk-resident database systems, it shows poor performance on in-memory database systems due to frequent instruction mispredictions and lack of locality [34]. The issues have led several modern main memory systems to depart from the algebraic operator model to query compilation strategies which compile queries and stored procedures into machine codes [34].

6. **Clustering and distribution:** There are two dominant architectural choices in handling the intensifying workloads and volumes of data in IMDBs: vertical scaling and horizontal scaling [25]. Scale-up (i.e., vertical scaling) is the capability of handling the growing workloads by adding resources into a given machine while in scale-out (i.e., horizontal scaling) the increasing workload would be dealt with by adding new machines to the system [6]. Systems like H-Store/VoltDB are built from the square one to scale-out by running on a cluster of shared-nothing machines [25]. On the other hand, systems like Hekaton are initially built to be deployed using a shared-everything architecture and scale up to larger multi-socket machines with massive amounts of resources [25]. Shared-everything within a database node is any deployment in which a single database node manages all available resources whereas, in shared-nothing deployment, several independent instances process the workload [35]. There are also some systems such as SAP HANA which leverage both approaches to enable scalability according to the requirements [36].
7. **Durability and recovery:** IMDBs require having a persistent copy and a log of transaction activities to protect against crashes and power loss [17]. The log should be kept in a non-volatile storage, and each transaction's activities must be recorded in the log [37]. Logging can affect response times and throughput and threatens to undermine the achieved performance advantages of memory resident data since each transaction demands a disk operation. To mitigate the problem, several solutions have been proposed [21, 38, 39, 29]. The first proposed solution is using a stable main memory for keeping a portion of the log. In this approach, each transaction commits by writing its log information in the stable memory, and a special process is required to replicate the log information to the log disks. The approach will alleviate the response times, yet the log bottleneck will not be remedied. The second proposed solution includes using the notion of pre-committed transactions. In this scheme, the transaction management system places a commit record into the log buffer whenever a transaction is ready to complete. The transaction does not wait for the commit record to be propagated to disk. The solution might reduce the blocking delays of other concurrent transactions. Finally, group commits have been introduced to amortize the cost of the log bottleneck. In the group committing, records of multiple transaction logs can be accumulated in the memory before being flushed to

disk. The group committing will improve application response times and transaction throughput. It is worth mentioning that many modern main-memory systems have employed new durability methods since the row-oriented log-ahead mechanisms bring about performance overheads [25]. For example, a study has shown 1.5X higher throughput by applying a command-logging technique which only records executed transactions [40]. The technique facilitates the recovery by replaying the logged commands on a consistent checkpoint.

2.1.4 Memory Wall

As explained in Section 2.1.2, the increasing availability of main memory and the paradigm shift toward many-core processors are the two major trends which can profoundly affect in-memory data management systems. The proliferations give rise to new possibilities yet new challenges. Processor caches are connected to main memory through a front side bus (FSB). In the past decades, advances in processing speed have outpaced advances in main memory latency [41]. Thus, CPU stalls while loading data from main memory to CPU cache has become a new bottleneck. The widening gap between the processing speed and the main memory access is widely known as the ”memory wall” [41]. In the following subsections, we study different mechanisms to hide the memory wall.

2.1.4.1 NUMA ARCHITECTURE

To take advantage of the increasing process capacity, FSB performance should keep up with the exponential growth of the processing power. Unfortunately, during the past decade, FSB performance has not been developed conforming with processing power as shown in Figure 4(a). In traditional symmetric multiprocessing (SMP) architecture, all processors are connected to the main memory via a single bus. Consequently, bus contention and maintaining cache coherency will intensify the situation. To partially circumvent this problem, non-uniform memory architectures (NUMA) have become the de-facto architecture of new generation of enterprise servers. NUMA is a new trend in hardware toward breaking a single system bus into multiple busses, each serving a group of processors. [6]

In the NUMA architecture, processors are grouped by their physical locations into NUMA nodes (i.e., clusters), and each node has access to its local memory module. Even though the nodes can access to memory associated with other nodes (called foreign memory or remote memory), accessing the local memory is faster. Figure 5 demonstrates an overview of memory architecture on Nehalem, a NUMA compatible processor produced by Intel. As shown in the figure, quick path interconnect (QPI) coordinates access to remote memory. To fully utilize the potentials of NUMA, applications should be implemented in a way to primarily load data from the local associated memory and avoid remote memory access latencies [7].

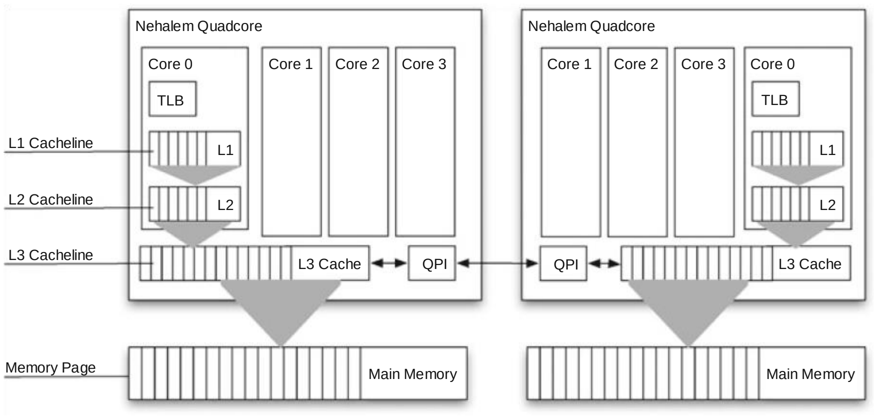


Figure 5 Memory architecture on Intel Nehalem [7]

2.1.4.2 Cache Efficiency

As described in Section 2.1.1, accessing the bottom levels in the memory hierarchy results in high latencies. Thus, it is a reasonable approach to avoid accessing the lower levels as much as possible. To this end, a crucial aspect in hiding the main memory latency is cache efficiency [41]. Cache efficiency can be achieved through a fundamental principle: reference locality. There are two kinds of the locality regarding memory access which are temporal locality and spatial locality [7]. Temporal locality refers to the fact that whenever CPU accesses an item in memory, it is likely to be reaccessed soon. Spatial locality refers to the likelihood of accessing the adjacent memory cells while accessing a memory address. Caches are organized in cache lines (e.g., the smallest unit of transfer between cache levels). Whenever CPU requests to access a particular memory item, the item will be searched within the cache lines. If the corresponding cache line is found, a cache hit will occur; otherwise, it results in a cache miss. A cache efficient strategy will achieve a high hit/miss ratio.

2.1.4.3 Prefetching

A complementary solution to overcome the memory wall is using data prefetching. Data prefetching is a technique that tries to guess which data will be accessed in advance and loads the data before the data access. Modern processors support software and hardware prefetching; Hardware prefetching utilizes multiple prefetching strategies to automatically identify access patterns whereas software prefetching can be regarded as a hint to the processor, implying the next address that will be accessed [7]. Data prefetching has been widely used in data management systems. For example, Calvin, a transaction scheduling and replication management layer for distributed storage systems, uses software prefetching in transaction level [42]. After receiving a transaction request, Calvin performs a cursory analysis of the transaction and sends a prefetch hint to storage back-ends contributing to the transaction while it begins executing the transactions.

2.2 Hybrid Analytical/Transactional processing System

Applications handled by database systems can be classified into two main types: OLTP and OLAP. The two next sections study the characteristics and requirements of the database systems.

2.2.1 Online Transactional Processing Systems

According to [43], "A transaction processing application is a collection of transaction programs designed to do the functions necessary to automate a given business activity." Transaction processing involves a wide variety of sectors of the economy like manufacturing, banking, media, transportation. Transaction processing workloads fall into two categories: batch processing and online processing. In batch transaction processing, a series of transactions (called a batch) are processed without user interaction. Payroll and billing systems are examples of the batch processing. Alternatively, in online transaction processing, a transaction is executed corresponding to a request from an end-user device or a front-end interface. Withdrawing money from an automated teller machine (ATM), placing an order using an online catalog, and purchasing an online airline reservation system are some examples of online transactions. In its early years, online transaction processing systems were driven mostly by large enterprises. Nowadays, OLTP systems are omnipresent even in small and mid-size businesses.

In the context of transaction processing, a transaction is a set of operations exhibiting a single unit of work. A transaction is characterized by four properties: atomicity, consistency, isolation, and durability (commonly referred as ACID). These properties [44] are discussed below. ACID-compliancy is one of the essential requirements of OLTP systems.

- Atomicity: A transaction should be considered as a single unit of operations meaning that either all the transactions' operations should be completed or none of them. If a transaction fails, all modifications applied by the transaction should be rolled back.
- Consistency: Running a transaction should maintain the consistency of the database state. In other words, running a transaction transforms the state of a DBMS from a consistent state to another consistent one. In particular, this includes that all integrity constraints are met by transactions.
- Isolation: Changes made by a transaction must be isolated from the changes made by other concurrent transactions accessing the same data. Put it differently, concurrent transactions should affect the system in a manner that the transactions are executed one at a time.
- Durability: Durability guarantees that after successful completion of a transaction, the results will be permanent even in case of failures like power outages and system crashes.

OLTP systems share some unique features which are listed as follows.

1. OLTP systems only rely on operational data and do not store historical data. In other words, the systems only store current version of data.
2. OLTP schemas are usually normalized; the schemas are typically in 3NF or Boyce-Code Normal Form (BCNF) to minimize the data entry volume and guarantee data consistency. The high degree of normalization also stimulates inserts, updates, and deletes while it might degrade data retrievals. [7]
3. OLTP queries are predominately simple and do not include complex joins, aggregations, and groupings [10].

4. Number of users who frequently issue modifying statements is significant in OLTP environments (OLTP environments are update-intensive) [11, 10]. As a result, the systems deal with high levels of concurrency.
5. Typical OLTP queries only access one or a small number of sets, and only a few tuples match their selection predicates [10].
6. OLTP systems mostly execute pre-determined queries [10]. In other words, ad-hoc queries are not common in the systems.
7. OLTP systems demand swift response times. Psychological studies suggest that the suitable maximum response time for a human is around three seconds [7]. To set a tangible example, a person trying to dispense cache from an ATM expects his/her transaction to be completed in few seconds. Considering that one or several transactions might incorporate only some parts of a user interaction, each transaction probably needs to be completed in milliseconds.
8. OLTP applications play a critical role in many enterprises, and there is no space for compromising reliability, availability, or scalability [43].

In OLTP architectures, database management systems play an essential role since they are the underlying entity managing the data shared by transaction processing applications. OLTP systems are the predominant use case for relational DBMSs. The reasons for the dominance are flexibility, performance, robustness, and simplicity in managing structured data. [15, 43]

2.2.2 Online Analytical Processing Systems

Computer-based analytics is not a new concept and have persisted even before the emergence of relational database systems [6]. Management Information Systems (MISs) can be regarded as the first generation of analytical systems introduced in 1965 with the development of mainframe systems. At that time, the management information systems did not support interactive data analysis. To support the interaction, decision support systems (DSSs) are introduced in the 1970s. During the time, spreadsheets are the typical form of DSSs widely used to derive information from raw data. However, the spreadsheets focus on single users and are not able to provide a single view for multiple end-users. During the time, continuous development of different transaction processing systems has instigated growing heterogeneity in data sources. The term OLAP is coined in 1993 by Ted Codd referring to a product which facilitates consolidation and of data from multiple sources in a multidimensional space based on twelve rules [45]. In a multidimensional data model, there is a set of measure attributes which represent the objects of analysis. Each of the attributes depends on a set of dimensions which provides the analysis contexts. Additionally, hierarchies can be defined within each dimension. Figure 6 demonstrates sale measurement among city, product, and date dimensions. In the data model, the product includes a hierarchy of industry and category.

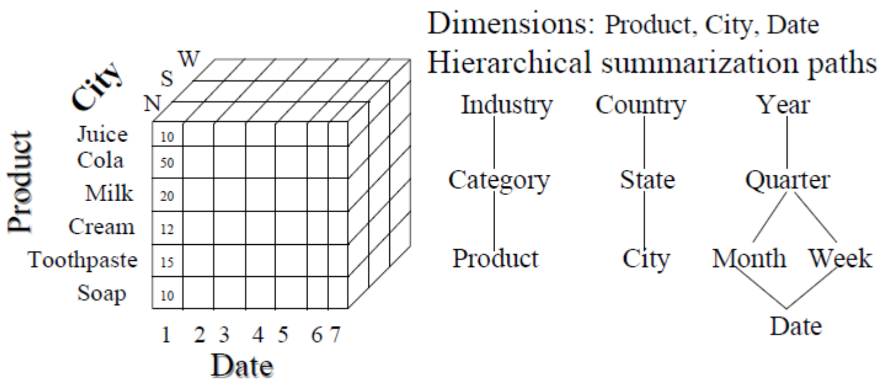


Figure 6 An example of Multidimensional Data [46]

Like OLTP system, OLAP schemes share some distinct characteristics [10] which are listed in the follows.

1. In OLAP systems ad-hoc queries are dominant.
2. OLAP queries predominately include complex joins, aggregations, and groupings.
3. Selection predicates in typical OLAP queries access a large number of sets.
4. OLAP queries are usually long-running.
5. OLAP queries are widely read-only.
6. Number of concurrent users running OLAP queries is small.

The substantial differences between transactional and analytical workloads are the reason that many companies began to separate their OLTP databases from OLAP. In the 1990s, Data Warehouses (DW, also called DWH) were developed as a foundation for analytical workloads. DWHs mostly model information into multidimensional data cubes and apply OLAP-oriented database management systems. To represent the multi-dimensional data model, DWHs enact different schemas among which star, snowflake, and fact constellations are the most widely used. Star schema includes a single fact table and a single table for each dimension. The connection between the fact tables and the dimension tables is coordinated using a foreign key. Figure 7 shows an example of a star schema. More recently, using columnar databases has become of particular interest for analytical processing [9]. The columnar databases are explained in sections 2.2.3 and 2.2.4.

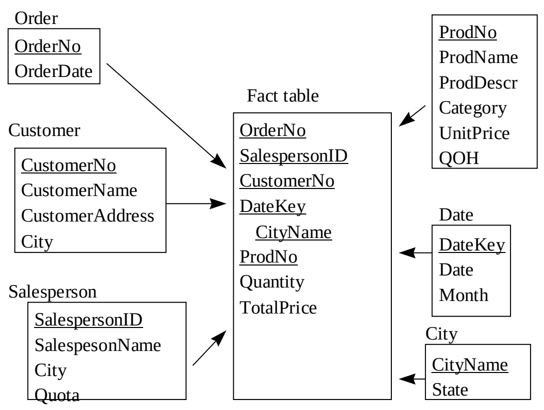


Figure 7 A star schema [46]

OLAP operations can be classified into four groups [46] as detailed below.

- Rollup is performing aggregation on a data cube by reducing dimensions or climbing up a concept hierarchy for a dimension.
- Drill-down is decreasing the amount of aggregation or expanding detail along one or more dimension hierarchies.
- Slice and dice is selecting and projecting a dimension of a cube as a new sub-cube.
- Pivot is rotating the multidimensional view of data.

Data warehouses might be implemented on top of relational DBMS by mapping multidimensional data into relations. The approach is called relational OLAP (ROLAP). It is also possible to apply specific data structures to store the multidimensional data, which is named multidimensional OLAP (MOLAP).

As mentioned, the data in a data warehouse is comprised of different OLTP systems and external sources. Consequently, a process is required to consolidate the data from various sources into DWHs. The method is named extract, transform, load (ETL) and consists of three primary steps. During the extraction, the desired data is extracted from data sources. The second stage includes converting the extracted data into a proper format consistent with OLAP data structure. The process is completed by materializing the transformed data into target data storages. To maintain data freshness, the ETL process should be done periodically (usually overnight).

2.2.3 Relational data layouts

In the relational data model, tables are used to represent the logical structure of data. Tables (also called relations) include attributes and tuples. Hence, each relation consists of two dimensions including rows (i.e., tuples) and columns (i.e., attributes). Table 1 demonstrates a straightforward relation with five attributes and two tuples. To store a relation inside memory, it is required to map the two-dimensional structure to a unidimensional memory address space. There are two approaches to storing a relation in memory: row and columnar layout [7].

ID	FName	LName	City	Country
1	Bahman	Javadi	Lappeenranta	Finland
2	Ted	Smith	Walldorf	Germany

Table 1 Sample Relation

The row-based layout is the most classical way of representing relations in memory. The layout stores relations in memory using a row-based (or record-based) structure. In other words, the record-based layout will store tuples consecutively and sequentially in memory. Considering the sample relation, the data would be stored as a sequence of tuples in memory as follows, where each line represents a record stored in a memory region.

1	Bahman	Javadi	Lappeenranta	Finland
2	Ted	Smith	Walldorf	Germany

The second approach in storing the two-dimensional structures is storing relations based on attributes. The approach is called columnar or column-oriented. In the columnar layout, values of columns are store together. The columnar layout of the sample relation would be as:

1	2
Bahman	Ted
Javadi	Smith
Finland	Germany

Using the different memory layouts has a significant impact on memory access patterns as shown in Figure 8 where A, B, and C represent three different columns of a table. Considering set-based operations like aggregate calculations which only access a small subset of columns, the columnar layout is more efficient since the values of columns will be scanned sequentially in fewer CPU cycles. On the other hand, the row-wise layout outperforms the column-wise for row-based operations which operate on a single or a set of tuples (e.g., a projection using SELECT *). As a result, considering the workload should be a significant factor in selecting the memory layout. Typically, the row-wise layout is mostly used in OLTP databases since transactional queries are associated with row operations such as accessing or modifying a few rows at a time. Conversely, columnar storages are more suitable for OLAP queries that are characterized by large sequential scans traversing a few attributes of a big set of tuples. It is also possible to use a combination of both row and columnar layouts, a hybrid design. [9]

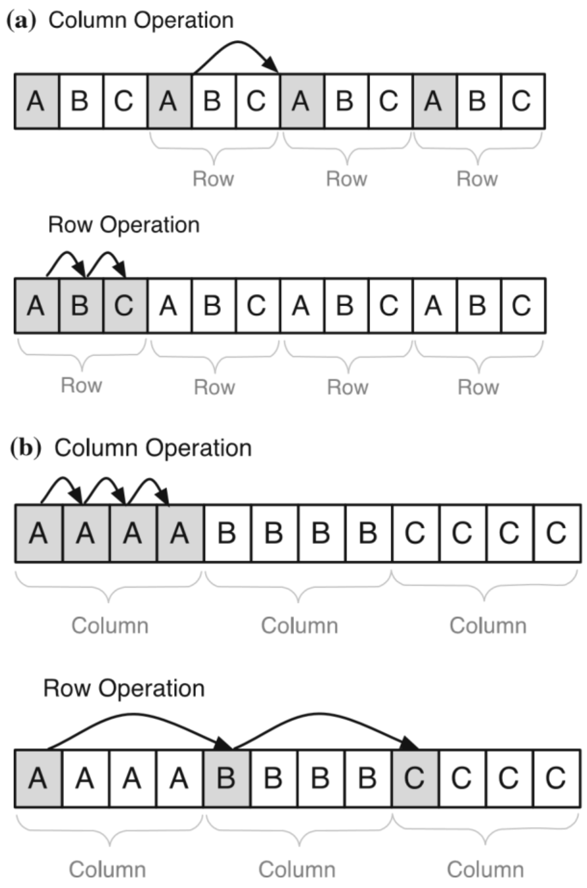


Figure 8 Memory access pattern for set-based and row-based operations on row and columnar data layouts [7]

2.2.4 Column-Oriented Data Layout

As mentioned in the previous section, row-wise databases can perform better in some scenarios. Nonetheless, there are some benefits in the usage of the columnar layout that are not applicable to the row stores. The benefits are highlighted in this section.

Even though main memory capacities are growing exponentially as discussed in section 2.1.2, enterprise data volumes are also becoming extremely large. Respectively, efficient compression techniques are of high importance to keep more data in main memory. Some compression techniques like dictionary encoding are applicable to both data layouts [7]. Dictionary encoding represents distinct values by a smaller value and typically reduces required space by a factor of five (factors of 47 are also reported for attributes with a relatively low number of distinct values like country name) [47]. However, several compression techniques like Run-Length Encoding (RLE) or indirect encoding can be only leveraged in the columnar layout. For instance, RLE algorithm stores consecutive distinct values as a single data value. Hence, the technique will not be efficient in row-layout which stores tuples including heterogeneous data types and semantics. It can be concluded that row storage with horizontal compression cannot compete its counterpart for memory usage. A study [9] reveals that a relation with 34 million tuples using the row layout as the underlying database consumes about 35 GB of space; while the same table stored in columnar layout uses eight GB of memory.

As mentioned in section 2.1.4, cache efficiency plays a significant role in overcoming the memory wall. It is discussed that the columnar layout is more cache-efficient due to two reasons [47, 7]. First of all, considering a relation with many attributes stored in a row layout, almost every access to the next value of an attribute causes a cache miss even when utilizing compression techniques and prefetching; CPU cache is limited in size and storing a complete row in a cache could cause many evictions. Put it differently, storing data in column chunks is more cache-friendly. Also, the layout could exhibit a better data locality since cache lines are full of related values (attributes) and only the data of interest will be brought into cache.

Moreover, using the columnar layout will simplify data parallelism. In data parallelism, data is partitioned into data sets, and a query involves running operators of the query on the separate data sets in parallel. Figure 9 shows data parallelism for a JOIN and SORT operator while evaluating a predicate. Although data partitioning is also possible in the row-wise layout, the columnar layout implicitly partitions data vertically. The implicit vertical partitioning allows vectorized query execution using single instruction/ multiple data (SIMD) processing. SIMD, as the name suggests, allows performing a single operation on multiple data words stored in specific CPU registers in one instruction. Using SIMD can dramatically improve the efficiency of aggregate functions like SUM, AVG, and COUNT. [7]

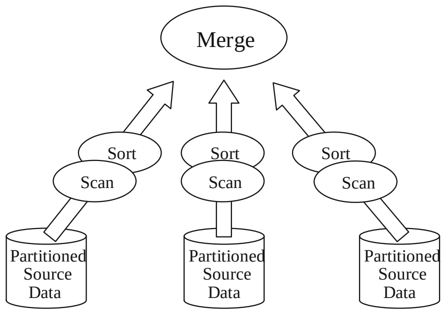


Figure 9 Sample Data Parallelism [7]

2.2.5 Breaking the Wall Between Transaction and Analytical Processing

As noted previously, different characteristics of transactional and analytical workloads led many organizations to separate OLTP and OLAP databases. The separation drove the adoption of ETL to migrate data from several operational data sources into data warehouses. The approach resulted in successful business intelligence (BI) implementations. Nonetheless, this separation has its downsides [12, 9]. First, ETL tools and methods are complex and error-prone. Besides the complexity and the error-proneness, the approach increases the total cost of ownership (TCO) since companies need to invest in acquiring and maintaining two distinct systems. On top of the challenges above, ETL is time-taking and imposes data latency. For instance, analytical queries will run on at least one-day old data if the ETL jobs are executed at the end of each business day. The latency compromises real-time business intelligence which is highly desired nowadays. Recent years have seen the emergence of big data applications and Internet of Things (IoT) which demand real-time analytics over large datasets. To fill the gap, the industry, as well as academia, have targeted building data management solutions supporting mixed workloads without requiring data duplication. Hybrid transactional/analytical processing (HTAP) is a term coined by Gartner to define such systems [48].

Several vendors currently offer HTAP systems such as HANA, VoltDB, and HyPer. Two questions then arise: What are the primary enablers of the hybrid systems and how the solutions mainly differ? It is discussed that in-memory database technologies and advances in modern hardware (e.g., increasing main memory capacity, the advent of multi-core processors, and levels of memory caches) can be considered as the principal drivers for rising the systems [48, 12, 9, 13]. To support a single system for both OLTP and OLAP, HTAP solutions today apply a variety of design practices like resource management and data layout. For instance, HyPer can be configured as a row or column store and may utilize a virtual memory (VM) snapshot to manage resource utilization for mixed workloads [13]. The VM snapshot architecture generates consistent snapshots of the transactional data for OLAP query sessions. The snapshots are created by forking a single OLTP process, and the consistency of the snapshots are implicitly maintained by an OS/processor-controlled lazy copy-on-update synchronization mechanism. By injecting OLAP-style queries into a different queue, OLTP transactions will not wait for long-running analytical queries while still access the current memory state of OLTP process. Likewise, SAP HANA employs different design practices to handle mixed workloads. The system incorporates a row engine which is suitable for extreme OLTP workloads as well as a column store optimized to support OLAP and mixed workloads. The design of the column store enables both highly efficient analytics and at the same time very decent OLTP performance, allowing both workloads on a single copy of the data in main memory [12]. To support co-existence of OLTP and OLAP queries, HANA utilizes a dynamic task scheduling mechanism for servicing analytical queries expressed as a single or multiple tasks [49]. One worker thread per hardware context continuously fetches tasks from queues and processes them. The scheduler is responsible for balancing the number of worker threads according to the number of hardware contexts. The scheduler also decides how OLTP and OLAP queries consume resources according to an adjustable configuration.

As discussed in sections 2.2.1 and 2.2.2, OLTP workloads are characterized by update-intensive and tuple-oriented operations while OLAP workloads are attributed to sequential scans over a few attributes but many rows of the database. However, the typical DBMS interaction pattern are also changing over the time: A study [50] turns out that read-oriented set operations dominate actual workloads in modern enterprise applications. In other words, OLTP and OLAP systems are not necessarily as different as typically explained. In the study, the customers' workloads of a business suite are analyzed as shown in Figure 10. The study demonstrates that more than 80% of all OLTP and OLAP queries are read-access. Whereas both systems deal with permanent modifications and inserts, the number of inserts and modifications are a little higher on OLTP side. Also, lookup rate is only 10% higher in OLTP systems compared to OLAP systems. The study concludes that a read-optimized data layout will satisfy update operations for both workloads.

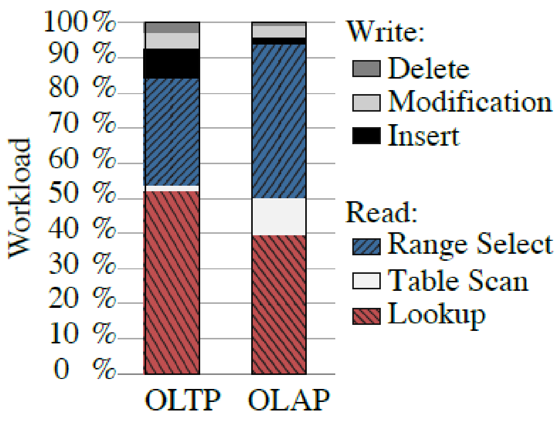


Figure 10 Comparison of OLTP and OLAP workloads based on distribution of query types extracted from a customer database statistics [50]

2.3 OLTP WORKLOAD BENCHMARKS

Currently, a variety of benchmarks are available to measure the performance of database management systems. These benchmarks not only provide a tool for vendors to improve their products but also customers can achieve a comparison baseline using the benchmarks' results. This section presents a brief study of two OLTP benchmarks:

- TPC-C (an open source benchmark provided by TPC)
- Sales and distribution (SD) benchmark (a proprietary benchmark provided by SAP)

2.3.1 TPC-C Benchmark

TPC is formed in 1988 as a non-profit corporation with the goal of standardizing objective, and verifiable data-centric benchmarks [51]. From then on, the council has published about 16 benchmarks to measure the performance of different systems such as OLTP, OLAP, big data, IoT, and so on. Among the standardized benchmarks, TPC-C is an online transaction processing benchmark approved in 1992 and since then has been widely used in the industry [50, 52].

The benchmark simulates activities related to an order-entry system for a wholesale parts supplier (known as the company). The company works out of several warehouses and their associated sales districts as demonstrated in Figure 11. TPC-C is a scalable benchmark meaning that it is possible to scale out the benchmark just like the company expands and new warehouses are created. Each warehouse covers ten districts, and each district serves 3000 customers. The test configuration of the benchmark consists of driver(s), a system under test (SUT), and Driver/SUT communications interfaces. The driver is used to emulate customers during the benchmark run. The driver also records response times and statistical accounting. The SUT consists of a single or multiple processing units running the transactions. [52]

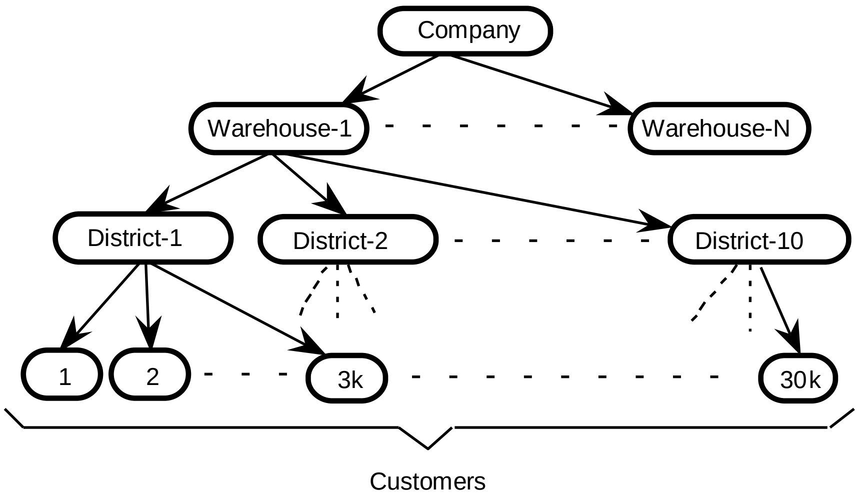


Figure 11 TPC-C's business environment [52]

The workload of the benchmark consists a mix of five concurrent transaction types [52] as given below.

- New-order: The transaction represents entering a complete order. It is a read-write transaction having a high frequency of execution.
- Payment: This transaction represents updating a customer's balance and reflecting the payment on the company and the district sales statistics. Just like the new-order transaction, it is a read-write transaction with a high frequency of execution.
- Delivery: The transaction incorporates delivering a batch up to 10 new orders. This is a read-write transaction with a low execution frequency.
- Order-status: This is a read-only transaction with a low frequency of execution. The order-status transaction queries the position of a customer's last order.
- Stock-level: This is a read-only transaction with a low frequency of execution. It queries the number of recently sold items below a specific threshold.

TPC-C requires that all ACID properties be maintained during the test. The benchmark demands that at least 90% of all transactions except the stock-level to be completed within 5 seconds while the stock level transactions should be completed within 20 seconds. The benchmark measures two metrics: One performance metric is in terms of the number of completed new-order transactions per minute (called tpmC). The benchmark also requires reporting a price-per-tpmC metric. The benchmark starts with a ramp-up phase in which tpmC reaches a steady level. Then, the measurement interval starts and should continue for at least 120 minutes. After the measurement interval, a ramp-down stage closes the benchmark test-run. Figure 12 depicts a sample run graph of the benchmark. The x-axis portrays the elapsed time from the beginning of the run as the y-axis sketches the Maximum Qualified Throughput (MQTh) rating expressed in tpmC. TPC-C implementations must scale both the number of customers and the size of the database proportionally to the measured throughput. [52]

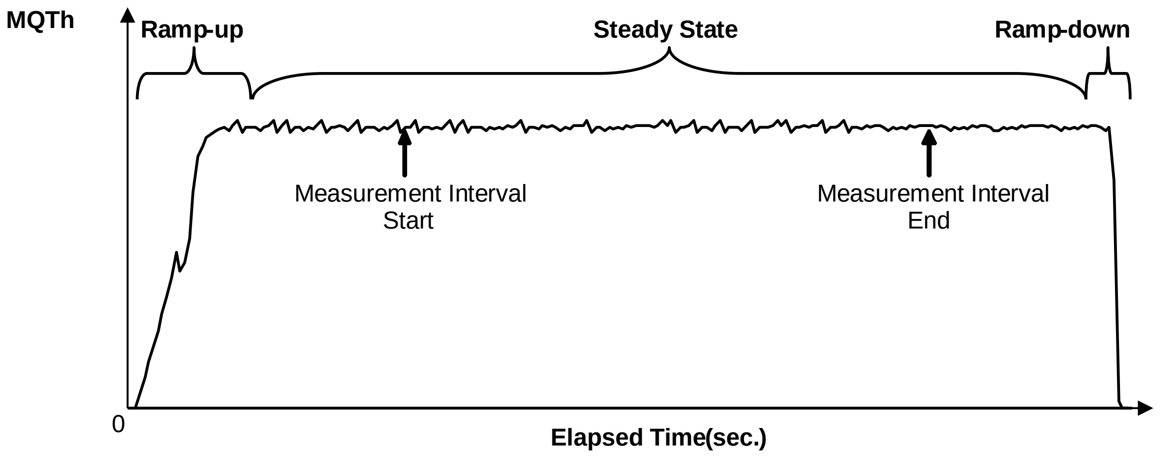


Figure 12 Sample TPC-C run graph [52]

The benchmark’s database comprises nine individual tables as sketched in Figure 13. Numbers inside the entity blocks exhibit the cardinality of the tables whereas those numbers starting with W denotes a scaling factor of the number of warehouses. The numbers next to relationship arrows show the average cardinality of the relationships. The plus symbol after the relationships’ cardinality demonstrates that the number is subject to a small variation in the initial database population over the measurement interval. [52]

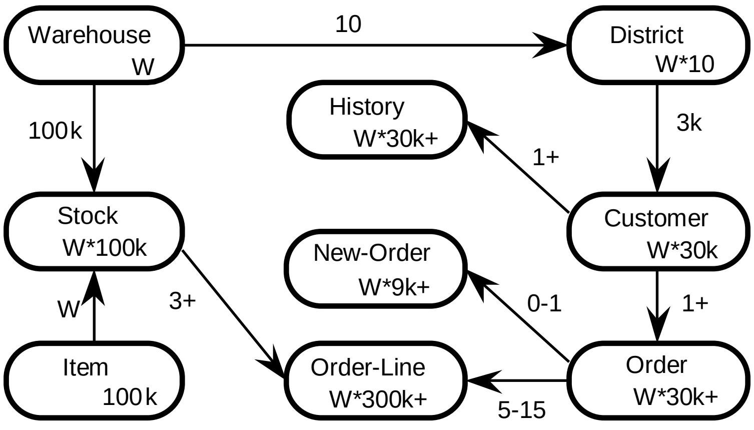


Figure 13 TPC-C ER diagram of tables and relationships among them [52]

2.3.2 SD Benchmark

Similarly to TPC, SAP offers a variety of benchmarks for different business scenarios under the umbrella of SAP Standard Application Benchmark suite. The business scenarios include Sales and Distribution (SD), Assemble-to-Order (ATO), production planning (PP), and many more. The suite is developed and published in 1993 to facilitate necessary sizing recommendations of SAP systems and for platform comparisons. SAP Application

Benchmark Performance Standard (SAPS) is the metric of measurement in the suite and expresses the performance of a system configuration in the SAP environment. SAPS is derived from the Sales and Distribution (SD) benchmark in a manner that 2000 fully processed order line items per hour are equivalent to 100 SAPS. Fully processed here means that the entire process of an order line item including creating the order, creating the delivery note for the order, viewing the order, making changes to the delivery, posting an item issue, listing orders, and generating an invoice has to be completed. In technical terms, this is equivalent to 6000 dialog steps plus 2000 postings per hour in the SD benchmarks, or 2400 SAP transactions. A dialog step imitates a screen change corresponding to a user request. [53]

The SD benchmark measures the maximum number of users in a SAP sales and distribution scenario satisfying a defined average dialog response time. The business scenario covers a sell-from-warehouse scheme that includes six transactions. Each transaction can be mapped to a real dialog step in SAP sales and distribution environment. The list of transactions and dialog steps are provided in Table 2. [54]

Transaction Code	Dialog step
VA01	Generating a sale order with five line items
VL01N	Generating an outbound delivery schedule
VA03	Displaying the customer order
VL02N	Modifying the outbound delivery
VA05	Generating a list of sales orders
VF01	Generating invoice for an order

Table 2 Transactions and dialog steps in the SD benchmark

Like TPC-C, the SD benchmark starts with a ramp-up phase during which the number of concurrent users increases gradually until all users are active. After the stage, the test interval starts (the interval is also called high load phase). During the high load phase, the performance level (i.e., throughput) must be maintained for at least 15 minutes. Then, users are continuously taken off the system in a ramp-down stage until there is no active user. The benchmark comprises three components which are: presentation layer, application layer, and database layer. The presentation layer (also called benchmark driver) simulates users logging to the system and placing a fully business processed order. Configurations for a benchmark simulation comes in a 2-tier or 3-tier flavor. In the 2-tier architecture, the application layer and the database layer reside on a single system while in the 3-tier architecture the layers reside on separate systems. The architectures are shown in Figure 14. [54]

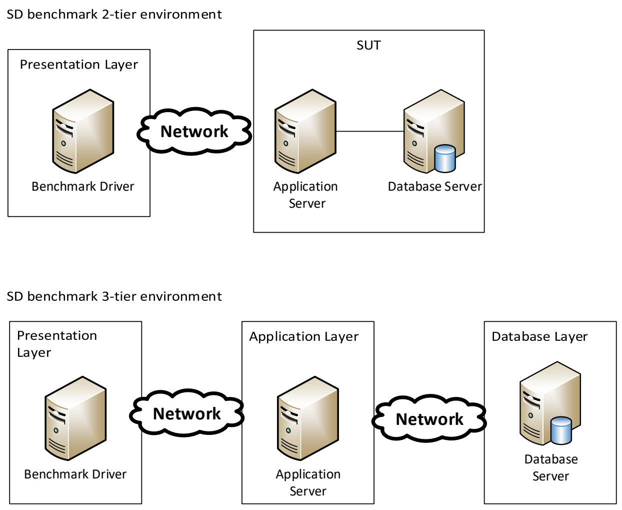


Figure 14 SD Benchmark 2-tier and 3-tier environment

2.4 SAP HANA

SAP HANA is an in-memory database offered by SAP. Initially, the system was built from the ground up to support only analytical workloads [12]. However, it unfolded over the course of time from a pure analytical appliance to a system capable of handling mixed workloads. The evolutionary process of this system is not a one-time journey: In fact, the system evolved within three steps. The following subsections study the steps and the major developments in each stage.

2.4.1 HANA for Analytical Workloads

The initial architecture of the scheme was based on providing a sound basis for analytical processing. SAP employed three design principles [12] in developing HANA: (1) performing extensive parallelization, (2) embracing a scan-friendly data layout, and (3) supporting advanced analytical engine capabilities.

Massive parallelization at all levels is one of the core design principles of SAP HANA motivated by recent trends in developing many-core CPUs. HANA supports parallel query processing at different levels. Inter-query parallelism is achieved by maintaining multiple concurrent user sessions. Intra-query parallelism is gained by running different operations within a single query in parallel. HANA also supports intra-operator parallelism by executing individual operators in multiple threads.

Moreover, HANA relies on a columnar data layout to provide a scan-friendly foundation for analytical queries. HANA columnar layout is accompanied by dictionary compression and hardware prefetchers to minimize memory consumption while hiding memory access latencies. Besides, SAP HANA presents a rich collection of analytical engines including geospatial, graph, text, and planning engines.

2.4.2 HANA for Transactional Workloads

Over the course of time, SAP decided to broaden the scope of HANA from a pure analytical processing toward a system also supporting OLTP workload. Although the system comes with a row-store suitable for transactional workloads, the evolution of HANA toward transactional processing was mostly based on optimizing the column store. SAP enacted several tunings to maintain OLTP workloads, as follows.

- Query compilation in OLTP queries can dominate query run-times; To avoid re-compiling frequently executed statements, the system inserts the compiled query plans into a cache (i.e., query plan cache) [12]. When a query needs to be executed later, HANA checks for a corresponding execution plan in the cache. The system reuses the cached plan it finds, saving the overhead of recompilation.
- As previously mentioned, the column store in SAP HANA is encoded using a dictionary-based compression. Nevertheless, using the compression has an overhead of re-encoding for update operations. To minimize the overhead of frequent updates, each column in the column store is composed of two tables: a read-optimized main table, and a write-optimized delta table [55]. The main table uses a sorted dictionary to speed up scans while the delta tables use an unsorted dictionary to enhance update operations. The delta table includes recently added, deleted, and updated data. In other words, update operations only affect this table. During the read operations, both tables will be queried. The delta tables will be periodically merged into the main tables. Figure 15 portrays the use of the main and delta tables in HANA columnar storage.

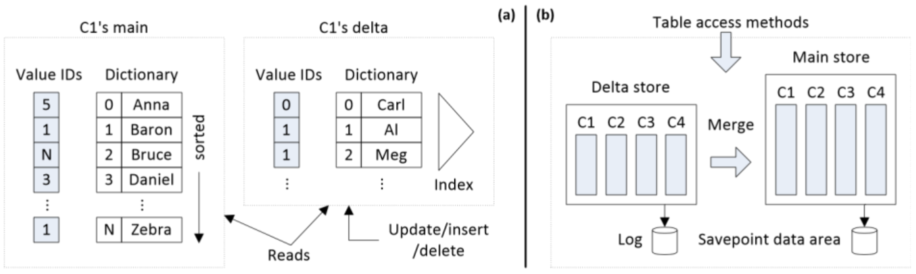


Figure 15 (a) The core data structures of the main and the delta parts of a column. (b) The delta merge operation. [55]

- In OLTP scenarios, it is often found columns that store only a single or empty value. In case of finding a single default value, HANA bypasses storing the value in a columnar representation and stores it inside the column header. This optimization could amplify throughput and improve CPU consumption. [12]
- SAP HANA relies on snapshot isolation concurrency control in transaction management. The transaction manager in its initial version was based on a visibility tracking mechanism via an explicit bit-vector per transaction on table-level.

However, the tracking mechanism turned out to be expensive and memory-consuming for transactional workloads. To handle this shortfall, HANA applied a new row-based visibility tracking mechanism depending on time-stamps associated with each row. The timestamp indicates when the row is created or deleted. Further, the timestamps can be periodically replaced by a bit indicating the rows' visibility to reduce memory consumption overhead. [12]

- Efficient synchronization of in-memory data structures has a critical effect on scalability and performance of transactional database systems. To maintain both the performance and the scalability, HANA carefully optimizes table latching and applies advanced synchronization primitives. For instance, Intel Transaction Synchronization Extensions (TSX) is used in the system to decrease lock contentions. [12]
- SAP HANA exploits application-server/DBMS co-design for efficient data transfer. Advanced Business Application Programming (ABAP) is a platform for developing business applications on top of SAP HANA. The platform comprises ABAP programming language and its runtime including an application server. HANA natively optimizes for the platform. For instance, Fast Data Access (FDA) is a feature which enables efficient data transfer by directly reading and writing into special data structures shared between the database system and ABAP application server. [12]

2.4.3 HANA for Mixed Workloads

In the final step of the journey, SAP took a disruptive approach toward extending HANA to an HTAP system on top of OLTP-style database schema [12]. SAP employed three design practices to achieve this goal:

- Resource management is a major challenge in handling mixed workloads since analytical queries are resource-intensive and might result in delayed transactional queries. Within SAP HANA, a scheduler is responsible for running queries and monitoring resource utilization as described in section 2.2.5.
- In HANA, full columns are loaded into main memory during the first access; subsequently, the loaded columns might be unloaded in case of memory pressure [12]. Keeping both historical and operational data inside main memory might be expensive as well as inefficient since the rarely accessed, historical data might cause

eviction of frequently accessed columns. SAP HANA make use of a data aging process to identify certain data as cold (A.K.A aged data) or warm. There are two techniques to store the cold data. The aged columns can be declared as page-loadable inside the system [56]. The page-loadable columns are partially loaded into main memory upon a request. It is also possible to store the aged data on disk to reduce the memory footprint in HANA. Storing the cold data on disk using a separate storage engine is called dynamic-tiering [57].

- Executing analytical queries on normalized database schemas requires data-models suitable for reporting purposes. SAP HANA employs a layered architecture of database views to facilitate analytics queries; the hierarchy of views are called Core Data Services (CDS) views [58]. These views provide a rich semantic data model consisting of layered views on top of normalized relational schemas.

2.4.4 SAP HANA SQLSCRIPT

As of today, there are two approaches to implement data-intensive business logic. A classical approach is executing application logic in an application layer and leaving the database only to perform limited functionality using SQL. This approach has two main drawbacks [59]. First, running business logic in another layer than database requires data transfer within the two layers; the data transfer could be expensive regarding processor and transfer time. Secondly, in this approach developers mostly follow a single-tuple-at-a-time semantic that decreases the chance for leveraging query optimization and parallelization. In the second model, the application logic will be shipped into the database layer. Relational databases traditionally offer imperative language extensions using a dialect of SQL such as Procedural Language/Structured Query Language(PL/SQL) or Transact-SQL(T-SQL) [60]. SAP HANA exposes an interface for pushing the application logic to the database which is called SQLScript.

SQLScript addresses several limitations with pure SQL statements. First, decomposing complex SQL queries is only possible using views. The decomposition using views requires that all intermediate results be visible and explicitly typed. The SQL views also cannot be parameterized. SQLScript facilitates the decomposition by assignments and parametrization. Secondly, SQL statements do not have features for expressing business logic (e.g., currency conversion). SQLScripts provides three extensions to the SQL dialect of HANA: an imperative (procedural), a declarative (functional), and a data extension. Furthermore, an SQL query can only return single result at a time. Hence, computation of related result sets should be split into usually unrelated, separate queries. SQLScript offers multiple input and output parameter to overcome this deficit. [60]

2.4.4.1 SQLScript Data Extension

The data extension in SQLScript is based on the SQL-92 type system. The built-in supported scalar data types comprise of the ones shown in Table 3. The extension also allows defining table types for tabular values. The syntax for defining table variables is similar to the SQL syntax for defining a new table. For instance, “CREATE TYPE tt_year AS TABLE (year VARCHAR(4), price DECIMAL, cnt INTEGER)“ defines a table type named tt_year representing price and count per a specific year. Local variables are declared by the DECLARE keyword. Local variables are bound using the equality operator and referenced via their name prefixed by <:> like <:var>. [59]

Numeric Types	TINYINT, SMALLINT, INT, BIGINT, DECIMAL, SMALLDECIMAL, REAL, DOUBLE
Character String Types	VARCHAR, NVARCHAR, ALPHANUM
Date-Time Types	TIMESTAMP, SECONDDATE, DATE,TIME
Binary Types	VARBINARY
Large Object Types	CLOB NCLOB BLOB
Spatial Types	ST_GEOMETRY

Table 3 SQLScript Scalar Data Types [59]

2.4.4.2 SQLScript Procedural Extension

With SQLScript's procedural extension, it is possible to define orchestration logic using imperative constructs. The supported imperative constructs in SQLScripts include conditionals (IF, ELSE, and ELSEIF) and loops (while and for loops). Using cursors is also supported in the procedural extension to iterate through result sets. Data definition and data manipulation statements (i.e., updates, deletes, and inserts) are allowed inside procedures of this kind. Additionally, the extension supports array-typed variables. The arrays are indexed collections of elements of a single data type declared by the keyword ARRAY. For example, "DECLARE arr INTEGER ARRAY" declares an array of type INTEGER. In SQLScript, The syntax ":<array_variable_name> '['<array_index>']' " is used to refer to an element in an array. There are some functions which operate upon arrays like UNNEST, ARRAY_AGG, TRIM_ARRAY, and CARDINALITY. Altogether, the procedural extension presents a solid foundation for developing imperative business logic in the database layer. However, the procedures of this kind cannot be efficiently optimized and parallelized due to their single-tuple-at-a-time semantics. [59]

ROLLBACK and COMMIT are natively supported in SQLScript's procedural extension [59]. The COMMIT statement makes all the modifications performed since the start of the procedure a persistent part of the database. On the other hand, the ROLLBACK statement undoes all the modification performed by the procedure since the last COMMIT, if any, otherwise from its beginning. The transaction boundary in SQLScript is not tied to the procedure block. In other words, if a nested procedure contains a COMMIT/ROLLBACK, then all statements of the invoking procedure are also affected.

2.4.4.3 SQLScript Functional Extension

SQLScript also supports a functional extension to tackle the optimization difficulties in the procedural extension. The functional extension is designed to construct and encapsulate declarative data-intensive computations. Put in other words, procedures in SQLScript are either functional and apply a set-oriented semantics or they are of a procedural type and follow one-tuple-at-a-time paradigm. [59]

Two prerequisites should be fulfilled in defining declarative functions. First, they should be free of side-effect (i.e., read-only) and they should be transformable into a static dataflow graph where each node denotes a data transformation. Read-only means that the operators which make modifications to the database or its structures are not allowed. The reason for the prerequisites is that SQLScript's optimizer will translate the functional logic into a highly parallelizable data-flow. Language constructs in the functional extension are single assignments and calls to other read-only procedures. The assignments can be used to bind the tabular result of a SQL statement. Cyclic dependencies caused by intermediate result assignments or calling other functions are not permitted in the functional procedures. [59]

2.4.4.4 Creating and Calling Procedures

The CREATE PROCEDURE statement can be used to define both types of procedures. However, the functional extension requires marking the procedures as read-only in the signature of the procedure via READS SQL DATA [60]. The orchestration logic (i.e., the procedural extension) can call functional code; however, this is not allowed vice versa [59].

Figure 16 exhibits two examples of procedures named orchestrationProc and analyzeSales. The orchestrationProc has no input or output parameter and features multiple imperative constructs including using a cursor and several local scalar variables. The procedure also calls other procedures (i.e., init_proc and ins_msg_proc) via the CALL statement. The analyzeSales procedure follows a declarative semantic and is defined as read-only. It accepts multiple table-types and scalars as input and output parameters. This procedure utilizes two local table variables to store intermediate results that are big_pub_books and big_pub_ids.

```
CREATE PROCEDURE orchestrationProc LANGUAGE SQLSCRIPT
AS
BEGIN
  DECLARE v_id BIGINT;
  DECLARE v_name VARCHAR(30);
  DECLARE v_pmnt BIGINT;
  DECLARE v_msg VARCHAR(200);
  DECLARE CURSOR c_cursor1 (p_payment BIGINT)
     FOR
     SELECT id, name, payment FROM control_tab
     WHERE payment > :p_payment
     ORDER BY  id ASC;
  CALL init_proc();
  OPEN c_cursor1(250000);
  FETCH c_cursor1 INTO v_id, v_name, v_pmnt;
  v_msg = :v_name || ' (id ' || :v_id || ') earns ' || :v_pmnt ||
' $.';
   CALL ins_msg_proc(:v_msg);
   CLOSE c_cursor1;
END
```

(a)

```
CREATE PROCEDURE analyzeSales (IN cnt INTEGER, IN year INTEGER,
OUT output_pubs t t_publishers , OUT output_year tt_years)
LANGUAGE SQLSCRIPT
READS SQL DATA AS
BEGIN
   --Query Q1
   big_pub_ids = SELECT pub_id FROM books
      GROUP BY pub_id HAVING COUNT (isbn) > : cnt ;
  --Query Q2
   big_ pub_books = SELECT o.price , o. year , o.pub_id
       FROM :big_pub_ids p , orders o
       WHERE p.pub_id = o.pub_ id ;
  --Query Q3
   output_pubs = SELECT SUM(price) , pub_id
      FROM : big_ pub_books
      GROUP BY pub_id ;
  --Query Q4
   output_ year = SELECT SUM(price ) , year
       FROM : big_pub_books
       WHERE year BETWEEN : year −10 AND :year
       GROUP BY year ;
 END;
```

(b)

Figure 16 (a) A procedural extension [59], (b) A functional extension [60]

With SQLScript, application logic can be defined using both the procedural and functional extensions. The invoke activity while calling a procedure can be divided into two stages: a compilation stage and an execution step. The compilation step generates a data-flow graph (called calculation model) for the procedure. The Language L [12] is used as an intermediate language for expressing the calculation models. The generated calculation models then are bound to actual parameters and further optimized for the concrete input by a calculation engine within SAP HANA. The optimization distinguishes between declarative and imperative logic. As the declarative logic is guaranteed to be free of side-effects, the resulting calculation models can be better optimized and parallelized during execution. For instance, the procedure in Figure 16 (b) is comprised of four queries. In the calculation model for the procedure, the intermediate results generated by query Q2 can be consumed by queries Q3 and Q4 in parallel. [59]

As mentioned earlier, calling a procedure is possible via the CALL statement. There are two approaches for calling the procedures with input parameters. Considering the analyzeSales procedure in Figure 16, it can be called by using query parameters in the callable statement like “CALL analyzeSales (cnt=>?, year=>?, output_pubs =>?, output_year=>?)”. Besides, the query can be called without query parameters using constant values directly like “CALL analyzeSales (cnt=>1000, year=>2015, output_pubs =>?, output_year=>?)”. Like mentioned before, HANA exploits a query plan cache (see section 2.4.2). In the first approach, the cached query plan can be re-used even if the values of variables cnt and year change. Notwithstanding, calling with constant values will lead to generating the most optimal query at the cost of frequent query compilations for different parameter values.

2.5 TPC-E Benchmark

TPC-E is an OLTP benchmark approved by TPC in 2007. This benchmark models the activities of a stock brokerage firm as illustrated in Figure 17 (b). The activities include (1) managing customer accounts, (2) executing customer trade orders, and (3) organizing interactions between customers and financial markets. The benchmark focuses on measuring the performance of the central database running transactions associated to the firm's customer accounts. Although the benchmark exhibits the activities of a brokerage firm, its design is based on simulating the activities found in a complex transactional environment. [61]

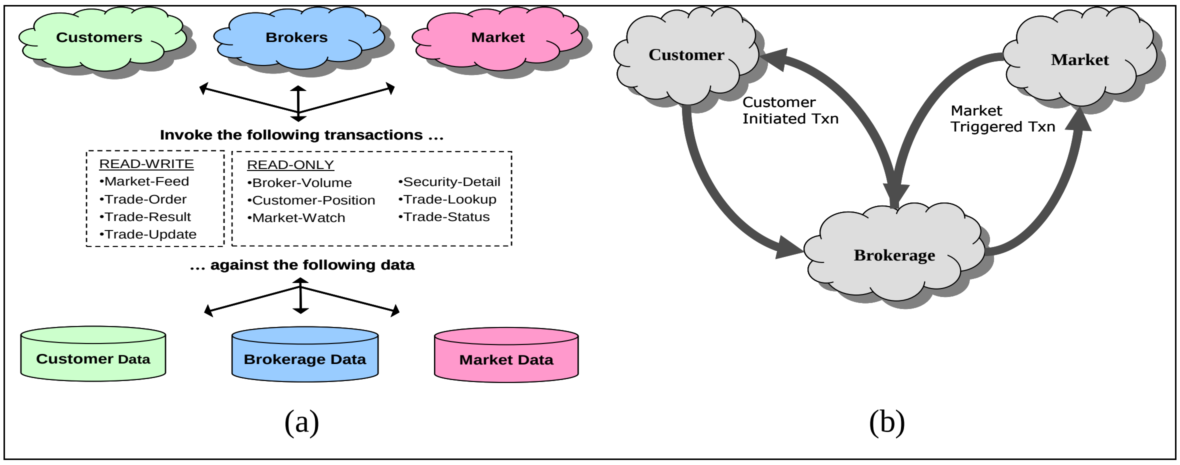


Figure 17 (a) TPC-E application components (b) TPC-E business model transaction flow [61]

As highlighted in section 2.3.1, TPC-C is approved in 1992, and it follows an old-fashioned OLTP environment. Consequently, TPC-E is designed to incorporate more current requirements like realistic data skews and referential integrity requirements. Table 4 compares TPC-E with its predecessor, TPC-C. Firstly, TPC-E defines over three times as the number of tables as TPC-C. Secondly, TPC-E has twice as number of columns as its ancestor. Thirdly, TPC-E is more read-intensive than TPC-C, and the number of transaction types is twice as defined in TPC-C. Furthermore, TPC-E exhibits realistic data skews by populating the database with pseudo-real data. TPC-E data generator is based on U.S. census data and actual listings on New York Stock Exchange (NYSE). Finally, TPC-C lacks multiple features that are found in real-world transactional systems like check constraints and referential integrity while TPC-E incorporates such requirements. In summary, TPC-E is a more accurate OLTP benchmark compared to TPC-C, yet its implementation and test setup is more sophisticated. [62]

	TPC-E	TPC-C
Business Model	Brokerage house	Wholesale supplier
Tables	33	99
Columns	188	92
Column per table	2 – 24	3 – 21
Transaction mix	4 RW (23.1%) 6 RO (76.9%)	3 RW (92%) 2 RO (8%)
Data generation	Pseudo-real, based on census data	Random
Check constraints	22	0
Referential Integrity	YES	NO

Table 4 Comparison between TPC-C and TPC-E features [62]

2.5.1 TPC-E Transactions

TPC-E is composed of 10 transactions (see Figure 17-a) following a target mixed percentage. A short description [61] of each transaction is provided in the follows. Just like TPC-C as described in section 2.3.1, a TPC-E test run includes three stages: a ramp-up, a steady, and a ramp-down state. The benchmark requires a measurement interval of at least 120 minutes. Besides, at least 90 percent of each transaction type should meet a specified response-time during the measurement interval. Each transaction within TPC-E is invoked as a single or multiple frames. In fact, the frames are the execution units of the transactions and the benchmark increases complexity by using multiple frames within a transaction.

1. Broker-Volume emulates a business intelligence type of query in the brokerage house like reporting the current performance potential of different brokers. It is consisted of a single frame and has a target mix of 4.9 percent.
2. Customer-Position is a transaction with a target mix of 13 percent and emulates the process of fetching the customer’s profile and outlining their total standing based on current market values for all assets. The transaction includes three frames.
3. Market-Feed emulates tracking the current market activity with a mix of one percent. It is a single-frame transaction.
4. Market-Watch emulates a customer tracking the current daily trend of a collection of securities. The transaction has a mix of 18 percent and includes one frame.

5. Security-Detail represents a customer investigating a security before deciding about executing a trade. This single-frame transaction comprises 14 percent of total transactions.
6. Trade-Lookup exhibits information retrieval by a customer or a broker to analyze a set of trades. This transaction comprises of four frames and incorporates eight percent of the whole transactions.
7. Trade-Order is designed to imitate a customer, broker, or authorized third-party that sells or buys a security. The trading person can trade at the current market price or place a limit order. Transactions of this type take in 10.1 percent of the total mix. Also, it encompasses six frames.
8. Trade-Result emulates the process of finalizing a stock market trade within six frames. The transaction involves 10 percent of the total mix.
9. Trade-Status is a single-frame transaction with 19 percent mix percentage that portrays a customer checking a summary of the recent trading actions for one of their accounts.
10. Trade-Update is a transaction with three frames which emulates the process of updating a set of trades. In total, 2 percent of total transactions are of this type.

As mentioned earlier, TPC-E imposes constraints on response times during the measurement interval. According to the benchmark’s specification, 90 percent of the Trade-Status transactions must be completed within 1 second. Likewise, the Market-Feed, Trade-Order, and Trade-Result transactions must have a response time below two seconds. All other transactions that are part of the maintained transaction mix have a required response time within the bounds of three seconds. Besides the mentioned transactions, there are two other transactions which are not a part of the mixed transactions including Data-Maintenance and Trade-Cleanup. The Data-Maintenance is a time-triggered transaction that must be invoked once each minute and completed in 55 seconds or less. It emulates periodic modifications to the database and is similar to updating data that seldom changes. The Trade-Cleanup transaction runs once at the start of test-run and cancels pending or submitted trades from the database. [61]

2.5.2 TPC-E Required Isolation Levels

The benchmark demands to enforce full ACID properties during the test run. TPC-E defines four concurrency anomalies: Dirty-read, dirty-write, non-repeatable read, and phantom read. The dirty-write phenomenon happens while a transaction can modify an intermediate, uncommitted data element from another transaction and commit the changes. In the same way, the dirty-read occurs when a transaction can access any intermediate, uncommitted data element from another transaction. The non-repeatable read occurs, when a data element is retrieved twice during a transaction, and the values differ between reads. Finally, the phantom read happens, when two identical read queries in a transaction obtain different sets of data elements. [61]

According to [61], three types of isolations must be retained during a test run. The dirty-read and dirty-write anomalies must not occur in the Broker-Volume, Customer-Position, Data-Maintenance, Market-Watch, Security-Detail, Trade-Lookup, and Trade-Status transactions. The Market-Feed and Trade-Order transactions should also be isolated from the non-repeatable reads. Besides, the Trade-Result transactions should keep the highest level of isolation and be prevented from the phantom reads.

2.5.3 Scaling the Benchmark

TPC-E has three primary metrics including a performance metric, a price metric, and an availability date. The price metric is TPC-E three years pricing divided by the reported throughput. The availability date is the date that all products required to achieve the reported throughput will be available. The performance metric is of particular interest to the thesis; more explicitly, the other metrics are ignored. The performance metric is expressed in transactions-per-second-E (tpsE). The tpsE is calculated by the number of Trade-Result transactions that complete in a one-minute interval divided by 60. Measuring the throughput should be done during a measurement interval with at least 120 minutes. Besides, the measurement interval must entirely occur during steady state. The computed throughput during the measurement interval is called measured throughput. [61]

The benchmark database schema includes 33 tables which can be classified into four groups: Customer, broker, market, and dimension. The customer tables contain customer-related data. The broker tables keep the data related to the brokerage firm and brokers. In addition, the market tables store data for the financial market like exchanges, companies, and securities. The dimension tables contain generic information such as addresses and zip codes. The benchmark also enforces referential integrity (i.e., primary keys and foreign keys). [61]

As stated by the benchmark, the measured throughput should scale with the database size; to maintain throughput proportional to database size, more customers, and their associated data must be set up. The cardinality of the CUSTOMER table is the base for database sizing and scaling. The minimum cardinality for the table is 5000, and it can be increased in increments of 1000 customers (called load unit). For each load unit, 20 percent of the customers belong to Tier1, 60 percent to Tier2, and others to Tier3. Tier1 customers have an average of 2.5 accounts while the Tier2 customers have averagely five accounts. Customers of Tier3 have 7.5 accounts on average. Tier2 Customers trade twice as often as customers in Tier1. In the same way, Tier3 customer trade three times as often as Tier1 customers. TPC-E benchmark defines three types of tables: Fixed, scaling, and growing tables. The fixed tables have a fixed cardinality regardless of the database size. Moreover, the scaling tables have a defined cardinality with a constant relationship to the number of rows in the CUSTOMER table. Finally, the growing tables have an initial cardinality with a defined relationship to the number of customers. However, the growing tables increase at a rate that is relative to transaction throughput rates. [61]

TPC-E defines the concept of a nominal throughput. The nominal throughput is calculated based on the number of customers configured for data generation. The nominal throughput for every 1000 customers is equal to 2.00 tpsE. For instance, a database configuration with 5000 customers has a 10.00 tpsE nominal throughput. The measured throughput should be in the range of 80% to 102% of the nominal throughput. Similarly, the measured throughput for the database sized for 5000 customers must be in the range of 8.00 tpsE and 10.20 tpsE. If the measured throughput is between 80% and 100% of the nominal throughput, the measured throughput should be reported as the gained performance. If the measured throughput is between 100% and 102% of the nominal throughput, the nominal throughput must be reported as the achieved performance. All other values are not valid results and should not be reported. [61]

2.5.4 TPC-E Functional Components

Functional components of the benchmark can be divided into a Driver and SUT. The Driver includes three pieces: Customer emulator (CE), Market Exchange Emulator (MEE), and Data-Maintenance (DM) generator. The CE emulates customers interacting with the brokerage house. The CE Driver generates transactions and their inputs, submits them to the SUT, receives the transaction responses from SUT, and measures the response times. In the same way, the MEE emulates stock exchanges; it receives trade request from the SUT and simulates the behavior of the market. The MEE initiates market-triggered transactions (i.e., Trade-Result and Market-Feed), sends the transactions to the SUT, and measures the response times. The DM generator simulates the periodic Data-Maintenance transactions. It generates data for and executes the Data-Maintenance transaction while supplies an interface to invoke the Trade-Cleanup transaction once prior to the test-run. The Driver focuses on the essential transactional performance; application functions linked to user interface and display have been excluded from the benchmark. [61]

The SUT is defined to be the sum of two tiers: Tier A and Tier B. The Tier A operates as an intermediary (i.e., application layer) between the Driver and the database server. The database server is called Tier B. TPC-E mandates the use of a network between Driver and Tier A. It is possible for the Driver and SUT to share implementation resources providing that the Driver and Tier A communicate through a network layer. Also, the benchmark permits using both synchronous and asynchronous network architecture for the communication between the Driver and Tier A. [61]

3 TPC-E BENCHMARK IMPLEMENTATION FOR SAP HANA

TPC-E comes with a software package to facilitate the benchmark implementation; the software package is called *EGen* and implemented in C++. In fact, *EGen* is a software environment that must be used in the implementation of the benchmark. **Figure 18** demonstrates the functional components of an implemented TPC-E test configuration. The core components of the *EGen* are *EGenLoader*, *EGenDriver*, and *EGenTxnHarness*. The *EGenLoader* is the part of *EGen* that generates the initial data to populate the database. The *EGenLoader* uses several text files (i.e., *EGenInputFiles*) to generate the data, and it comes with two data loaders, one that generates flat files, and the other that provides functionality for direct loading of a Microsoft SQL Server database via Open Database Connectivity (ODBC) interface. The *EGenDriver* aids the implementation of the benchmark's driver. It uses the *EGenInputFiles* to generate the transactions inputs. It has three classes: *EGenDriverCE* (Customer Emulator), *EGenDriverMEE* (Market Exchange Emulator), and *EGenDriverDM* (Data Maintenance Generator). Furthermore, the *EGenTxnHarness* defines a set of interfaces that should be implemented by the benchmark sponsor (the company officially submitting the results). These interfaces control the invocation of the transactions' frames according to the input generated by the *EGenDriver*. [61]

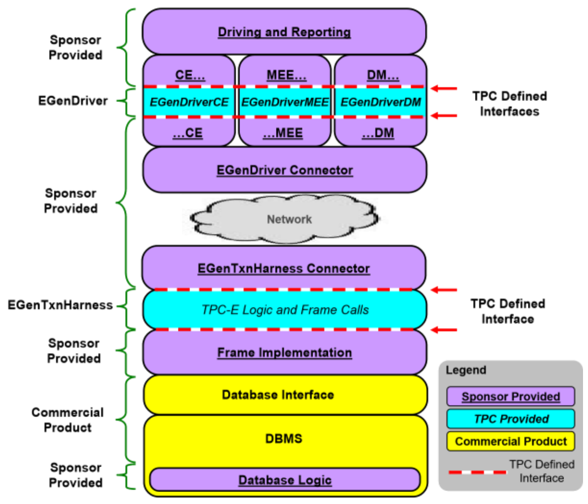


Figure 18 Functional Components of the TPC-E Test Configuration [61]

As shown in **Figure 18**, a sponsor is accountable for writing the code to implement these functionalities: The test driver, the emulators, the network connectors (i.e., *EGenDriver Connector* and *EGenTxnHarness Connector*), and the defined *EGenTxnHarness* interfaces.

The *EGenDriver* Connector is invoked from the *EGenDriver* and is responsible for sending the generated transactions data to, and receiving the corresponding resulting data from, the *EGenTxnHarness Connector* through the network. The *EGenTxnHarness Connector* receives the transactions data from the *EGenDriver Connector* and communicates with *EGenTxnHarness* via a TPC defined interface. In the same way, the *EGenTxnHarness* invokes the sponsor's implementation of the transactions frame and return the resultant data to the *EGenTxnHarness Connector*. [61]

In this work, all of the necessary functionality to be provided by a sponsor to run TPC-E against SAP HANA are implemented. The benchmark is implemented using C++ and SQLScript. C++ is used to code the sponsor-provided functionalities while SQLScript is applied to implement the transactions' frames. Our TPC-E implementation consists of almost 11000 lines of C++ code and 2000 lines of SQLScript code. In total, several primary modules collaborate to provide the functional requirements of the benchmark, as described in the following subsections.

3.1 Data Loader

An extended database loader is implemented via the *EGenLoader*. The extended loader can be employed for generating the flat files, bulk importing from the flat files into HANA or a combination of both operations. Data generation and data import are separated to provide more flexibility since the data generation is time-consuming and can be done only once.

The data generation is implemented by using the *CGenerateAndLoad* class shipped with the *EGenLoader*. The class delivers routines for generating and loading the data tables which among them we used only the data generation interfaces. The data generation can be configured by command line arguments to generate fixed, scaling, growing tables or a mixture of them.

The data import is completed in five stages. First, the tables are generated in a schema called TPCE. In HANA, databases can be divided into logical sub-databases known as a schema. After generating the TPCE schema, the loader imports the delimited flat files using *IMPORT FROM* statement supported by HANA. Then, the TPC-E referential integrity constraints are enforced at the third step. Afterwards, several indexes are generated to speed up the search operations. Finally, the transactions' procedures are created in the database. The data loader uses HANA ODBC driver to communicate with the DBMS.

3.2 Common Functionalities

There are several functionalities in the benchmark which are shared between the driver and Tier A (the application layer). The common functionalities can be classified into multi-tasking, networking, and logging features. This section briefly explains the design principles and architectural choices applied to them.

Firstly, some parts of the benchmark demand parallel execution. For example, a multi-threading architecture is necessary for replicating CEs and MEEs as single instances of the customer emulator and market exchange emulator can achieve a limited throughput compared to the nominal throughput. The job execution framework of the HANA DBMS kernel is utilized for thread pooling and running job nodes. The job execution framework is NUMA-aware and exploits task scheduling to prevent CPU saturation. The classes that define job nodes follow a naming convention; the job node classes end with a 'JobNode' postfix like DMJobNode, CEJobNode, and MEEJobNode. The job node classes should inherit from a base class and implement a pure virtual function named *run*. The *run* function contains the code that needs to be executed as a parallel task.

As mentioned before, TPC-E demands a mandatory network layer between the driver and the Tier A. Two class named CNetworkServer and CClientConnector are implemented to handle streaming data over network sockets. The CClientConnector is the class used for transmitting transaction requests and transaction orders over the network (from driver to the Tier A, and from the Tier A to MEE server). SendReqReceiveResp is the method implemented for sending the requests and receiving the response. Before the transmission, the transactions are serialized into a union data type. CNetworkServer class is responsible for receiving the request from the network client, processing the request, and sending back the results. The network server class uses synchronous data transfer architecture; however, a job is executed upon receiving each request to prevent blocking concurrent requests. The

CNetworkServer can be launched by calling the *run* method. After receiving any request, it calls the processMessage method of the derived class (the processMessage is defined as a pure virtual function class inside CNetworkServer).

Furthermore, a class named BenchMLogger is implemented for logging transactions' response times. The log files later can be employed to analyze the validity of the results. It uses a TPC-provided class (CEGenLogger) for data logging. In other words, BenchMLogger is a decorator class extending CEGenLogger.

3.3 Driver

The driver is mainly responsible for: 1) Executing the Trade-Cleanup transaction prior to the test-run; 2) Emulating the customers (CE); 3) Emulating the market exchange (MEE); 4) Executing the time-triggered Data-Maintenance transaction; 5) Measuring and logging the response times. Figure 19 demonstrates the structure of the primary classes and their essential attributes and methods.

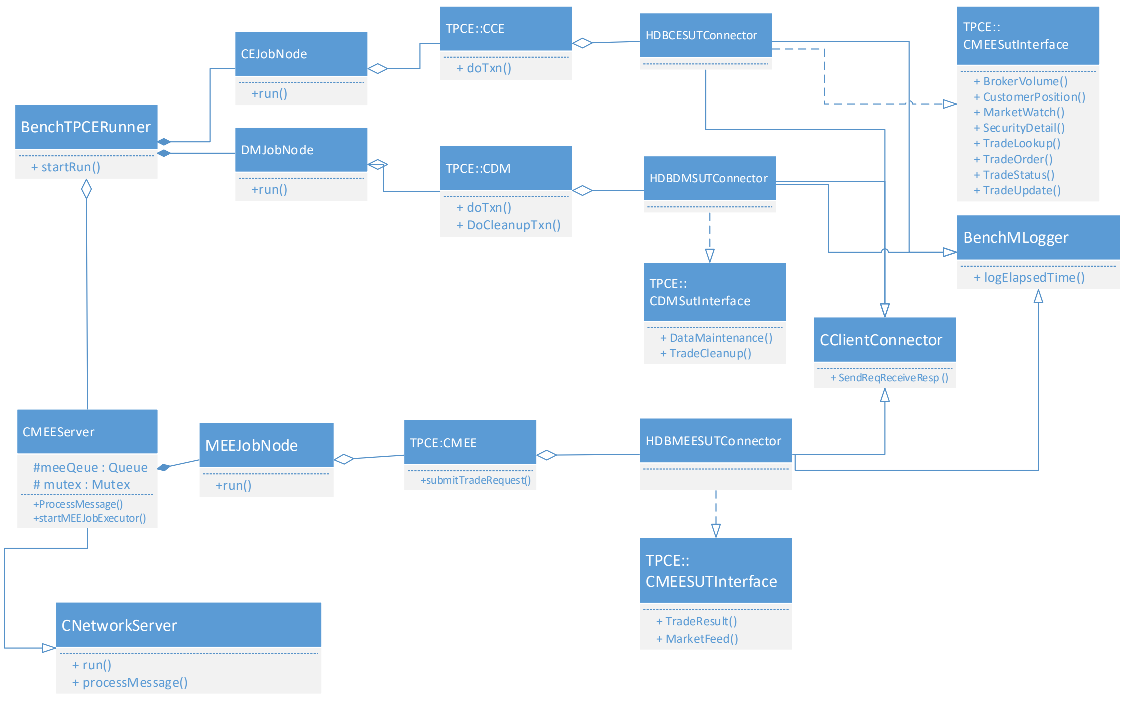


Figure 19 High-level class diagram of the implemented driver

As shown in the class diagram, BenchTPCERunner is the class implemented for launching and orchestrating the test run. It executes job nodes of data maintenance (DMJobNode) and customer emulator (CEJobNode). It also starts the market exchange emulator server (CMEEServer).

DMJobNode is the job node for executing Trade-Cleanup and Data-Maintenance transactions. The job node is dispatched only once (single thread) and calls the methods of the CDM class. CDM class is a part of EGen package and delivers the data maintenance and trade cleanup operations by CDM::DoTxn and CDM::DoCleanupTxn member functions. The Data-Maintenance transaction is a time-triggered transaction called in intervals of 60 seconds. The CDM receives a class derived from CDMSutInterface in its constructor; HDBDMSUTConnector class is implemented to transmit data-maintenance and trad-cleanup transaction requests to the Tier A. The class logs the response times and response values into the corresponding log file.

To achieve the necessary nominal throughput, there can be multiple instances of customer emulator and market exchange emulator. The number of threads is configurable using the driver's command line arguments. Each CE thread cycles through calling DoTxn member function of an instantiated CCE class. The CCE class is a part of EGen software package and generates the next transaction type and its required inputs. The produced transaction data is then sent to the HDBCESUTConnector class. HDBCESUTConnector realizes CMEESutInterface (an interface provided by TPC); it is in charge of sending customer-initiated transactions to the SUT, receiving the results, measuring the response times, data logging through an instance of BenchMLogger.

The implemented CMEEServer listens on a specified network port and receives the trade requests from the brokerage house. The MEE enqueues any received trade request to a queue shared among the MEE job nodes (i.e., threads). The threads continuously check the queue and try to dequeue a trade result from the queue. A mutex is used to protect the shared queue from being simultaneously accessed by the multiple threads. The MEE passes the request to the brokerage house via HDBMEESUTConnector (an implementation of CMEESUTInterface interface).

3.4 Tier A

Figure 20 shows the structure of the primary classes and their important attributes and methods used in the Tier A (also called application layer). CTxnHarnessConnector is primarily accountable for listening on a specific network port. The class inherits from CNetworkServer; it checks the transaction type upon receiving any customer-initiated or market-triggered transaction. Subsequently, CTxnHarnessConnector instantiates a TPC-provided class corresponding to the requested transaction. The instantiated classed can be of types: CBrokerVolume, CCustomerPosition, CDataMaintenance, CMarketFeed, CMarketWatch, CSecurityDetail, CTradeCleanup, CTradeLookup, CTradeOrder, CTradeResult, CTradeStatus, or CTradeUpdate. Any of these classes requires implementing a class conforming a specific interface. For instance, CBrokerVolume requires an implementation of CBrokerVolumeDBInterface (HdbBrokerVolume in our implementation). The classes in the class diagram starting with "Hdb" are implementations for specific interfaces. The Hdb-starting classes receive transactions' inputs, bind stored procedures' parameters, and call the equivalent stored procedure using ODBC. Finally, the Hdb-starting classes return transactions output to CTxnHarnessConnector. The stored procedures are implements in SQLScript language (see section 2.4.4). In total, 30 stored procedures incorporate the benchmark's transactions.

As shown in the application layer's class diagram, two classes (i.e., CMarketFeed and CTradeOrder) contain references to CSendToMarket class. The CSendToMarket class inherits from CClientConnector and CSendToMarketInterface; it controls sending trade requests to market exchange emulator server (via SendToMarket member function) through the network.

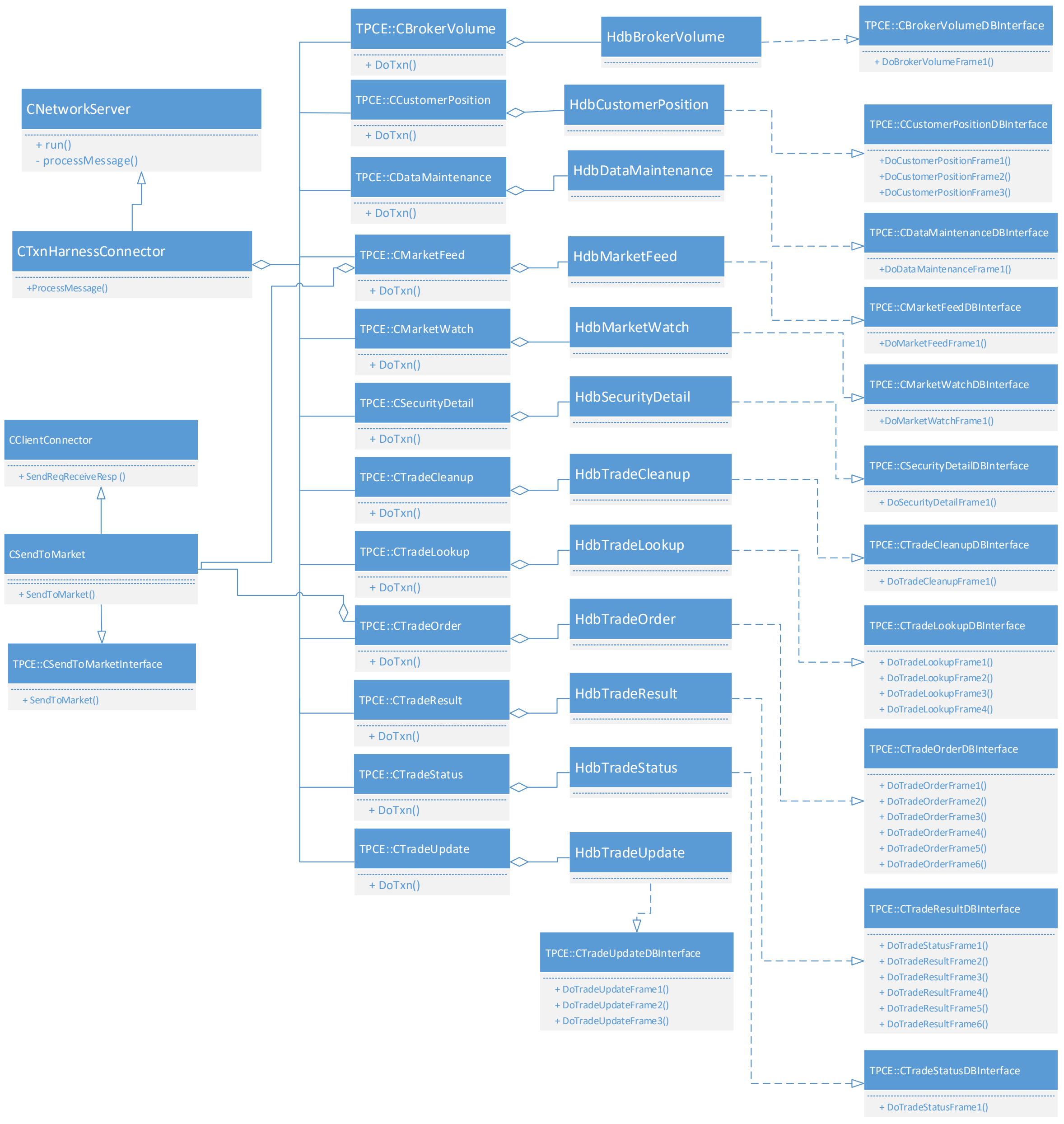


Figure 20 High-level class diagram of the implemented Tier A

4 EXPERIMENT

This section explores the experiment’s results. First, the underlying experiment configuration is provided including the database management system and the hardware. Then, the benchmark is run against both row and columnar data stores to answer RQ1. Afterwards, the results of profiling are provided to explore RQ2. Finally, SQLScript is evaluated for OLTP workload (RQ3).

4.1 Experiment Configuration

4.1.1 Database Management System

To launch the benchmark, a research version of SAP HANA 2 is used as the underlying database management system. In the experiment, the benchmark is configured with 20000 customers (see section 2.5.3 for a detailed explanation about scaling the benchmark). The reason for selecting 20000 customers is that higher number of customers demand complex hardware configurations (e.g., a server cluster with multiple terabytes of memory). Furthermore, data generation and import become significantly time-consuming while the number of customers increases. Also, a configuration with 20000 provides an acceptable initial database size. An initial trade days (ITD) of 300 days and a scale factor (SF) of 500 are used for data generation. Table 5 shows the initial cardinality of tables after the database population.

In total, the generated data for the database population amounts to 142 GB of raw flat files. The initial database size for storing the generated data in the columnar layout (aka column store) is 51 GB, and the initial size for storing the same data in the row-wise layout (aka row store) is 151 GB. The initial database size is the allocated space for storing all database entities including data, indexes, and database metadata [63]. Even though both the row-store and column store employ compression mechanisms to save space, the column store achieves a significant space saving compared to the row store (a factor of 2.96). This implicates the benefits of the columnar layout regarding memory saving as explained in section 2.2.4.

Table	Cardinality	Table	Cardinality
ACCOUNT_PERMISSION	141.979	INDUSTRY	102
ADDRESS	30.004	LAST_TRADE	13.700
BROKER	200	NEWS_ITEM	20.000
CASH_TRANSACTION	317.950.537	NEWS_XREF	20.000
CHARGE	15	SECTOR	12
COMMISION_RATE	240	SECURITY	13.700
COMPANY	10.000	SETTLEMENT	345.600.000
COMPANY_COMPETITOR	30.000	STATUS_TYPE	5
CUSTOMER	20.000	TAXRATE	320
CUSTOMER_ACCOUNT	100.000	TRADE	345.600.000
CUSTOMER_TAXRATE	40.000	TRADE_HISTORY	829.434.764
DAILY_MARKET	17.878.500	TRADE_REQUEST	0
EXCHANGE	4	TRADE_TYPE	5
FINANCIAL	200.000	WATCH_ITEM	1.999.003
HOLDING	17.664.875	WATCH_LIST	20.000
HOLDING_HISTORY	463.172.112	ZIP_CODE	14.741
HOLDING_SUMMARY	993.000		

Table 5 Initial cardinality of tables

4.1.2 Underlying Hardware

A single server is utilized to execute the benchmark; the driver, Tier A, and Tier B share hardware resources. The server has four 10-core processors Intel Xeon Processor E7-4870 at 2.40 GHz; in total, 80 hardware contexts are supported using hyper-threading. Each core has 32 KB L1d (i.e., L1 data cache), 32 KB L1i (i.e., L1 instruction cache), and 256 KB of L2 cache. Besides, each processor employs 30 MB of L3 cache that is shared among its cores. The processors incorporate four NUMA nodes (each node includes ten cores). Also, the server has 512 GB of RAM and 5.7 TB of rotating disks.

The operating system (OS) installed on the server is a 64-bit SUSE Linux Enterprise Server 12 with service pack 1 (SP1). The operating system runs a 3.12 Linux kernel.

4.2 Throughput Evaluation

The evaluation is run in two primary stages. First, the column store engine of HANA is used to evaluate the achievable throughput. Then, the benchmark is executed against the row store engine. The gained throughput is measure in tpsE (see section 2.5.3). Due to confidentiality concerns and SAP legal policies, we cannot disclose the absolute throughputs; the achieved throughputs are normalized to a percent. This does not hinder us from presenting results of the experiment since the focus is on comparing the performance of the data stores.

As discussed in section 3.3, the implemented driver receives the number of CEs and MEEs from the command line. This helps us to configure the number of threads to replicate customer emulators and market exchange emulators to generate the necessary nominal throughput for database size with 20000 customers. The nominal throughput for a database with 20000 customers is 40 tpsE (2.00 tpsE for every 1000 customers). Also, the measured throughput for such a database sizing must be in the range of 32 tpsE and 40.8 tpsE (80 to 102 percent of the nominal throughput) according to the benchmark rules. Hence, the test is executed multiple times to find the number of threads necessary to achieve an acceptable measured throughput for the column store. During the experiment, a single instance of the driver configured with 35 threads of CE and five threads of MEE is used. The throughput evaluation incorporates several critical steps, as follows.

1. The flat files are generated.
2. The column store is populated via the data loader.
3. The benchmark is performed against the columnar engine to measure its throughput. Each test run takes 140 minutes: one-minute ramp-up, 138 minutes of the measurement interval, and one-minute ramp-down. The test is repeated five times to achieve verifiable results. The throughput expressed in this thesis is the average of the five test-runs.
4. The row store is populated using the loader.
5. The procedure explained in step 3 is executed for the row store.

The steps explained above will aid understanding how an in-memory columnar HTAP perform with OLTP workload comparing to the row store (RQ1).

4.2.1 Achieved Throughput and Response-times

As shown in Figure 21, the row-store engine outperforms the column-store engine for the OLTP workload with a 26% difference; the normalized throughput of the column-store is

74% of the achieved throughput for the row-store engine. The x-axis in the figure shows the achieved throughput in a percent scale.

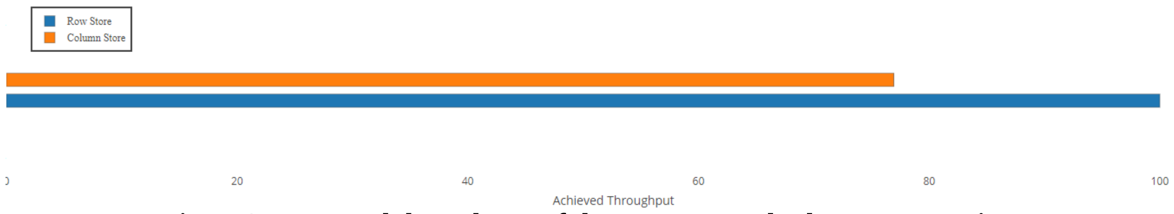


Figure 21 measured throughputs of the row-store and column-store engines

While both test runs (column and row store engines) maintain the ninetieth percentile of the required response times, the valid response times are measured for two groups of transactions: read-only and read-write transactions. Figure 22 and Figure 23 render box plots of the response times per individual transactions for column store and row store engine. The y-axis in the figures sketches response times (log scale) while the x-axis includes boxes representing transactions grouped into the column and row store. The ends of the whiskers show the minimum and maximum response times. The bottom and top of the boxes show first and third quartiles, whereas the bands inside the boxes denote the medians. Also, the Trade-Cleanup transaction is omitted since it is executed only once at the beginning of the test run and does not affect the throughput.

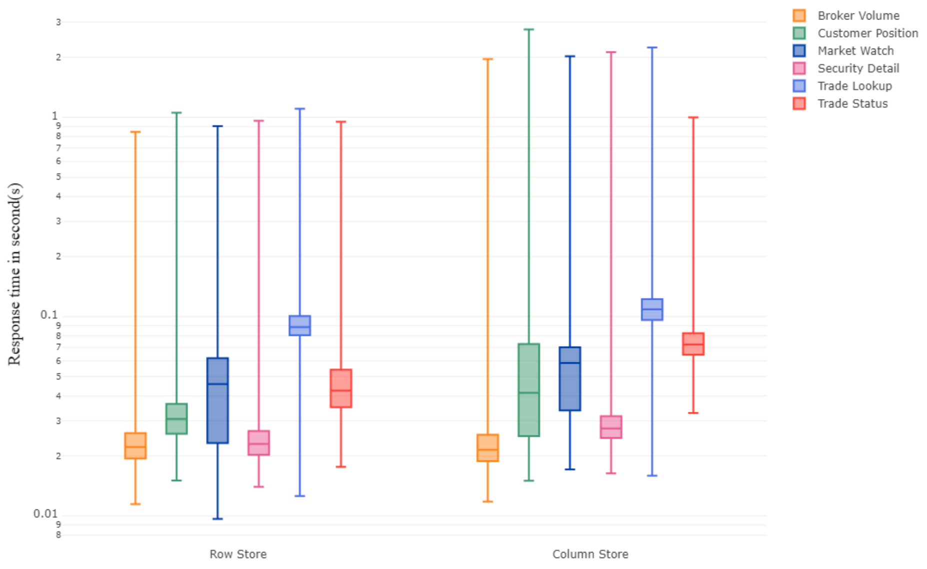


Figure 22 Response times of the read-only transactions

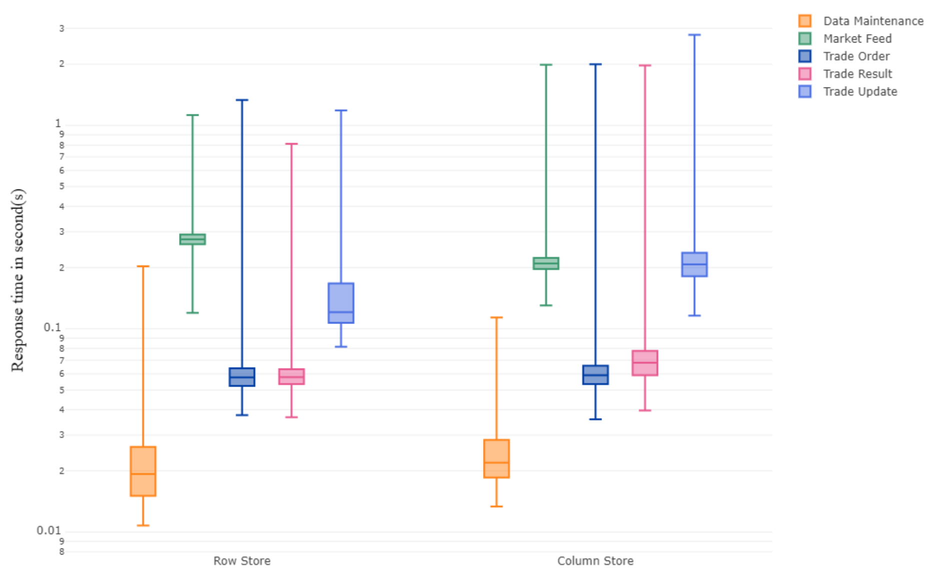


Figure 23 Response times of the read-write transactions

As the figures illustrate, the minimum and maximum response times exhibit more variations in the column store due to three major reasons. Firstly, the column store applies a more aggressive parallelism. Secondly, the row-based operations dominance the workload; hence, accessing a single or a set of tuples demands more memory accesses in the column store (see section 2.2.4). Thirdly, the data manipulation language (DML) operations that constitute a significant part of the workload are more expensive for the column store. Table 6 and Table 7 express the measured response times for individual transactions in the row and column store respectively.

Response Times in Seconds					
Transaction	**Minimum**	**Maximum**	**First Quartile**	**Median**	**Third Quartile**
Broker-Volume	0.0114	0.8432	0.0194	0.0221	0.0260
Customer-Position	0.0150	1.0536	0.0258	0.0306	0.0364
Market-Feed	0.1196	1.1243	0.2602	0.2750	0.2910
Market-Watch	0.0096	0.9030	0.0232	0.0458	0.0618
Security-Detail	0.0139	0.9602	0.0202	0.0229	0.0266
Trade-Lookup	0.0125	1.1019	0.0806	0.0885	0.1007
Trade-Order	0.0375	1.3337	0.0522	0.0576	0.0639
Trade-Result	0.0367	0.8119	0.0534	0.0578	0.0632
Trade-Status	0.0176	0.9496	0.0351	0.0425	0.0540
Trade-Update	0.0815	1.1832	0.1070	0.1207	0.1673
Data-Maintenance	0.0107	0.2027	0.0150	0.0193	0.0262

Table 6 Response times summary for the row store

Response Times in Seconds					
Transaction	**Minimum**	**Maximum**	**First Quartile**	**Median**	**Third Quartile**
Broker-Volume	0.0118	1.9577	0.0188	0.0214	0.0255
Customer-Position	0.0150	2.7597	0.0251	0.0414	0.0729
Market-Feed	0.1301	1.9863	0.1966	0.2093	0.2229
Market-Watch	0.0171	2.0236	0.0338	0.0585	0.0701
Security-Detail	0.0163	2.1202	0.0245	0.0274	0.0316
Trade-Lookup	0.0159	2.2371	0.0961	0.1087	0.1221
Trade-Order	0.0358	1.9998	0.0535	0.0591	0.0658
Trade-Result	0.0396	1.9734	0.0590	0.0680	0.0778
Trade-Status	0.0328	0.9983	0.0643	0.0724	0.0826
Trade-Update	0.1159	2.7909	0.1811	0.2073	0.2363
Data-Maintenance	0.0133	0.1134	0.0185	0.0219	0.0283

Table 7 Response times summary for the column store

Next section inspects how the workload breaks down into main components of HANA.

4.3 Profiling Results

HANA architecture consists of several servers; index server is one of the core components among them. The index-server consists of the in-memory data stores and data processing engines. During the test runs, a profiler embedded in HANA is employed as an instrument to collect information about the performance of the index server. The profiler operates by sampling the index server’s call-stacks at regular intervals. Using the profiler assist us in analyzing the call stacks and the processor time spent in individual function calls as well as identifying wait conditions. The output of the profiler is two graphs created via DOT [64] language: a wait graph and a processor utilization graph. Consequently, the profiling results’ contributions are twofold. First, it assists analyzing how OLTP workloads breakdown into key components of an HTAP system (RQ2). Second, the results aid identifying the bottlenecks affecting the benchmark throughput.

The whole profiler graphs are not provided here since they are huge and cannot be fit in the text size. However, an excerpt of the profiling graph is given in Figure 24. Each node in the graph represents a process/function, and each edge denotes the calling relationship between a caller and a callee. The graph nodes include two numbers: ‘I’ is an abbreviation for inclusive time and ‘E’ stand for exclusive time. The inclusive time is the amount of processor time used by a function including the time spent in the child functions. On the other hand, the exclusive time shows the amount of time spent purely in a function excluding the child functions. Also, the numbers next to the arrows show the percentage of CPU time spent in the child functions. Moreover, the more reddish boxes express the higher processor time spent in a function. In the figure, *ptime::Query::_execute* is the query execution function taking almost 62 percent of the total CPU time. It calls *ptime::proc_update_trex::operator* (the function responsible for SQL update statement), *ptime::proc_delete_trex::operator* (the function corresponding to SQL delete statement), and *ptime::proc_insert_trex::operator* (the function applying SQL insert statement). By looking at the graph, it can be understood that 6.8% of the processor time is taken for DML operations (4.4% update + 1% delete + 1.4% insert). The main findings of the profiling process are explained in the next subsections.

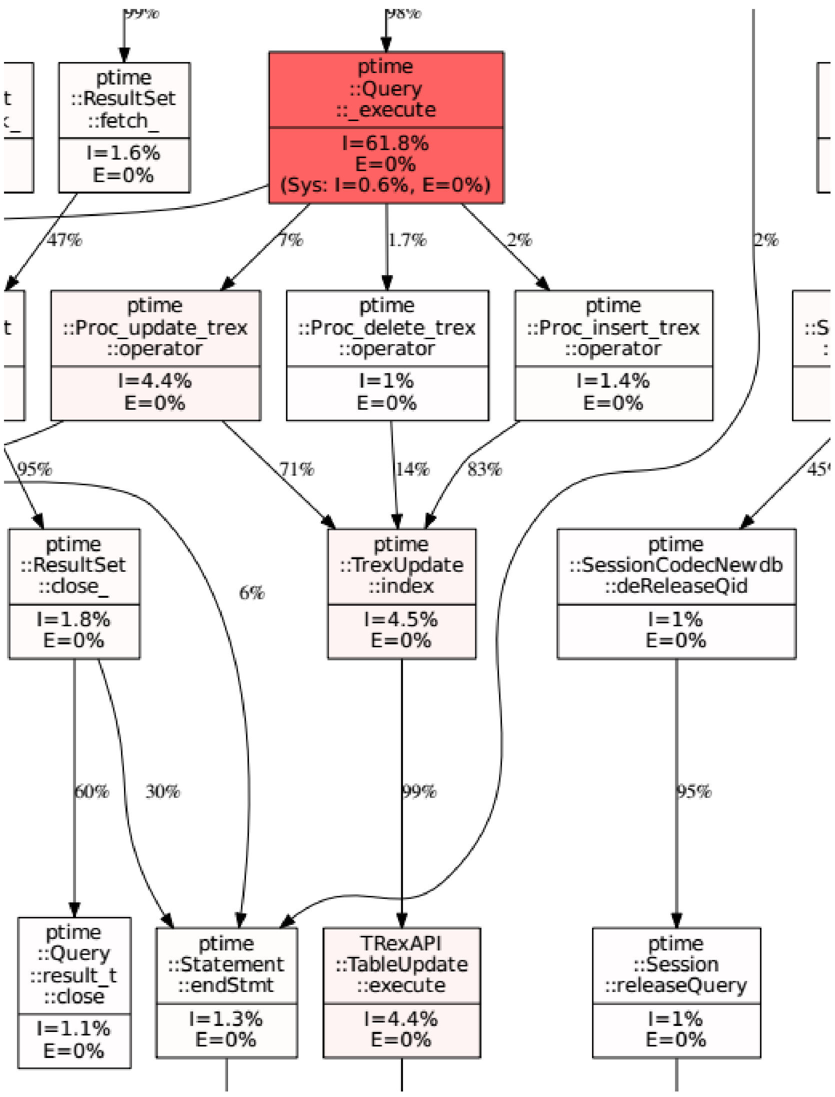

99%
98%
ptime ::ResultSet ::fetch_
I=1.6% E=0%
ptime ::Query ::_execute
I=61.8% E=0% (Sys: I=0.6%, E=0%)
47%
7%
1.7%
2%
2%
ptime ::Proc_update_trex ::operator
I=4.4% E=0%
ptime ::Proc_delete_trex ::operator
I=1% E=0%
ptime ::Proc_insert_trex ::operator
I=1.4% E=0%
95%
71%
14%
83%
45
6%
ptime ::ResultSet ::close_
I=1.8% E=0%
ptime ::TrexUpdate ::index
I=4.5% E=0%
ptime ::SessionCodecNewdb ::deReleaseQid
I=1% E=0%
60%
30%
99%
95%
ptime ::Query ::result_t ::close
I=1.1% E=0%
ptime ::Statement ::endStmt
I=1.3% E=0%
TRexAPI ::TableUpdate ::execute
I=4.4% E=0%
ptime ::Session ::releaseQuery
I=1% E=0%

Figure 24 An excerpt of the profile graph for the column store

4.3.1 Workload Decomposition

The benchmark's workload breakdown is shown in Figure 25 and Figure 26 for the column store and the row store. Only the main cost drivers are included in the charts because the focus is on the key drivers (miscellaneous costs are shown as others in the figures). The key drivers are classified into sorting operation, data store access and predicate evaluation, memory management, DML operations, query compilation and validation, network transfer and communication, SQLScript execution and overhead, and index access and join processing.

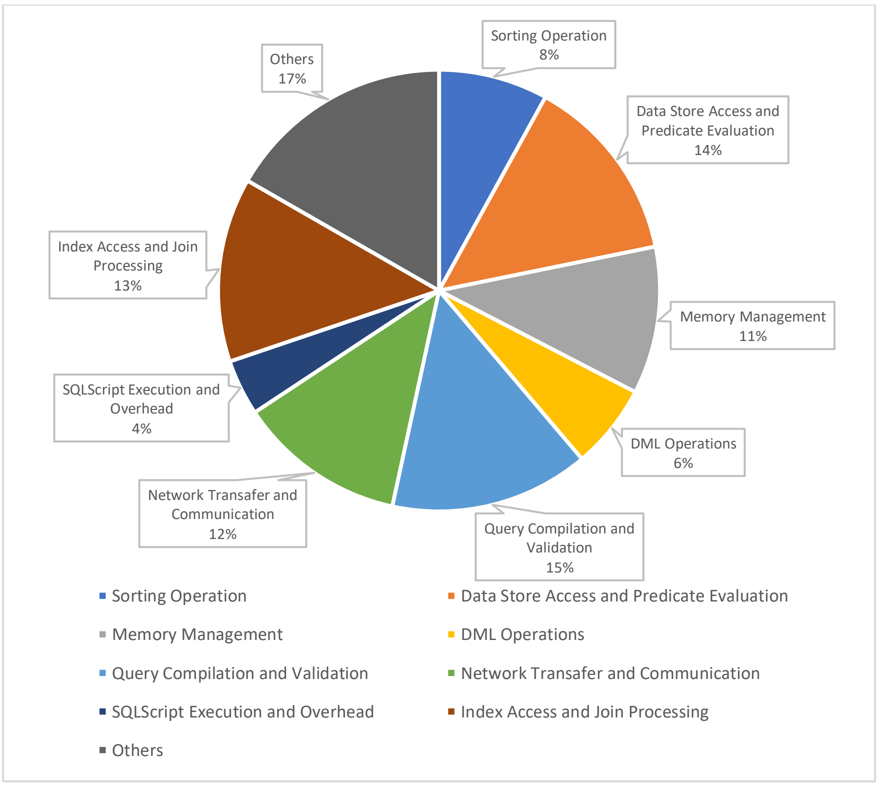


Figure 25 Workload breakdown for the row store engine

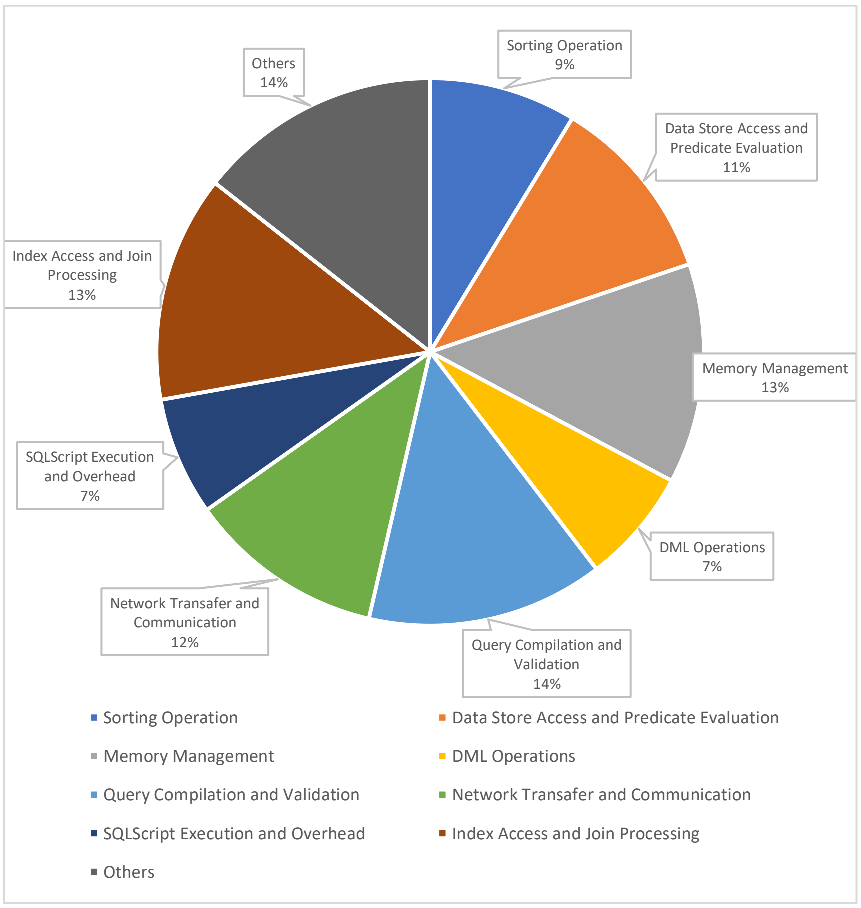


Figure 26 Workload breakdown for the column store engine

As shown in the figures, query compilation and validation incorporates a significant part (roughly 15%) of the workload for both engines. The query compilation comprises activities such as looking up in the HANA SQL plan cache, compiling queries, and query validation. The primary reason for the costly query compilation is due to the iterative nature of TPC-E transactions; we identified a typical pattern among most of the transactions. All TPC-E transactions except the Broker-Volume and Trade-Status require at least one form of iterative constructs (e.g., conditional statements, loops, and cursors). This matter is explained in detail in section 4.4.

Besides, index access and join processing constitute almost 13.5% of the workload for both engines. This includes tasks like scanning indexes, index range scan, and join evaluations. While implementing the transactions, the transactions are analyzed regarding predicates and cardinality of the tables accessed by the predicates. HANA implicitly generates indexes on primary key attribute(s). In total, 17 additional indexes are generated to avoid full table scans.

Also, data-store access and predicate evaluation is another cost driver of the experiment workload. The store access and predicate evaluation take 11.1% of the total processor time for the column store and 13.8% for the row store. This includes both sargable (i.e., predicates that could take advantage of indexes to accelerate query execution) and non-sargable predicates.

Furthermore, 13% of the CPU time is spent in memory management for the column store. The memory management takes 10.8% of the processor time for the row store. HANA utilizes a memory manager which pre-allocate and manages memory pools. Memory management mostly consists of memory allocation and deallocation. It is worth mentioning that the memory management and query compilation costs are intertwined; the less query compilation decreases the overhead of memory allocation.

Besides, network transfer and communication is also a key part consuming 11.6% of the processor time for the column store and 12.3% for the row store. This includes accepting new network connections, session management, and data transfer.

Furthermore, almost nine percent of the total processor time is spent for sorting operations during the benchmark run (8.7% for the column store and 8% for the row store). This can be justified by the fact that majority of the transactions (all except Market-Watch) include at least one ORDER BY clause (for intermediate tables and/or final results).

In addition, DML handling constitutes 6.8% of the workload for the column store and 6.2% for the row store. This includes insert, update, and delete operations. Finally, execution of the SQLScript procedures and the overhead of the execution (e.g., converting arguments, binding intermediate results to internal tables, and creating contexts to store data globally) incorporate 7% of the total workload for the column store and 4.1% for the row store engine.

4.3.2 Checkpointing and Recovery

HANA uses a persistence layer server to store a persistent copy of data and transaction logs; they ensure database recovery after failures such as crashes and power loss. In HANA, all changed pages are persisted to disk periodically (called savepoint or checkpoint). However, the periodical savepoints by themselves cannot guarantee the durability of all changes since persistence is not synchronized with the end of write transactions. Hence, the system stores log files (redo logs and undo information); the redo log contains committed changes while the undo log stores entries about rolled-back changes. The log entries are persisted while a transaction is committed or rolled-back. [65]

During a recovery process, HANA performs a log replay process upon the last version of the persisted data to store database to a consistent state. It should be mentioned that the recovery process is possible even without running checkpoints since logs can be replayed upon the initial version of the persistent data (the version of data loaded into memory). Nevertheless, periodical save-points accelerate the recovery process because fewer log entries must be replayed. The checkpointing interval is by default 300 seconds, yet it can be configured or even disabled. [65]

The checkpointing in HANA includes three stages: A page-flush, a critical, and a post-critical phase. During the page-flush, all modified pages are identified and written to disk. Next, all changes made throughout the page-flush stage are written to disk asynchronously in the critical phase. Also, the current log position is altered and stored on disk through the critical phase. While running the critical phase, all concurrent update transactions are blocked. Lastly, the post-critical phase waits for finishing all the asynchronous I/O operations and marks the save-point as complete. [65]

In the initial runs of the benchmark, it was found out that the checkpointing process causes fluctuations during the benchmark's steady state. Thus, the checkpointing interval is changed in several steps to understand effects of the checkpointing on the test run. First, the benchmark is run with checkpointing every five minutes as shown in Figure 27. The x-axis in the figure shows the elapsed time while the y-axis demonstrates the achieved throughput (the throughput is normalized to 100). Then, the checkpointing interval is increased to ten minutes (see Figure 28). Afterwards, the checkpointing interval is expanded to 60 minutes as can be seen in Figure 29. Finally, Figure 30 exhibits the experiment run graph while checkpointing is disabled. The graphs manifest running experiment on the row store, yet, the instabilities also exist with the column store.

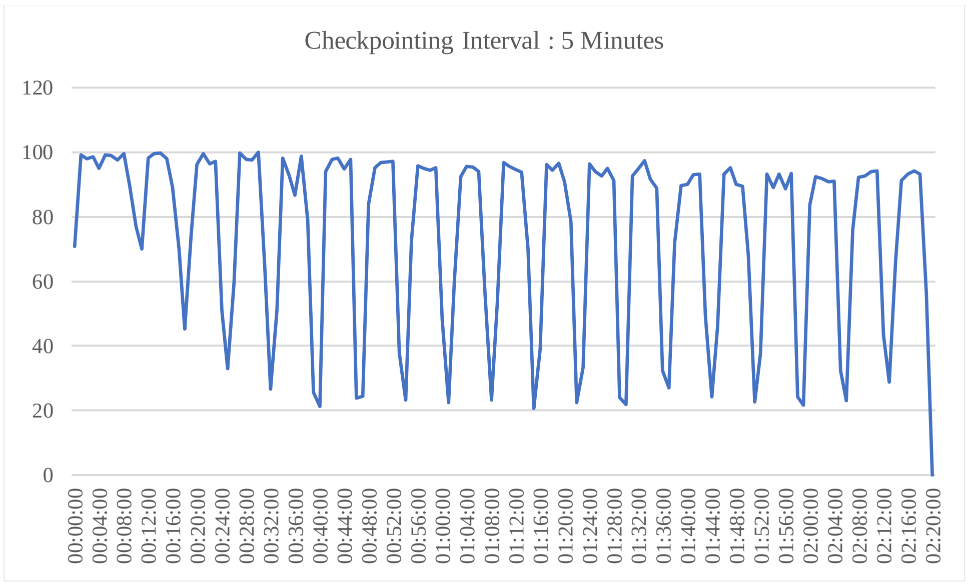


Figure 27 Experiment run graph with checkpointing at intervals of 5-minute

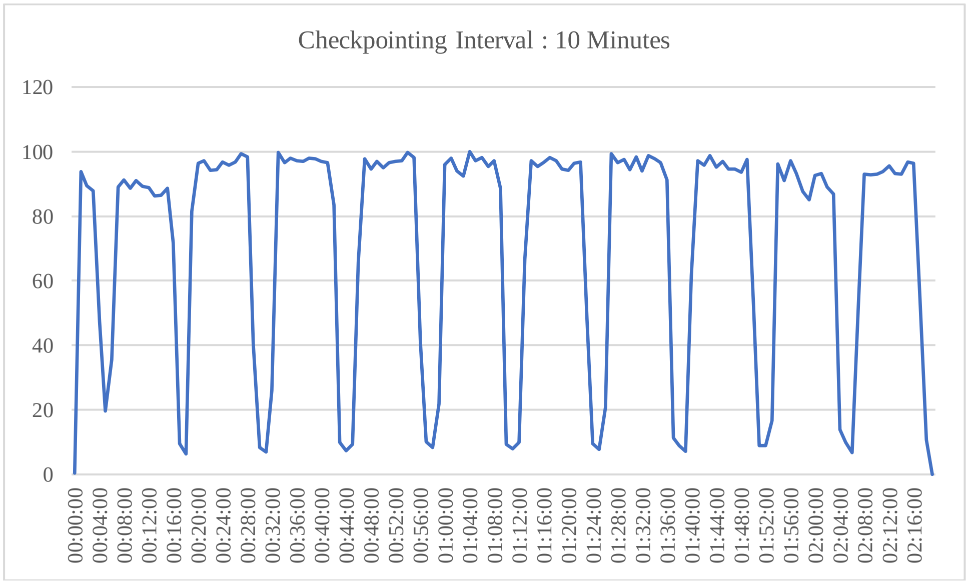


Figure 28 Experiment run graph with checkpointing at intervals of 10-minute

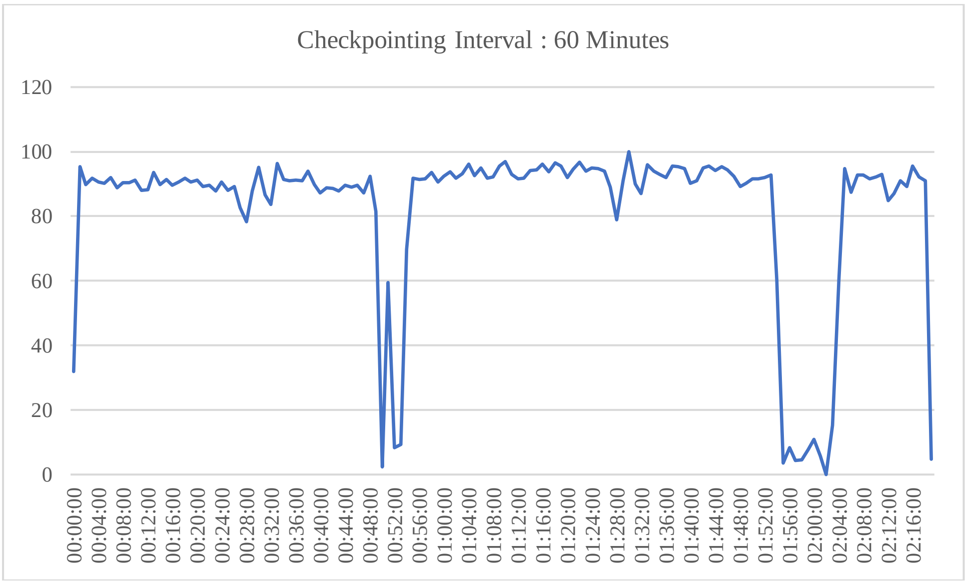


Figure 29 Experiment run graph with checkpointing at intervals of 60-minute

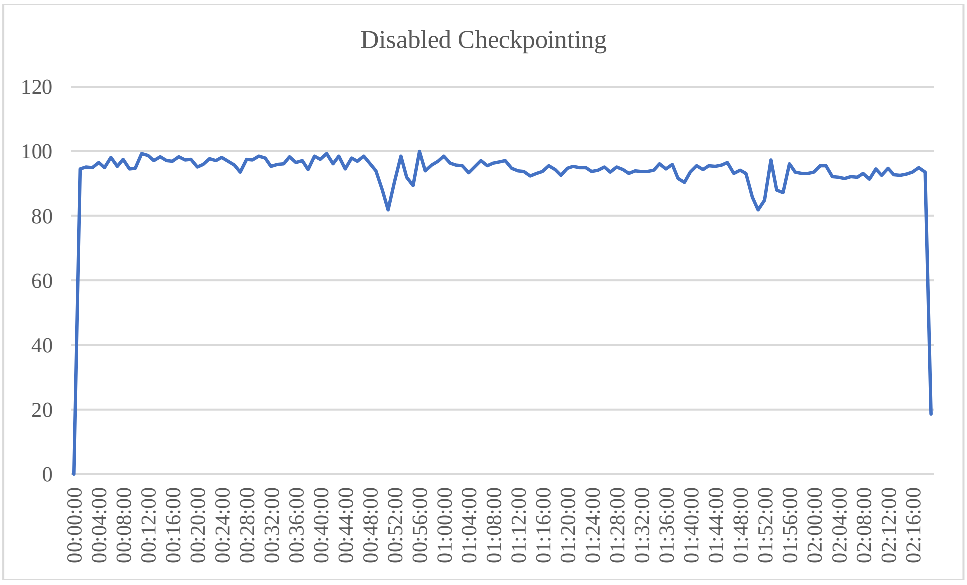


Figure 30 Experiment run graph while checkpointing is disabled

The figures validate implication of the checkpoints on the experiment. To begin with, the number of variations drops by enlarging the checkpoint intervals; though, the duration of the fluctuations increase since more changes must be synchronized each time. Also, the fluctuations are diminished by disabling the checkpoints.

The throughputs explained in section 4.2 are measured without checkpointing. The checkpointing issues mostly stem from poor I/O performance; the underlying server used for the experiment employs rotating disks. Consequently, using more performant non-volatile storages like solid-state drive (SSD) might alleviate the issue. However, future work is needed to establish this. At the time, SAP is adopting non-volatile RAM (called NVRAM or NVM) technologies like Intel 3D XPoint in HANA’s architecture [66]. There is room for further research in determining how using the NVRAM technologies could alleviate the throughput variations during the experiment.

4.4 SQLScript Evaluation for OLTP Workload

Relational databases traditionally offer imperative language extensions using a dialect of SQL such as Procedural Language/Structured Query Language(PL/SQL), Transact-SQL(T-SQL), and SQLScript [60]. Even though the offered iterative extensions ease pushing application logic to the database, performance requirements also of concern while using such constructs. The performance requirements play a crucial factor for OLTP workloads. In this section, it is explored how optimal an HTAP-oriented stored procedure language like SQLScript is for OLTP workloads (RQ3).

During the experiment, it was found out that query compilation and validation is one of the major cost drivers while running the benchmark (roughly 15% of the total processor time). Therefore, this matter was investigated in a greater detail, and the iterative nature of TPC-E transactions turned out to be the primary reason of the costly query compilations. We identified a typical pattern among most of the transactions; all TPC-E transactions except the Broker-Volume and Trade-Status require at least one form of iterative constructs (e.g., conditional statements, loops, and cursors). Put it differently, SQLScript provides a suboptimal performance for queries of this kind. In some situations, iterative-approach can be converted to a set-based logic; however, this is not always possible. For instance, FOR loops containing dependent SQL statements are less probable to be converted into a set-based logic. Hence, it was decided to produce a simplified version of the situation and examine our theory using it.

Two exemplified transactions are built on top of TPC-E schema called L1 and L2. L1 and L2 access four tables of TPC-E schema as shown in Figure 31. The only change made to the TPC-E schema is dropping the primary key from the TRADE_HISTORY table since it is needed to insert non-unique data into the table. The initial cardinality of the TRADE and SETTLEMENT tables are roughly 345.600.000 records while the cardinality is 830.000.000 records for the TRADE_HISTORY table. Also, the TRADE_TYPE relation contains five records.

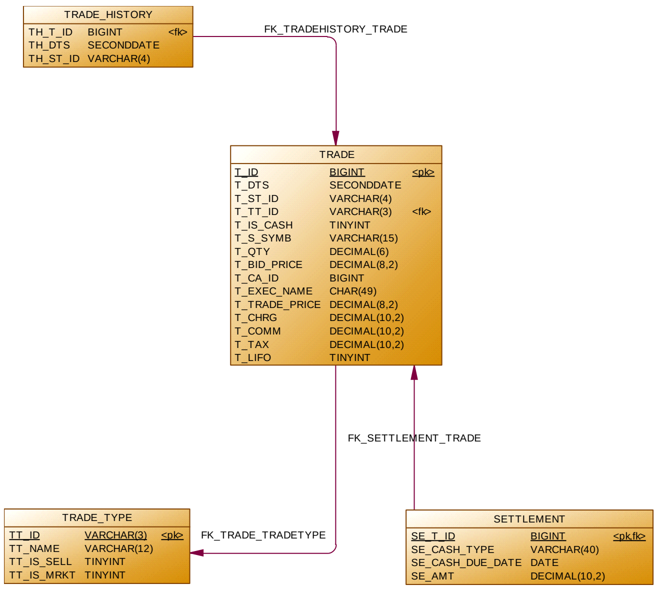


Figure 31 ER diagram of the tables accessed by L1 and L2

L1 is a read-only transaction that retrieves trade and settlement information about a set of trades. The transaction receives an integer (ids_count) indicating the number of trade IDs which should fetch information about. The transaction first fetches the trade IDs into a table variable named trade_ids. Then, it retrieves the trade and settlement information about the IDs stored in the trade_ids. The transaction is implemented using two approaches. First, an iterative approach (by means of a FOR loop) is used to fetch the information record by record as shown in Figure 32 (a); the procedure is called L1_Iteration. Secondly, L1 is implemented as a procedure called L1_SetBased and using SQL set-based paradigm (Figure 32- b).

```
CREATE PROCEDURE L1_Iteration(IN ids_count INT)
LANGUAGE SQLSCRIPT AS
BEGIN
DECLARE i INT;
DECLARE trade_ids TABLE(tid BIGINT);
DECLARE trade_id BIGINT;

trade_ids = SELECT TOP : ids_count T_ID as tid FROM TRADE;

FOR i IN 1.. ids_count DO
    trade_id = :trade_ids.tid[:i];

      SELECT T_BID_PRICE, T_EXEC_NAME, T_IS_CASH,
      TT_IS_MRKT, T_TRADE_PRICE
      FROM TRADE, TRADE_TYPE WHERE T_ID = :trade_id
      AND T_TT_ID = TT_ID;

      SELECT SE_AMT, SE_CASH_DUE_DATE, SE_CASH_TYPE
      FROM SETTLEMENT WHERE SE_T_ID = :trade_id;

END FOR;

END;
```

(a)

```
CREATE PROCEDURE L1_SetBased(IN ids_count INT)
LANGUAGE SQLSCRIPT AS
BEGIN
DECLARE i INT;
DECLARE trade_ids TABLE(id BIGINT);

trade_ids = SELECT TOP : ids_count T_ID as id FROM TRADE;

SELECT T_BID_PRICE, T_EXEC_NAME, T_IS_CASH,
TT_IS_MRKT, T_TRADE_PRICE
FROM TRADE, TRADE_TYPE WHERE T_ID in
(select id from :trade_ids) AND T_TT_ID = TT_ID;

SELECT SE_AMT, SE_CASH_DUE_DATE, SE_CASH_TYPE
FROM SETTLEMENT WHERE SE_T_ID in
(select id from :trade_ids);

END;
```

(a)

Figure 32 (a) L1 implementation using iterative constructs, (b) L1 implementation using a set-based approach

In addition, L2 is a read-write transaction that updates timestamp of the trades (T_DTS) and inserts the updated trade information into the TRADE_HISTORY table. Just like L1, the transaction receives an integer (ids_count) expressing the number of trades which have to be updated. The transaction is implemented using three styles. First, an iterative approach (by a FOR loop) is used to retrieve the information record by record as shown in Figure 33(a); the procedure is called L2_Iteration. The L2_Iteration procedure performs L2 in a single-tuple-at-a-time fashion; SELECT, UPDATE, and INSERT operations are iteratively performed in a loop. Furthermore, another implementation of L2 is provided in Figure 33(b). The procedure is named L2_Mixed and differs from L2_Iteration in the way it handles UPDATE operations; IDs of the trades are stored in a table variable (inserts_itab), and the update operation is executed in a single execution. Finally, the L2_SetBased procedure (Figure 33 - c) performs L2 using a SQL set-based approach (Figure 32- b).

```
CREATE PROCEDURE L2_Iteration(IN ids_count INT,
OUT updated INT, OUT inserted INT)
LANGUAGE SQLSCRIPT AS
BEGIN

DECLARE now_dts SECONDDATE;
DECLARE i INT;
DECLARE tid BIGINT;

updated = 0;
inserted = 0;
now_dts = NOW();

FOR i IN 1.. ids_count DO
     SELECT TOP 1 T_ID INTO tid FROM TPCE."TRADE"
     WHERE T_DTS != :now_dts;

     UPDATE TPCE."TRADE" SET T_DTS = :now_dts WHERE
     T_ID = :tid;

     updated = updated + ::ROWCOUNT;

      INSERT INTO TPCE."TRADE_HISTORY"
      (TH_T_ID, TH_DTS, TH_ST_ID)
      VALUES(tid, :now_dts, 'SBMT');
      inserted = inserted + ::ROWCOUNT;

       SELECT tid from dummy;
END FOR;

COMMIT;
END;
```

(a)

```
CREATE PROCEDURE L2_Mixed(IN ids_count INT,
OUT updated INT, OUT inserted INT)
LANGUAGE SQLSCRIPT AS
BEGIN

DECLARE now_dts SECONDDATE;
DECLARE i INT;
DECLARE tid BIGINT;
DECLARE inserts_itab TABLE(id BIGINT, dts SECONDDATE,
status VARCHAR(4));

updated = 0;
inserted = 0;
now_dts = NOW();

FOR i IN 1.. ids_count DO
    SELECT TOP 1 T_ID INTO tid FROM TPCE."TRADE"
    WHERE T_DTS != :now_dts;

    UPDATE TPCE."TRADE" SET T_DTS = :now_dts WHERE
    T_ID = :tid;
    updated = updated + ::ROWCOUNT;

    :inserts_itab.insert((:tid, :now_dts, 'SBMT'));
END FOR;

INSERT INTO TPCE."TRADE_HISTORY"(TH_T_ID, TH_DTS,
TH_ST_ID) SELECT id, dts, status FROM :inserts_itab;
inserted = inserted + ::ROWCOUNT;

COMMIT;

SELECT id from :inserts_itab;
END;
```

(b)

```
CREATE PROCEDURE L2_SetBased(IN ids_count INT, OUT updated INT, OUT inserted INT)  LANGUAGE SQLSCRIPT AS
BEGIN

DECLARE now_dts SECONDDATE;
DECLARE i INT;
DECLARE trades TABLE(id BIGINT, dts SECONDDATE, status VARCHAR(4));

updated = 0;
inserted = 0;
now_dts = NOW();

trades = SELECT TOP : ids_count T_ID as id, :now_dts as dts, 'SBMT' as status FROM TPCE."TRADE" WHERE T_DTS != :now_dts;

UPDATE TPCE."TRADE" SET T_DTS = :now_dts WHERE T_ID in (SELECT id from :trades);
updated = updated + ::ROWCOUNT;

INSERT INTO TPCE."TRADE_HISTORY"(TH_T_ID, TH_DTS, TH_ST_ID) SELECT id, dts, status FROM :trades;
inserted = inserted + ::ROWCOUNT;

COMMIT;

SELECT id from :trades;
END;
```

(c)

Figure 33 (a) L2 implementation using iterative constructs, (b) L2 implementation using a mixed approach, (c) L2 implementation using a set-based approach

The L1 and L2 procedures are called with an increasing sequence of ids_count to comprehend how the procedures differ in connection with response times. It also facilitates understanding how increasing the ids_count correspond with the procedures' response times. A client application is implemented using C++ to execute the procedures and measure response times. To achieve verifiable results, each procedure is called 100 times and the average response time is reported.

Figure 34 portrays how the procedures performed in respect of response time. The x-axis characterizes a sequence of ids_count (number of trade IDs). The y-axis describes the response times (log2 scale). It is apparent from the figure that L1_SetBased and L2_SetBased outperform their counterparts. The set-based procedures also excel regarding the growth rate. While the running times for the procedures using iterative constructs increase almost linearly in relation to ids_count, the L1_SetBased and L2_SetBased grow at a sub-linear scale. Besides, despite the fact that L2_Mixed executes fewer SQL statements inside the loop (INSERT statement is done in a single execution), there is no significant difference between the performance of L2_Iteration and L2_Mixed.

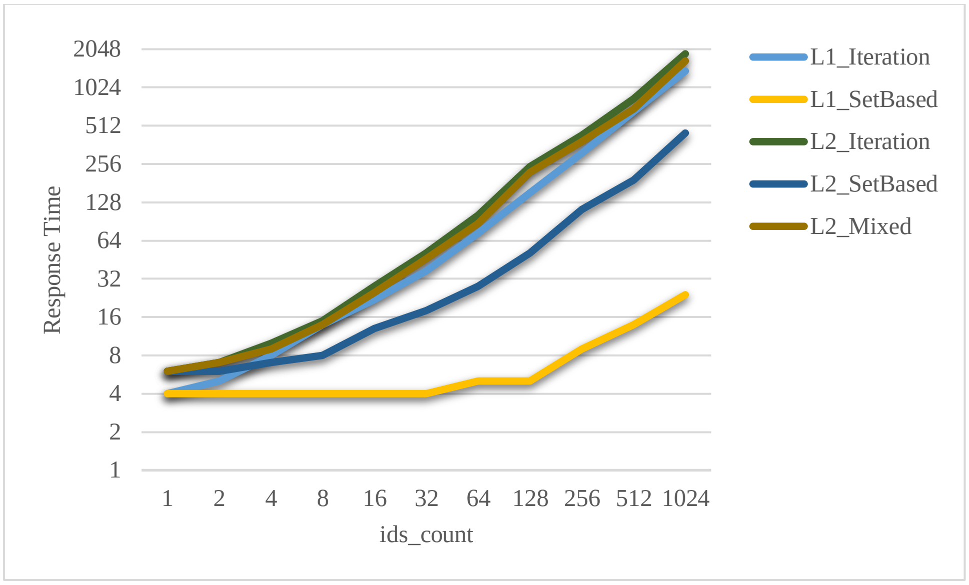


Figure 34 L1 and L2 response times

The profiling tool explained in section 4.3 is applied to compare cost drivers while executing the L1_Iteration and L1_SetBased. It is shown that query compilation cost is orders of magnitudes higher for L1_Iteration; query compilation takes 4.5% and 19.5% of CPU service time for L1_SetBased and L1_Iteration respectively. The query compilation also affects memory management costs. The L1_Iteration takes 17% process time for memory allocation and deallocation while the costs are almost zero for L1_SetBased. The results validate our theory about the connection between query compilation cost and the iterative nature of TPC-E transactions. Accordingly, we strongly believe that the experiment's throughput and workload decomposition dramatically improves if the benchmark transactions are converted to set-based approach.

Application logic is becoming more complex, and it is not always possible to implement the logic only via native SQL statements. To this end, languages like SQLScript could be equipped with some mechanisms converting imperative logic to pure SQL statements during query optimization. This is an important issue for future research; one optimization approach can be converting iterative SQL queries into SQL nested queries and set-based operation (like what is done in L1_SetBased and L2_SetBased manually) during query compilation and optimization. This also might require a dependence analysis (data dependency and control dependency) to determine whether operations inside iterative constructs can be un-nested or unrolled. To this end, some studies [67, 68, 69] have been conducted to analyze identifying batch-safe iterations and replacing imperative loops with single batch calls. This impovement is picked up for future HANA development efforts.

5 CONCLUSION

5.1 Scope and Background

Typically, the “one size does not fit all” has been the dominant paradigm used to separate OLTP and OLAP data into different database management systems. Even though the separation could be advantageous, it also gives rise to several deficiencies like data redundancy and lack of real-time analytics. To blur boundaries between analytical and transactional data management systems, some disruptive approaches have been taken toward building HTAP systems. HTAP systems mostly rely on in-memory computation to present profound performance improvements. In addition, columnar data layout has become popular mainly for OLAP use-cases.

The primary goal of this thesis is evaluating the performance of an in-memory HTAP system using a columnar data layout with OLTP workload. Firstly, it investigates how a columnar HTAP perform with transactional workload comparing to a row-wise data storage (RQ1). Secondly, the thesis examines the main cost drivers of OLTP workload in an HTAP system (RQ2). Thirdly, it studies how optimal an HTAP-oriented stored procedure language (SQLScript) is for OLTP workloads (RQ3). To answer the research questions, a systematic literature review is combined with a quantitative experimental research. A research version of SAP HANA is used as the underlying HTAP system during the experiment. Also, an industry-grade OLTP benchmark (TPC-E) is implemented to generate the needed workload for the research.

Studies on the performance of columnar databases have mostly focused on OLAP and mixed workloads [55, 70, 71, 72, 73, 74, 75]. However, far little attention has been paid to how column-oriented data layout perform with pure transactional processing. For instance, a study by D.J. Abadi, S.R. Madden and N. Hachem [70] has compared the performance of a column store database with several row-store systems using star schema benchmark (SSMB), a data warehousing benchmark. Likewise, A. Kemper and T. Neumann [71] have used a mixed workload benchmark (TPC-CH) to compare the performance of an HTAP system supporting columnar data layout, HyPer, with several OLTP and OLAP-oriented databases. Similarly, I. Psaroudakis et al. [55] investigate the performance of two HTAP systems with a mixed workload benchmark (CH-benCHmark). In the same way, Z. Feng et al. in their study [72] assess the performance of data scan and lookup operations in an in-memory column store with TPC-H (a decision support benchmark provided by TPC). Also, the study conducted by E. Petraki, S. Idreos and S. Manegold [73] measures the performance of an indexing mechanism for column-oriented database architectures via TPC-H. In the same manner, I. Alagiannis, M. Athanassoulis and A. Ailamaki [74] utilize TPC-H and SSB (two analytical benchmarks) to analyze scaling up queries with column stores. J. Wang et al. [75] analyze the performance of a column store SQL engine with a TPC-H like benchmark as well. Hence, the thesis tries to fill the gap between the performance of columnar HTAP systems and transactional workload.

Besides, very few studies have investigated and applied TPC-E benchmark [76, 62, 77]. This is also the dominant trend in the industry, and the benchmark results have been published only for one DBMS (Microsoft SQL Server) [78]. This matter could stem from complex nature of the benchmark comparing to the other OLTP benchmarks such as TPC-C. TPC-E incorporates a three-tier architecture and requires a complex code base (our TPC-E implementation consists of almost 11000 lines of C++ code). Also, TPC-E transactions exhibit elaborate structures (roughly 2000 lines of SQLScript code in our implementation). TPC-E also demands sophisticated DBMS requirements such as referential integrity constraints and the highest ANSI transaction isolation level (i.e., serializability). Using TPC-E workload in this thesis aids achieving results representing requirements of a modern OLTP environment.

5.2 Main Findings

To evaluate the performance of an in-memory columnar data management system for OLTP workload, TPC-E benchmark is run against both the row and columnar data engines embedded in HANA. The column store exhibits more fluctuations regarding the transactions' response times due to three major reasons. Firstly, the column store engine applies a more aggressive parallelism. Secondly, the row-based operations dominance the benchmark workload, hence, accessing a single or a set of tuples demands more memory accesses in the column store. Thirdly, DML operations that constitute a significant part of the workload are more expensive for the column store. Despite the variations, our experiment shows that the column store achieves an acceptable throughput comparing to its counterpart (the achieved throughput for the column-store is 74% of the row-store throughput). Therefore, the evidence from this study suggests that the in-memory columnar data management system can keep up with OLTP use-cases.

Furthermore, a profiling tool is employed to inspect decomposition of the workload into main HANA components. It is identified that the experiment workload breaks down into eight primary cost drivers: Query compilation and validation, data store access and predicate evaluation, memory management, network transfer and communication, index access and join processing, sorting operation, DML operations, and SQLScript execution.

Among the identified cost drivers, the query compilation and validation constitutes a major part (roughly 15% of the total processor time). Therefore, this matter was investigated in greater detail, and the iterative nature of TPC-E transactions turned out to be the primary reason of the costly query compilations. We identified a typical pattern among most of the transactions; all TPC-E transactions except the Broker-Volume and Trade-Status require at least one form of iterative constructs (e.g., conditional statements, loops, and cursors). Hence, it was decided to produce two simplified transactions (called L1 and L2) and examine our theory using them. The transactions are implemented using SQLScript in two ways: A set-based approach and a single-tuple-at-a-time paradigm. The transactions are also utilized to examine how optimal SQLScript performs for transactional requirements.

Running the profiler on L1 transactions validates our theory about the connection between query compilation cost and the iterative nature of TPC-E transactions. It is shown that the query compilation cost is a factor of more than 4X higher for the iterative-based implementation comparing to the set-based one. The query compilation also affects memory management costs. Then, the transactions are analyzed regarding the response times and the growth rates. Running L1 and L2 shows that transactions using SQL set-based operations outperform those applied iterative constructs in terms of response time and growth rate. Put it differently, SQLScript provides a suboptimal performance for queries applying iterative extensions.

5.3 Future Work

Some questions remain unanswered and need future research. First, it is found out that checkpointing causes throughput variations during the experiment. This matter could stem from the experiment's underlying hardware configuration; however, future work is needed to pinpoint the situation. At the time, SAP is adopting non-volatile RAM (called NVRAM or NVM) technologies like Intel 3D XPoint in HANA's architecture [66]. There is room for further research in determining how using the NVRAM technologies could alleviate the throughput instabilities during the experiment.

Also, further research is required to study the optimization of stored procedures using iterative paradigm. One optimization approach can be converting iterative SQL queries into SQL nested queries and set-based operation (like what is done in section 4.4 manually) during query compilation and optimization. This also might require a dependence analysis (data dependency and control dependency) to determine whether operations inside iterative constructs can be un-nested or unrolled. To this end, some studies [67, 68, 69] have been conducted to analyze identifying batch-safe iterations and replacing imperative loops with single batch calls. This improvement is picked up for future HANA development efforts.

Moreover, the experiment could be repeated to understand other factors contributing to the results. First, TPC-E defines 22 check constraints on the benchmark schema; the check constraints put overhead for DML operations since more operations are required for each insert, update, and delete statement. Hence, it can be inspected how dropping the constraints could improve the throughput. Also, the workload breakdown can be analyzed to comprehend the cost of enforcing the constraints. Secondly, the Trade-Result transaction is executed with serializable isolation level. The experiment could be further executed with degrading the isolation level to repeatable read; it is expected that this would improve the measured throughput since the Trade-Result transactions incorporate 10 percent of the total workload. Overhead of locking and latching perhaps would go down by changing the isolation level as well. In addition, the effects of data partitioning on the experiment can be investigated. No partitioning is used at the current experiment; a further study with more focus on this matter is therefore suggested. In other words, vertical and horizontal partitioning for the row store, and horizontal partitioning for the column store can be applied to evaluate how partitioning is in tune with performance optimization.

6 LIST OF TABLES

7 LIST OF FIGURES

8 REFERENCES

[1] A. Silberschatz, H. F. Korth and S. Sudarshan, Database systems concepts, Estados Unidos: McGraw-Hill Companies, Inc., 2011.

[2] C. Diaconu, C. Freedman, E. Ismert, P.-A. Larson, P. Mittal, R. Stonecipher, N. Verma and M. Zwilling, "Hekaton: SQL Serverś Memory-optimized OLTP Engine," in *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2013.

[3] R. Kallman, H. Kimura, J. Natkins, A. Pavlo, A. Rasin, S. Zdonik, E. P. C. Jones, S. Madden, M. Stonebraker, Y. Zhang, J. Hugg and D. J. Abadi, "H-store: A High-performance, Distributed Main Memory Transaction Processing System," *Proceedings of VLDB Endow.*, vol. 1, pp. 1496-1499, Aug 2008.

[4] S. Idreos, F. Groffen, N. Nes, S. Manegold, K. S. Mullender and M. L. Kersten, "MonetDB: Two Decades of Research in Column-oriented Database Architectures," *IEEE Data Engineering Bulletin*, vol. 35, pp. 40-45, 2012.

[5] A. Lamb, M. Fuller, R. Varadarajan, N. Tran, B. Vandiver, L. Doshi and C. Bear, "The Vertica Analytic Database: C-store 7 Years Later," *Proceedings of VLDB Endow.*, vol. 5, pp. 1790-1801, August 2012.

[6] H. Plattner and A. Zeier, In-Memory Data Management, Berlin, Heidelberg: Springer Berlin Heidelberg, 2012.

[7] H. Plattner, A Course in In-Memory Data Management, Berlin: Springer Berlin, 2014.

[8] G. P. Copeland and S. N. Khoshafian, "A Decomposition Storage Model," *SIGMOD Rec.*, vol. 14, pp. 268-279, May 1985.

[9] H. Plattner, "A Common Database Approach for OLTP and OLAP Using an In-memory Column Database," in *Proceedings of the 2009 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2009.

[10] C. D. French, "&Ldquo;One Size Fits All&Rdquo; Database Architectures Do Not Work for DSS," *SIGMOD Rec.*, vol. 24, pp. 449-450, May 1995.

[11] M. Stonebraker and U. Cetintemel, ""One Size Fits All": An Idea Whose Time Has Come and Gone," in *Proceedings of the 21st International Conference on Data Engineering*, Washington, 2005.

[12] N. May, A. Böhm and W. Lehner, "SAP HANA - The Evolution of an In-Memory DBMS from Pure OLAP Processing Towards Mixed Workloads," in *Datenbanksysteme für Business, Technologie und Web {(BTW} 2017)*, Stuttgart, 2017.

[13] A. Kemper and T. Neumann, "HyPer: A Hybrid OLTP&OLAP Main Memory Database System Based on Virtual Memory Snapshots," in *Proceedings of the 2011 IEEE 27th International Conference on Data Engineering*, Washington, 2011.

[14] M. Stonebraker and A. Weisberg, "The VoltDB Main Memory DBMS," *{IEEE} Data Eng. Bull.*, vol. 36, pp. 21-27, 2013.

[15] "Overview of Database Management System," in *Fundamentals of Relational Database Management Systems*, Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 1-30.

[16] V. Cuppu, B. Jacob, B. Davis and T. Mudge, "A Performance Comparison of Contemporary DRAM Architectures," in *Proceedings of the 26th Annual International Symposium on Computer Architecture*, Washington, 1999.

[17] H. Garcia-Molina and K. Salem, "Main memory database systems: an overview," *IEEE Transactions on Knowledge and Data Engineering,* vol. 4, pp. 509-516, December 1992.

[18] J. Lindström, V. Raatikka, J. Ruuth, P. Soini and K. Vakkila, "IBM solidDB: In-Memory Database Optimized for Extreme Speed and Availability," *{IEEE} Data Eng. Bull.,* vol. 36, pp. 14-20, 2013.

[19] T. J. Lehman, E. J. Shekita and L.-F. Cabrera, "An Evaluation of Starburstś Memory Resident Storage Component," *IEEE Trans. on Knowl. and Data Eng.*, vol. 4, pp. 555-566, December 1992.

[20] H. Lu, Y. Y. Ng and Z. Tian, "T-Tree or B-Tree: Main Memory Database Index Structure Revisited," in *Proceedings of the Australasian Database Conference*, Washington, 2000.

[21] D. J. DeWitt, R. H. Katz, F. Olken, L. D. Shapiro, M. R. Stonebraker and D. A. Wood, "Implementation Techniques for Main Memory Database Systems," *SIGMOD Rec.,* vol. 14, pp. 1-8, June 1984.

[22] V. Sikka, F. Färber, W. Lehner, S. K. Cha, T. Peh and C. Bornhövd, "Efficient Transaction Processing in SAP HANA Database: The End of a Column Store Myth," in *Proceedings of the 2012 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2012.

[23] T. Lahiri, M.-A. Neimat and S. Folkman, "Oracle TimesTen: An In-Memory Database for Enterprise Applications," *{IEEE} Data Eng. Bull.,* vol. 36, pp. 6-13, 2013.

[24] J. L. Hennessy and D. A. Patterson, Computer Architecture, Fourth Edition: A Quantitative Approach, San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2006.

[25] J. Levandoski, "Modern Main-Memory Database Systems," 2016.

[26] K.-Y. Whang and R. Krishnamurthy, "Query Optimization in a Memory-resident Domain Relational Calculus Database System," *ACM Trans. Database Syst.,* vol. 15, pp. 67-95, March 1990.

[27] P. Pucheral, J.-M. Thévenin and P. Valduriez, "Efficient Main Memory Data Management Using the DBgraph Storage Model," in *Proceedings of the Sixteenth International Conference on Very Large Databases*, San Francisco, CA, USA, 1990.

[28] T. J. Lehman and M. J. Carey, "A Recovery Algorithm for a High-performance Memory-resident Database System," *SIGMOD Rec.*, vol. 16, pp. 104-117, December 1987.

[29] K. Salem and H. Garcia-Molina, "System M: a transaction processing testbed for memory resident data," *IEEE Transactions on Knowledge and Data Engineering,* vol. 2, pp. 161-172, March 1990.

[30] V. Leis, A. Kemper and T. Neumann, "The Adaptive Radix Tree: ARTful Indexing for Main-memory Databases," in *Proceedings of the 2013 IEEE International Conference on Data Engineering (ICDE 2013)*, Washington, 2013.

[31] T. J. Lehman and M. J. Carey, "A Study of Index Structures for Main Memory Database Management Systems," in *Proceedings of the 12th International Conference on Very Large Data Bases*, San Francisco, CA, USA, 1986.

[32] J. J. Levandoski, D. B. Lomet and S. Sengupta, "The Bw-Tree: A B-tree for New Hardware Platforms," in *Proceedings of the 2013 IEEE International Conference on Data Engineering (ICDE 2013)*, Washington, 2013.

[33] G. Graefe and W. J. McKenna, "The Volcano Optimizer Generator: Extensibility and Efficient Search," in *Proceedings of the Ninth International Conference on Data Engineering*, Washington, 1993.

[34] T. Neumann, "Efficiently Compiling Efficient Query Plans for Modern Hardware," *Proceedings of VLDB Endow.*, vol. 4, pp. 539-550, Jun 2011.

[35] D. Porobic, I. Pandis, M. Branco, P. Tözün and A. Ailamaki, "OLTP on Hardware Islands," *Proceedings of VLDB Endow.*, vol. 5, pp. 1447-1458, #jul# 2012.

[36] F. Färber, S. K. Cha, J. Primsch, C. Bornhövd, S. Sigg and W. Lehner, "SAP HANA Database: Data Management for Modern Business Applications," *SIGMOD Rec.*, vol. 40, pp. 45-51, Jan 2012.

[37] J. Gray and A. Reuter, Transaction Processing: Concepts and Techniques, 1st ed., San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1992.

[38] M. H. Eich, "A classification and comparison of main memory database recovery techniques," in *1987 IEEE Third International Conference on Data Engineering*, 1987.

[39] M. H. Eich, "Mars: The Design of a Main Memory Database Machine," in *Database Machines and Knowledge Base Machines*, M. Kitsuregawa and H. Tanaka, Eds., Boston, MA: Springer US, 1988, pp. 325-338.

[40] N. Malviya, A. Weisberg, S. Madden and M. Stonebraker, "Rethinking main memory OLTP recovery," in *2014 IEEE 30th International Conference on Data Engineering*, 2014.

[41] P. A. Boncz, M. L. Kersten and S. Manegold, "Breaking the Memory Wall in MonetDB," *Commun. ACM*, vol. 51, pp. 77-85, December 2008.

[42] A. Thomson and D. J. Abadi, "Modularity and Scalability in Calvin," *{IEEE} Data Eng. Bull.*, vol. 36, pp. 48-55, 2013.

[43] P. A. Bernstein and E. Newcomer, Principles of Transaction Processing, 2nd ed., San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2009.

[44] M. T. Ozsu, Principles of Distributed Database Systems, 3rd ed., Upper Saddle River, NJ, USA: Prentice Hall Press, 2007.

[45] E. F. Codd, S. B. Codd and C. T. Salley, Providing OLAP (On-line Analytical Processing) to User-analysts: An IT Mandate, Codd & Associates, 1993.

[46] S. Chaudhuri and U. Dayal, "An Overview of Data Warehousing and OLAP Technology," *SIGMOD Rec.*, vol. 26, pp. 65-74, Mar 1997.

[47] H. Plattner and B. Leukert, The In-Memory Revolution: How SAP HANA Enables Business of the Future, Springer Publishing Company, Incorporated, 2015.

[48] F. Özcan, Y. Tian and P. Tözün, "Hybrid Transactional/Analytical Processing: A Survey," in *Proceedings of the 2017 ACM International Conference on Management of Data*, New York, NY, USA, 2017.

[49] I. Psaroudakis, T. Scheuer, N. May and A. Ailamaki, "Task Scheduling for Highly Concurrent Analytical and Transactional Main-Memory Workloads," in *International Workshop on Accelerating Data Management Systems Using Modern Processor and Storage Architectures - {ADMS} 2013, Riva del Garda, Trento, Italy, August 26, 2013.*, 2013.

[50] J. Krueger, C. Kim, M. Grund, N. Satish, D. Schwalb, J. Chhugani, H. Plattner, P. Dubey and A. Zeier, "Fast Updates on Read-optimized Databases Using Multi-core CPUs," *Proceedings of VLDB Endow.*, vol. 5, pp. 61-72, September 2011.

[51] K. Shanley, "History and Overview of the TPC," Transaction Processing Performance Council, February 1998. [Online]. Available: http://www.tpc.org/information/about/history.asp.

[52] "TPC Benchmark C Standard Specification Revision 5.11," 2010.

[53] "SAP Standard Application Benchmarks," SAP, [Online]. Available: https://www.sap.com/about/benchmark.html. [Accessed 27 Sep 2017].

[54] "Benchmark Overview SAP SD Standard Application Benchmark," 2015.

[55] I. Psaroudakis, F. Wolf, N. May, T. Neumann, A. Böhm, A. Ailamaki and K.-U. Sattler, "Scaling Up Mixed Workloads: A Battle of Data Freshness, Flexibility, and Scheduling," in *Performance Characterization and Benchmarking. Traditional to Big Data: 6th TPC Technology Conference, TPCTC 2014, Hangzhou, China, September 1--5, 2014. Revised Selected Papers*, R. Nambiar and M. Poess, Eds., Cham, Springer International Publishing, 2015, pp. 97-112.

[56] R. Sherkat, C. Florendo, M. Andrei, A. K. Goel, A. Nica, P. Bumbulis, I. Schreter, G. Radestock, C. Bensberg, D. Booss and H. Gerwens, "Page As You Go: Piecewise Columnar Access In SAP HANA," in *Proceedings of the 2016 International Conference on Management of Data*, New York, NY, USA, 2016.

[57] N. May, W. Lehner, P. Shahul Hameed, N. Maheshwari, C. Müller, S. Chowdhuri and A. K. Goel, "SAP HANA - From Relational OLAP Database to Big Data Infrastructure," in *{EDBT}*, 2015.

[58] N. May, A. Böhm, M. Block and W. Lehner, "Managed Query Processing within the SAP HANA Database Platform," *Datenbank-Spektrum*, vol. 15, pp. 141-152, 2015.

[59] "SAP HANA SQLScript Reference," [Online]. Available: https://help.sap.com/doc/6254b3bb439c4f409a979dc407b49c9b/2.0.00/en-US/SAP_HANA_SQL_Script_Reference_en.pdf.

[60] C. Binnig, N. May and T. Mindnich, "SQLScript: Efficiently Analyzing Big Enterprise Data in SAP HANA," in *{BTW}*, 2013.

[61] "TPC-E Standard Specification, Revision 1.14.0," 2015.

[62] S. Chen, A. Ailamaki, M. Athanassoulis, P. B. Gibbons, R. Johnson, I. Pandis and R. Stoica, "TPC-E vs. TPC-C: Characterizing the New TPC-E Benchmark via an I/O Comparison Study," *SIGMOD Rec.*, vol. 39, pp. 5-10, February 2011.

[63] "TPC-E," TPC, [Online]. Available: http://www.tpc.org/tpce/. [Accessed 05 Oct 2017].

[64] "The DOT Language," [Online]. Available: http://www.graphviz.org/doc/info/lang.html. [Accessed 23 Nov 2017].

[65] "Persistent Data Storage in the SAP HANA Database," SAP, [Online]. Available: https://help.sap.com/doc/6b94445c94ae495c83a19646e7c3fd56/2.0.01/en-US/be3e5310bb571014b3fbd51035bc2383.html. [Accessed 24 Nov 2017].

[66] M. Andrei, C. Lemke, G. Radestock, R. Schulze, C. Thiel, R. Blanco, A. Meghlan, M. Sharique, S. Seifert, S. Vishnoi, D. Booss, T. Peh, I. Schreter, W. Thesing, M. Wagle and T. Willhalm, "SAP HANA Adoption of Non-volatile Memory," *Proceedings of VLDB Endow.*, vol. 10, pp. 1754-1765, August 2017.

[67] K. V. Emani, T. Deshpande, K. Ramachandra and S. Sudarshan, "DBridge: Translating Imperative Code to SQL," in *Proceedings of the 2017 ACM International Conference on Management of Data*, New York, NY, USA, 2017.

[68] R. A. Ganski and H. K. T. Wong, "Optimization of Nested SQL Queries Revisited," *SIGMOD Rec.*, vol. 16, pp. 23-33, December 1987.

[69] R. Guravannavar and S. Sudarshan, "Rewriting Procedures for Batched Bindings," *Proc. VLDB Endow.*, vol. 1, pp. 1107-1123, #aug# 2008.

[70] D. J. Abadi, S. R. Madden and N. Hachem, "Column-stores vs. Row-stores: How Different Are They Really?," in *Proceedings of the 2008 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2008.

[71] A. Kemper and T. Neumann, "One Size Fits all, Again! The Architecture of the Hybrid OLTP&OLAP Database Management System HyPer," in *Enabling Real-Time Business Intelligence: 4th International Workshop, BIRTE 2010, Held at the 36th International Conference on Very Large Databases, VLDB 2010, Singapore, September 13, 2010, Revised Selected Papers*, M. Castellanos, U. Dayal and V. Markl, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 7-23.

[72] Z. Feng, E. Lo, B. Kao and W. Xu, "ByteSlice: Pushing the Envelop of Main Memory Data Processing with a New Storage Layout," in *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2015.

[73] E. Petraki, S. Idreos and S. Manegold, "Holistic Indexing in Main-memory Column-stores," in *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, New York, NY, USA, 2015.

[74] I. Alagiannis, M. Athanassoulis and A. Ailamaki, "Scaling Up Analytical Queries with Column-stores," in *Proceedings of the Sixth International Workshop on Testing Database Systems*, New York, NY, USA, 2013.

[75] J. Wang, H. Duan, G. Min, G. Ying and S. Zheng, "Goldfish: In-Memory Massive Parallel Processing SQL Engine Based on Columnar Store," in *iThings/GreenCom/CPSCom/SmartData*, 2016.

[76] Y. Li and C. Levine, "Extending TPC-E to Measure Availability in Database Systems," in *Topics in Performance Evaluation, Measurement and Characterization: Third TPC Technology Conference, TPCTC 2011, Seattle, WA, USA, August 29-September 3, 2011, Revised Selected Papers*, R. Nambiar and M. Poess, Eds., Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 111-122.

[77] R. O. Nascimento and P. R. M. Maciel, "DBT-5: An Open-Source TPC-E Implementation for Global Performance Measurement of Computer Systems," *Computing and Informatics*, vol. 29, pp. 719-740, 2010.

[78] "TPC-E - All Results," TPC, [Online]. Available: http://www.tpc.org/tpce/results/tpce_results.asp. [Accessed 02 11 17].