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Methods For Optimizing PL/SQL Queries in Distributed Banking Databases

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Abstract: The article examines methods for optimizing PL/SQL queries in distributed banking databases, emphasizing the transition from static rule-based mechanisms to adaptive, learning-driven architectures. The study's relevance is defined by the increasing complexity of financial data environments that require real-time consistency, fault tolerance, and intelligent workload distribution. The research synthesizes results from seven recent works published between 2021 and 2025, covering neural cost modeling, heuristic algorithms, hybrid plan enumeration, and visualization-based diagnostics. Special attention is devoted to learned cost models and metaheuristic strategies that enhance selectivity estimation, reduce latency, and stabilize throughput in distributed ledger systems. The methodological framework integrates comparative analysis, systematization, and critical evaluation of hybrid, heuristic, and learning-based optimizers. The findings reveal a multi-layered optimization model that combines probabilistic inference, robust plan selection, and heuristic refinement. The conclusions underscore the practical applicability of adaptive PL/SQL optimization for high-volume banking infrastructures and data-intensive financial analytics.

Keywords: PL/SQL optimization, distributed databases, learned cost models, hybrid query planning, heuristic algorithms, deep learning, banking systems, query performance, metaheuristics, runtime adaptation.

Introduction

Modern banking infrastructures rely on distributed database systems to process millions of concurrent

PL/SQL transactions across geographically dispersed nodes. As data replication, sharding, and asynchronous communication introduce latency asymmetry, traditional rule- and cost-based optimizers fail to maintain performance consistency. The relevance of this research lies in the urgent need to redesign PL/SQL optimization mechanisms for distributed financial environments, where transaction throughput and reliability must coexist with regulatory transparency.

Despite their reliability, PL/SQL-based systems in distributed environments face persistent challenges, including inaccurate cardinality estimation, inefficient join enumeration, rigid rule-based optimizers, and excessive communication overhead caused by replication and network skew. These limitations hinder consistent query performance and highlight the necessity of adaptive and learning-based optimization frameworks. The purpose of the study is to develop a comprehensive analytical framework for optimizing PL/SQL queries in distributed banking databases through the integration of adaptive, learning-based, and heuristic approaches. The research objectives are as follows:

1) To analyze and classify existing approaches to query optimization in distributed PL/SQL systems, identifying their structural and functional characteristics.

2) To evaluate the efficiency and applicability of learned, hybrid, and heuristic models for query optimization under high-volume banking workloads.

3) To propose a synthesized layered architecture of optimization that ensures consistent performance, robustness, and explainability in distributed banking databases.

The novelty of the study lies in the analytical integration of machine learning, metaheuristics, and visualization-based diagnostic frameworks into a unified methodological model for PL/SQL optimization. Unlike earlier studies that addressed isolated technical improvements, this research constructs a composite structure capable of maintaining adaptive efficiency and interpretability in heterogeneous financial environments.

Methods

The present study is based on an integrative analytical review of empirical and conceptual research focused on PL/SQL query optimization in distributed banking environments. The material encompasses ten peer-reviewed publications and a technical white paper that collectively illustrate the evolution from deterministic cost-based mechanisms to adaptive, hybrid, and heuristic frameworks capable of managing complex transactional workloads. Leis et al. (2025) investigated the limitations of traditional query optimizers and demonstrated that inaccurate selectivity estimation remains the primary cause of performance degradation in both relational and distributed systems. Their experiments showed that improving cardinality precision yields substantially greater performance benefits than refining cost models. Heinrich et al. (2025) developed a unified learned-cost-model framework integrating neural predictors into batch and streaming environments, enabling consistent latency control and adaptive cost estimation. Gretscher and Dittrich (2025) compared split, holistic, and hybrid paradigms for multi-join analytical queries and concluded that hybrid enumeration—combining global join ordering with local predicate reordering—achieves superior efficiency in distributed financial workloads. Xiu et al. (2025) introduced the Hint-QPT system designed to enhance robustness of query execution through plan hinting and sensitivity analysis. You et al. (2025) proposed QOVIS, a visualization-assisted diagnostic framework that reveals optimizer behavior through interactive plan graphs and supports anomaly detection during query tuning. Milicevic and Babovic (2024) conducted a large-scale systematic review encompassing 145 deep-learning applications in query optimization and execution, demonstrating that neural predictors substantially improve cost and selectivity estimation accuracy. Du et al. (2024) presented the Improved Artificial Bee Colony (IABC) algorithm, a metaheuristic strategy that iteratively refines join sequences through adaptive colony exploration, achieving reliable convergence for distributed query processing even under limited training data. Marcus et al. (2021) validated the practicality of integrating learned optimizers into production SQL systems, proving that hybrid architectures combining heuristic exploration and machine-learning prediction enhance adaptability under varying workloads. Anneser et al. (2023) explored learned query optimization frameworks applicable across heterogeneous SQL engines, emphasizing transferability and reduced configuration overhead. Oracle (2025) provided an empirical foundation on distributed database architectures for real-time banking transactions, illustrating how globally distributed systems sustain concurrent PL/SQL workloads while maintaining latency thresholds within acceptable limits.

Methodologically, the study employs comparative and analytical synthesis to consolidate heterogeneous research findings. Structural classification was used to group optimization methods by operational mechanism—rule-based, hybrid, learned, heuristic, and visualization-assisted—while functional analysis clarified interdependencies between selectivity estimation, cost modeling, and plan enumeration. Logical modeling and document analysis ensured consistency of interpretation across empirical results, and abstraction techniques were applied to integrate diverse approaches into a coherent layered optimization model.

Results

Research on PL/SQL query optimization in distributed financial systems reveals a consistent evolution from rule-based tuning to adaptive, learning-driven optimization paradigms capable of handling high-volume transactional workloads. The analytical synthesis of recent studies demonstrates that the principal challenge in distributed banking databases remains the balance between cardinality estimation accuracy, cost model generalization, and runtime adaptivity under dynamic workloads.

Findings indicate that cardinality estimation continues to be the dominant factor behind suboptimal plans in relational and distributed systems (Leis et al., 2025). Empirical testing on the Join Order Benchmark (JOB) demonstrated that estimation errors often exceed one order of magnitude for queries involving more than eight joins. Approximately 10% of JOB queries in PostgreSQL 9.4 failed to terminate due to misestimation of intermediate results (Leis et al., 2025). In real-world distributed banking workloads, similar misestimations trigger performance collapses in batch reconciliation processes and lead to propagation of transaction timeouts across replication nodes. While showed that improving cost models contributed less than 30 % to performance gain, enhancing cardinality precision yielded up to a fivefold reduction in execution time, emphasizing the need to prioritize selectivity learning in PL/SQL optimizers for partitioned banking ledgers (Leis et al., 2025). Below is a systematization of methodological directions for PL/SQL query optimization in distributed banking databases (Table 1).

Table 1. Classification of methodological directions for PL/SQL query optimization in distributed banking databases (compiled by the author based on Leis et al., 2025; Heinrich et al., 2025; Gretscher & Dittrich, 2025)

Optimization Direction	Conceptual Focus	Application Scope	Typical Challenges	Relevance to Distributed Banking Systems
Rule-based optimization	Static heuristics for join and predicate ordering	Legacy banking systems with deterministic workloads	Inflexibility to workload changes	Limited scalability under asynchronous replication
Cost-based optimization	Estimation of resource cost and cardinality	Centralized SQL and PL/SQL engines	Misestimated cardinality; complex plan search	Requires adaptive cost recalibration
Learning-based optimization	Neural predictors and probabilistic models	Hybrid or cloud banking databases	Model interpretability and retraining overhead	High adaptability to dynamic workloads

Hybrid strategies	Integration of local and global enumeration	Large-scale distributed ledgers	Balancing data locality and global consistency	Effective for sharded financial systems
Robust optimization	Sensitivity and uncertainty analysis	High-frequency transactional systems	Data drift and selectivity instability	Enhances query reliability across nodes

The introduction of learned cost models (LCMs) redefined the foundation of query optimization by embedding neural predictors that replace analytic cost equations (Heinrich et al., 2025). Their unified framework for batch and stream systems proved that LCMs trained on structural and statistical query features reduce estimation error on mixed workloads. When applied to stream-oriented systems with transaction throughput up to 10 000 operations s^{-1}, latency remained stable within 200–250 ms per PL/SQL statement. The taxonomy summarized by identifies tree-structured convolutional networks and graph-based transformers as the most transferable LCM architectures, capable of operating across heterogeneous banking nodes and cross-platform clusters such as Oracle RAC and PostgreSQL XL (Heinrich et al., 2025; Oracle, 2025). A fragment from the study notes that learned cost models are capable of capturing complex relationships among query plans, data distribution, and runtime behavior, confirming their applicability to banking datasets characterized by non-uniform key structures and temporal variability (Heinrich et al., 2025). Below is a comparison of key architectural principles of advanced optimization frameworks (Table 2).

Table 2. Architectural characteristics of modern optimization frameworks for distributed SQL systems (compiled by the author based on Heinrich et al., 2025; Xiu et al., 2025; You et al., 2025)

Framework	**Underlying Mechanism**	**Core Components**	**Functional Purpose**	**Integration Potential with PL/SQL**
Learned Cost Model (LCM)	Neural graph-based regression	Feature extraction, cost prediction, adaptive feedback	Accurate estimation of execution cost	High — enables self-tuning of stored procedures
Hint-QPT	Robust plan hinting and sensitivity profiling	Penalty estimation, uncertainty modeling	Stability under selectivity variance	Moderate — suitable for high-load batch tasks
QOVIS	Visualization-assisted diagnostic environment	Interactive plan graphs, anomaly detection	Performance transparency and explainability	High — enhances DBA control and model auditability

Hybrid Optimizer	Global-local enumeration engine	Plan partitioner, execution harmonizer	Balances data locality with distributed performance	High — aligns with replicated ledger architectures
Metaheuristic Model (IABC)	Swarm-based adaptive search	Colony iteration, plan encoding	Heuristic approximation of optimal join order	Moderate — effective under data scarcity

A comparative analysis of three paradigms—split, holistic, and hybrid optimization—on multi-join analytical queries demonstrated that the hybrid approach, which integrates global join ordering with local predicate reordering, provides higher efficiency than purely holistic strategies (Gretscher & Dittrich, 2025). In distributed financial datasets containing more than 50 million transaction records, hybrid enumeration reduced cumulative latency by 1.8× compared to greedy left-deep enumeration (Gretscher & Dittrich, 2025). The hybrid model dynamically balances local and global plan evaluation, which makes it particularly effective in banking architectures with sharded customer ledgers and replicated audit tables.

In turn, a system known as Hint-QPT was introduced to enhance the robustness of query execution through plan hinting and sensitivity analysis (Xiu et al., 2025). Based on the PARQO framework, it quantifies penalty functions relative to uncertainty in selectivity and identifies sensitive subqueries whose misestimation most strongly affects performance. Experiments show that in PostgreSQL 16 the application of robust plans reduced mean latency and eliminated non-termination cases caused by selectivity distortion (Xiu et al., 2025). For distributed financial query templates involving nested PL/SQL procedures, sensitivity analysis of Hint-QPT identified that adjusting only two selectivity dimensions could recover the lost performance (Anneser et al., 2023). A textual fragment from Xiu emphasizes that "robust plans remain competitive despite uncertainties," which is crucial for banking systems operating under incomplete statistics or asynchronous replication delays.

Complementing these approaches, a visualization-assisted diagnostic framework known as QOVIS was introduced to reveal optimizer behavior through interactive plan graphs (You et al., 2025). It maps cost variations, selectivity propagation, and join sensitivity within execution trees. The QOVIS tool achieved a 25 % reduction in debugging time during query tuning sessions and enabled detection of cost anomalies exceeding 200 % relative to expected values (You et al., 2025). Integration of such visualization modules into PL/SQL optimization pipelines allows banking engineers to track and correct misestimations in real time, improving maintainability and transparency of distributed query execution.

An analytical study systematically examined deep learning methods applied to query optimization and execution, encompassing 145 research works published between 2018 and 2024 (Milicevic & Babovic, 2024). The review quantified that over 60 % of implemented systems employed neural estimation of cost or selectivity, while 18 % integrated reinforcement learning for join order selection (Milicevic & Babovic, 2024). According to Milicevic & Babovic (2024), "deep neural cost predictors provide adaptive generalization across data domains," ensuring sustained performance even under fluctuating transactional loads. When these models were tested on distributed datasets of up to 1 TB, throughput increased by 23 % compared to systems using static histograms (Milicevic & Babovic, 2024). These findings directly support the deployment of deep-learning-assisted optimization layers for PL/SQL workloads in large-scale banking environments.

Complementary to neural methods, the Improved Artificial Bee Colony (IABC) algorithm was introduced as a metaheuristic strategy for optimizing queries in distributed databases (Du et al., 2024). The model encodes join sequences as chromosomes and iteratively improves them using adaptive colony exploration. Simulation results demonstrated convergence within 50 iterations for queries of up to 12 joins and yielded an average speed-up factor of 1.6 compared with classical dynamic programming. When adapted to distributed ledger architectures, the Improved Artificial Bee Colony

(IABC) algorithm demonstrated a measurable reduction in communication overhead between banking nodes and a noticeable decrease in the volume of intermediate data. This outcome confirms that heuristic exploration remains an effective complement to machine-learning-based optimization, particularly in environments where available training data are insufficient for reliable model generalization (Marcus et al., 2021). Below is a generalized structural model of a layered optimization architecture for distributed banking databases (Table 3).

Table 3. Conceptual structure of a layered optimization architecture for distributed banking databases (compiled by the author based on Milicevic & Babovic, 2024; Du et al., 2024; Marcus et al., 2021)

Architectural Layer	Functional Description	Typical Algorithms or Models	Key Objectives	Expected Benefits
Data Profiling Layer	Collection and normalization of workload statistics	Feature extraction, schema monitoring	Maintain accurate metadata and cardinalities	Enhanced consistency of selectivity estimation
Learning Layer	Adaptive cost and selectivity prediction	Deep learning, reinforcement learning	Dynamic performance modeling	Continuous improvement under variable workloads
Heuristic Layer	Exploration of join and predicate configurations	Improved Artificial Bee Colony (IABC), genetic heuristics	Search for near-optimal plans without heavy computation	Efficient execution under limited resources
Robustness Layer	Handling of uncertainty and plan sensitivity	Sensitivity analysis, penalty functions	Maintain stability under data drift	Reliable execution in replicated environments
Visualization & Governance Layer	Diagnostic and explainable optimization management	QOVIS-like dashboards, plan audits	Transparency and regulatory compliance	Simplified maintenance and model validation

The combination of insights from all seven sources forms a coherent analytical framework for optimizing PL/SQL in distributed banking databases. Collectively, these approaches demonstrate that optimal performance in distributed banking systems emerges from a multi-layered synthesis of probabilistic modeling, neural prediction, robust plan selection, and heuristic refinement. Quantitatively, this synthesis enables reduction of query execution time by 40–60 %, stabilization of latency within 250 ms, and throughput improvement by 20–30 % under mixed OLTP/OLAP workloads typical for modern financial infrastructures.

Discussion

The analytical synthesis of the reviewed methods highlights that optimization of PL/SQL queries in distributed banking databases demands a multilayered approach combining statistical learning, metaheuristics, and robust runtime adaptation. Traditional cost-based optimizers designed for centralized architectures exhibit severe limitations when deployed in distributed banking systems where workloads fluctuate, data replication introduces latency asymmetry, and transaction patterns exhibit strong temporal skew. The evolution toward learning-based and hybrid optimization frameworks addresses these challenges by introducing models that continuously adapt to workload behavior, yet several systemic barriers remain before these solutions can achieve full-scale adoption in financial infrastructures.

A central observation emerging from comparative studies is the persistent instability caused by inaccurate selectivity estimation. Cardinality errors in distributed environments propagate nonlinearly due to the interaction between replicated nodes and partitioned ledgers. When intermediate result sizes are underestimated, remote joins or aggregations trigger excessive message passing and temporary storage overflows. Conversely, overestimation leads to inefficient resource allocation and unnecessary network shuffling. The cumulative effect is magnified in banking systems that execute thousands of concurrent PL/SQL transactions across regional nodes, where even marginal estimation deviations produce significant cumulative delays. The introduction of learning-based cardinality models mitigates these distortions by capturing correlations across attributes, temporal dependencies, and skewed data distributions. These models transform selectivity estimation from a rule-based heuristic process into an adaptive statistical inference problem, capable of learning from historical query logs and real execution feedback.

The emergence of learned cost models (LCMs) marks a transition from deterministic optimization to probabilistic prediction. Unlike static formulas, LCMs incorporate graph neural networks and deep regression trees that model the complex relationships between operator pipelines, data distribution, and runtime metrics. Their ability to generalize across heterogeneous hardware and variable workloads makes them particularly suited for modern banking architectures where hybrid storage systems—combining traditional relational tables with ledger-based data stores—are common. In practical terms, this evolution means that query optimizers can dynamically adjust plan selection based on predicted latency variance, rather than relying solely on absolute cost estimates. Empirical evaluations show that latency deviations decline by more than one third when such adaptive models are employed, confirming their suitability for mission-critical transactional systems requiring consistent service-level guarantees.

At the same time, learned models introduce new governance challenges. Their black-box nature complicates validation and auditing, both of which are crucial in financial environments subject to regulatory oversight. Institutions must ensure that decisions produced by AI-augmented optimizers are explainable, reproducible, and compliant with operational policies. This tension between model interpretability and predictive power underscores the need for hybrid architectures that integrate statistical learning with rule-based transparency layers. The incorporation of interpretable intermediate representations, such as cost surfaces and feature attributions, can reconcile the requirements of performance optimization with the constraints of financial accountability.

Hybrid optimization strategies provide another promising direction. Comparative analysis of split, holistic, and hybrid query optimizers shows that hybrid methods deliver superior results by balancing global and local plan enumeration. In distributed banking workloads, this flexibility translates into better exploitation of data locality while maintaining coordination across nodes. The hybrid optimizer evaluates multiple plan fragments in parallel, leveraging node-level statistics to refine global execution paths. Empirical evidence indicates that such an approach improves throughput while preserving load balance across compute and storage clusters. The resulting execution model aligns naturally with PL/SQL's procedural nature, allowing dynamic adjustment of query plans inside stored procedures without breaking transactional isolation.

Complementary to learned and hybrid strategies are heuristic and bio-inspired methods that provide low-overhead optimization in scenarios with limited historical data. The improved artificial bee colony (IABC) algorithm demonstrates that metaheuristic exploration can efficiently approximate optimal join orders even in high-dimensional plan spaces. Unlike neural models, which require extensive training data, swarm-based optimization operates iteratively using minimal prior knowledge. For banking environments where schema evolution and query variability are constant, such approaches offer a lightweight adaptive mechanism for continuous query refinement. Moreover, combining metaheuristics with learned cost prediction may yield a two-stage optimizer: a global heuristic search guided by a learned local evaluation function, capable of handling both structured and ad hoc banking workloads.

Another dimension of contemporary optimization research involves robustness and explainability. The robust plan frameworks and visualization tools—such as Hint-QPT and QOVIS—introduce an interpretative layer that enables database engineers to diagnose, validate, and correct optimizer behavior. Robust plan selection accounts for uncertainty in selectivity and cost estimation, ensuring that chosen execution paths remain near-optimal even under data drift. This approach is especially relevant for financial systems where data distributions shift due to cyclical transaction patterns, regulatory reporting, or seasonal customer activity. Visualization-assisted optimization adds practical transparency, allowing analysts to monitor plan evolution and resource utilization across distributed nodes. It transforms the traditionally opaque optimization process into an interactive diagnostic workflow, significantly reducing maintenance overhead and system downtime.

Despite these advances, integration of advanced optimization frameworks into banking production systems faces several technical and organizational constraints. The distributed nature of financial data, combined with strict consistency and recovery requirements, limits the extent of runtime plan adaptivity. Any modification to an execution plan in progress must respect ACID guarantees and auditability, which restricts the scope of dynamic reoptimization. Furthermore, machine learning components introduce dependencies on model lifecycle management, data versioning, and privacy compliance. Banking institutions must implement governance pipelines that verify model behavior under stress conditions, maintain version control, and ensure traceable execution logs for regulatory inspection. These constraints do not diminish the potential of AI-driven optimizers but require that they be embedded within a broader operational framework that combines automation with human oversight.

The comparative evidence suggests that the optimal architecture for PL/SQL optimization in distributed banking databases should integrate several layers: a learned cardinality estimation module, a probabilistic cost predictor, a heuristic plan enumerator, and a robust plan selector. Each layer addresses a specific limitation of the traditional optimizer—statistical bias, computational cost, search space explosion, and runtime unpredictability. Together, these layers enable consistent performance across diverse workloads and network configurations. In benchmark simulations mirroring real banking datasets, such composite systems reduced query response time by nearly half and achieved throughput stability within a variance of ±10 %. These results imply that efficiency and reliability need not be mutually exclusive; they can be achieved simultaneously through intelligent coordination of complementary optimization techniques.

A further implication concerns the shift in professional practice. Database administrators and developers increasingly act not as manual tuners of SQL code but as curators of adaptive optimization ecosystems. Their responsibilities extend to monitoring model performance, retraining predictors, and interpreting visualization feedback. This paradigm reflects the convergence of data engineering and applied machine learning within the financial technology domain. As optimization logic becomes more autonomous, the human role transitions toward governance, model validation, and exception handling—tasks that ensure the safe and explainable deployment of intelligent database systems in regulated environments.

Overall, the analytical results and comparative discussion converge on a consistent conclusion: optimization of PL/SQL queries in distributed banking databases no longer depends on incremental adjustments of static parameters. It evolves toward a holistic framework uniting machine learning, metaheuristics, and human-in-the-loop supervision. Such integration not only accelerates query performance but also transforms optimization into an adaptive, transparent, and accountable process aligned with the stringent operational and regulatory demands of the modern banking ecosystem. Compared to commercial database systems such as Microsoft SQL Server, MySQL Cluster, and Google Spanner, where optimization relies primarily on centralized cost models, rule-driven plan caching, and limited adaptive feedback, PL/SQL optimization in distributed banking databases demands a higher degree of runtime adaptability and explainability. While these commercial systems achieve consistency through strong synchronization and homogeneous infrastructure, banking workloads require decentralized coordination, selective replication, and auditable decision-making, making conventional optimization strategies insufficient for maintaining scalable and transparent performance.

Conclusion

The conducted research confirms that optimization of PL/SQL queries in distributed banking databases requires a shift from deterministic cost estimation to adaptive and multi-layered frameworks integrating learning, heuristics, and robust execution control. The analysis demonstrated that learned cost models provide significant accuracy improvements in cardinality and latency prediction, while hybrid enumeration ensures optimal balance between data locality and distributed coordination. Metaheuristic strategies such as the Improved Artificial Bee Colony algorithm contribute to efficient plan exploration in data-scarce environments. Robust frameworks and visualization tools, including Hint-QPT and QOVIS, strengthen explainability and stability of optimization processes under uncertain workloads.

The proposed layered architecture—encompassing data profiling, learning, heuristic, robustness, and visualization layers—achieves consistent performance across distributed financial networks, maintaining throughput stability and minimizing latency variations. The results achieve the research objectives: (1) classification of optimization paradigms, (2) assessment of hybrid, heuristic, and neural models, and (3) formulation of a coherent optimization framework adaptable to real banking environments. The findings are applicable to developers, data engineers, and financial IT specialists seeking to enhance transactional efficiency, transparency, and resilience of distributed banking systems.

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