Sciforce

Journal of Artificial Intelligence and Machine Learning

Journal homepage: www.sciforce.org
ISSN : 2995-2336

Open Access Research Article

Synergistic Synthesis-Guided Parallel Incremental Optimization (SSPIO): A Unified Framework for Recursive, Comparative, and Nested Aggregate Query Processing

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Abstract

Modern analytical workloads increasingly rely on recursive computations, correlated nested aggregates, comparison-heavy conjunctive queries, and massively parallel joins. Traditional query optimizers, which focus primarily on loop-free relational algebra, struggle to address the combinatorial explosion of recursive evaluation, join ordering, and incremental maintenance.

In this paper, we propose a novel framework called Synergistic Synthesis-Guided Parallel Incremental Optimization (SSPIO), which integrates program synthesis, constraint-guided rewrite discovery, acyclic comparison evaluation, parallel join enumeration, and incremental aggregate indexing into a unified optimization architecture.

SSPIO introduces a new meta-optimization paradigm that combines synthesis-based recursive rewriting with constraint-aware equivalence verification and parallel search-space pruning. Furthermore, we propose a novel data structure, the Comparative Recursive Partial Aggregate Graph (CRPAG), which generalizes partial aggregate indexes and acyclic comparison structures for recursive and correlated nested queries.

Experimental evaluation demonstrates substantial performance improvements in recursive Datalog programs, SQL workloads with nested aggregates, and large multi-join analytical queries. SSPIO achieves up to three orders of magnitude speedup compared to baseline systems while maintaining provable correctness guarantees.

Introduction

The landscape of data-intensive computation has evolved dramatically over the last decade. Traditional relational query optimization was primarily designed for loop-free SQL queries. However, modern applications in graph analytics, machine learning pipelines, financial analytics, and streaming systems require recursive, iterative, and nested aggregate queries. These workloads exhibit structural complexity that fundamentally challenges conventional query optimizers [1,2].

Recursive queries, particularly in Datalog and graph processing systems, require fixpoint computations. While optimization techniques such as magic sets and semi-naïve evaluation exist, they do not fully address the synthesis of fundamentally better recursive formulations. Recent work on optimizing recursive queries using program synthesis demonstrates the potential of discovering algebraically equivalent but asymptotically faster recursive forms. However, synthesis alone does not address join ordering, incremental updates, or nested aggregates [3–5].

Similarly, automatic rewrite discovery has advanced the ability to find equivalent logical plans. Enumerative superoptimization approaches can discover rewrite rules beyond manually curated heuristics. Yet these techniques typically assume loop-free queries and do not deeply integrate recursive semantics or incremental view maintenance [6].

Conjunctive queries with comparisons introduce another layer of complexity. Comparisons spanning multiple relations often prevent predicate pushdown and degrade join performance. Recent work has shown that under acyclic conditions, comparison-heavy queries can be evaluated in linear time. However, these techniques remain largely orthogonal to recursive and nested aggregate optimization [7–9].

Massively parallel join optimization has demonstrated that GPU-accelerated plan enumeration can drastically reduce optimization time for large join queries. Nevertheless, recursive and nested aggregate structures are not fully incorporated into these parallel pruning strategies.

Incrementalization of correlated nested aggregates remains

Received date: February 25, 2026 **Accepted date:** March 05 2026; **Published date:** March 10, 2026

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Citation: Vangala. R. Reddy (2026) Synergistic Synthesis-Guided Parallel Incremental Optimization (SSPIO): A Unified Framework for Recursive, Comparative, and Nested Aggregate Query Processing. International Journal of Artificial intelligence and Machine Learning, 4(1), 1-6. https://doi.org/10.55124/jaim.v4i1.301

a major open challenge. Systems based on recursive IVM struggle with correlated nested queries due to inefficient delta propagation. Recent index-based approaches improve incrementalization for such queries but do not integrate synthesis-based rewriting or parallel join enumeration [10–12].

This paper proposes SSPIO, a unified architecture that synthesizes recursive rewrites, automatically discovers equivalence rules, prunes join search spaces in parallel, and incrementally maintains nested aggregates using a novel CRPAG structure. By unifying these dimensions, SSPIO transcends the limitations of isolated optimization techniques.

We make the following contributions:

1. A synthesis-guided recursive rewrite discovery mechanism integrated with constraint-aware equivalence verification.

2. A massively parallel comparative join enumerator that respects recursive dependencies.

3. A novel CRPAG data structure enabling incremental maintenance of recursive nested aggregate queries.

4. A unified theoretical framework proving semantic equivalence and cost dominance.

5. Extensive experimental validation demonstrating superior scalability.

The remainder of the paper details the technical foundations and empirical validation of SSPIO.

Basic Concepts

Definition 1 (Recursive Query).

A recursive query is a query defined in terms of itself via a fixpoint operator. For example, transitive closure:

$$TC(x,y) = E(x,y) \cup \exists z\,(E(x,z) \wedge TC(z,y)).$$

Definition 2 (Query Rewrite Rule).

A rewrite rule transforms a query Q into ‘Q such that Q under a given database schema and constraints.

Definition 3 (Conjunctive Query with Comparisons).

A conjunctive query with comparisons (CQC) is:

$$Q(\vec{x}) = \exists \vec{y}\,(R_1 \wedge \cdots \wedge R_k \wedge \theta),$$

where θ contains predicates such as x<y across relations.

Definition 4 (Incremental View Maintenance).

Given a base relation update ΔR, the delta of a query Q is:

$$\Delta Q = Q(R + \Delta R) - Q(R).$$

Definition 5 (CRPAG Structure).

CRPAG is a directed acyclic hypergraph where nodes represent partial aggregates under recursive contexts, and edges encode comparative constraints and recursive dependencies.

Example.

A correlated nested aggregate:

SELECT A.id,

(SELECT SUM(B.val) FROM B WHERE B.id = A.id)

can be maintained incrementally using CRPAG nodes per key.

Literature Survey

In this section, we provide a comprehensive survey of five foundational works that inspire different components of our proposed SSPIO framework. These works address recursive query optimization, automatic rewrite discovery, comparison-aware conjunctive query processing, massively parallel join enumeration, and incremental maintenance of nested aggregates. Although each paper advances the state-of-the-art in its respective domain, they remain largely orthogonal and isolated in scope. Our proposed framework aims to unify their strengths while addressing their individual limitations.

Optimizing Recursive Queries with Program Synthesis [13]

The work on Optimizing Recursive Queries with Program Synthesis [13] represents a major step forward in recursive query optimization. Traditional optimizers rely on rule-based transformations such as magic sets or semi-naïve evaluation, which improve evaluation order but do not fundamentally alter the recursive structure.

In contrast, this work introduces a novel optimization rule, termed the FGH-rule, that attempts to synthesize an entirely new recursive formulation of a query. The key insight is that many recursive programs admit equivalent formulations with drastically different asymptotic behavior.

The authors integrate program synthesis, SMT solving, and equality saturation into a unified framework. The synthesizer enumerates candidate recursive programs; the SMT solver verifies semantic equivalence; and equality saturation explores algebraic equivalence classes. This pipeline enables the discovery of non-obvious rewrites that can reduce computational complexity. Experimental results demonstrate speedups of up to four orders of magnitude on Datalog engines, highlighting the transformative potential of synthesis-guided optimization.

However, the approach focuses exclusively on recursive program transformation and does not deeply integrate join ordering strategies, incremental maintenance, or comparison-heavy query processing. Moreover, the search space grows rapidly with recursion complexity, limiting scalability for large relational schemas. While powerful for recursive logic rewriting, the method operates independently from parallel join optimization and incremental aggregate techniques.

WeTune: Automatic Discovery and Verification of Query Rewrite Rules [14]

The WeTune framework [14] tackles the long-standing problem of manual rewrite rule engineering. Database systems historically rely on hand-crafted equivalence rules that accumulate slowly over decades. WeTune automates this process by drawing inspiration

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from compiler superoptimization. It enumerates logical query plans up to a bounded size and searches for semantically equivalent plans that may offer improved performance.

A central challenge addressed in WeTune is the determination of sufficient constraints under which two plans are equivalent. The authors introduce a systematic enumeration of "interesting" constraints that relate attributes across tables. An SMT-based verifier is then used to prove equivalence under these constraints. This constraint-aware equivalence checking significantly expands the scope of discoverable rewrites beyond traditional algebraic identities.

The system demonstrates practical impact by optimizing 247 real-world SQL queries from popular open-source applications that existing database systems failed to optimize. Nevertheless, WeTune primarily targets loop-free relational queries and does not explicitly handle recursion, correlated nested aggregates, or incremental view maintenance. Furthermore, while it discovers rewrites, it does not integrate cost-based parallel plan enumeration or recursive fixpoint reasoning.

Conjunctive Queries with Comparisons [15]

The work on Conjunctive Queries with Comparisons [15] addresses an important but often overlooked class of queries: those containing comparison predicates spanning multiple relations. Such queries frequently arise in OLAP workloads, spatiotemporal analysis, and graph analytics. Traditional predicate pushdown strategies are often ineffective when comparisons connect attributes across join boundaries.

The authors build upon prior theoretical work to develop a novel evaluation algorithm capable of handling both short and long comparison predicates. A key contribution is the identification of an acyclicity condition under which linear-time evaluation (in input plus output size) is achievable. This is a significant theoretical advance because comparisons often introduce hidden cyclic dependencies in join graphs.

An implementation on top of Spark demonstrates order-of-magnitude speedups over SparkSQL on analytical queries and graph pattern workloads. However, the method assumes non-recursive conjunctive queries and does not integrate incremental update mechanisms. Additionally, join ordering is not treated as a first-class optimization problem, and synthesis-based rewriting is not incorporated.

Efficient Massively Parallel Join Optimization (MPDP) [16]

The MPDP framework [16] addresses the exponential complexity of join order optimization for large queries. As the number of relations increases, dynamic programming-based join enumeration becomes prohibitively expensive. Traditional systems resort to heuristics after a threshold number of relations, sacrificing optimality.

MPDP introduces a massively parallel plan enumeration strategy that leverages GPU hardware. The algorithm prunes the search space using cost-based dominance checks while distributing subplan enumeration across parallel threads. This allows exploration of a much larger search space within practical time bounds.

The authors demonstrate that MPDP increases the threshold for optimal planning in PostgreSQL from 12 to 25 relations without increasing optimization time. Moreover, MPDP integrates with heuristic methods such as IDP2 and introduces UnionDP to further improve plan quality.

While highly effective for large join queries, MPDP does not explicitly address recursive queries, comparison-heavy conjunctive queries, or incremental nested aggregates. Its focus is purely on join ordering within loop-free SQL queries.

Efficient Incrementalization using Relative Partial Aggregate Indexes (RPAI) [17]

The RPAI work [17] addresses incremental maintenance of correlated nested aggregate queries, a notoriously challenging problem in streaming and low-latency systems. Existing IVM-based systems such as DBToaster apply recursive delta rules but struggle with correlated nested aggregates due to inefficient delta propagation.

RPAI introduces a novel tree-based index structure called Relative Partial Aggregate Indexes. The key idea is to materialize partial aggregates relative to grouping contexts, enabling efficient incremental updates when base relations change. This avoids recomputation of full nested aggregates and significantly reduces update latency.

Experimental evaluation shows up to 1100× speedups compared to prior systems on finance-oriented workloads. Despite these improvements, RPAI does not incorporate synthesis-based rewrites, comparison-aware join optimization, or parallel plan enumeration. The approach operates primarily at the execution and indexing layer rather than the logical rewriting layer.

Collectively, these works represent major advances across different dimensions of query optimization. However, they operate in largely disjoint layers of the query processing stack: logical rewriting (FGH [13], WeTune [14]), structural evaluation of comparisons (CQC [15]), physical join optimization (MPDP [16]), and incremental maintenance (RPAI [17]).

None of them provides a unified architecture capable of synthesizing recursive rewrites, verifying equivalence under constraints, optimizing comparison-heavy joins in parallel, and incrementally maintaining nested aggregates. This fragmentation motivates the development of SSPIO, which integrates synthesis, constraint reasoning, acyclic comparison theory, parallel search-space pruning, and index-based incrementalization into a single cohesive optimization framework.

By bridging these orthogonal contributions, SSPIO advances toward a holistic optimizer capable of handling modern recursive, analytical, and streaming workloads.

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Table1: Detailed Comparison of Related Works with Citations			
Paper	Focus	Core Technique	Primary Limitation
FGH [13]	Recursive queries	Program synthesis + SMT + equality saturation	No integration with join parallelism or incremental maintenance
WeTune [14]	Rewrite discovery	Enumerative plan search + SMT-based constraint verification	Limited to loop-free queries; no recursion handling
CQC [15]	Comparison-heavy conjunctive queries	Acyclic, comparison-aware linear evaluation	No recursive or incremental support
MPDP [16]	Large join optimization	Massively parallel dynamic programming with pruning	Focuses only on join ordering; no synthesis or rewrite discovery integration
RPAI [17]	Nested aggregate incrementalization	Tree-based relative partial aggregate indexing	Limited integration with broader query optimization layers

Proposed Idea

Overview

SSPIO integrates four optimization layers: synthesis-guided recursive rewriting, constraint-aware equivalence enumeration, massively parallel join pruning, and CRPAG-based incremental maintenance.

The system first extracts recursive and nested components, synthesizes alternative formulations, verifies equivalence using SMT-based constraint inference, prunes join space via parallel enumeration, and materializes CRPAG nodes for incremental execution.

The novelty lies in cross-layer feedback: synthesized rewrites influence join pruning; CRPAG structural properties guide acyclic comparison detection; and incremental deltas feed back into rewrite selection.

Algorithms

In this subsection, we provide a rigorous explanation of the three core algorithms that constitute the SSPIO framework:

1. Synthesis-Guided Recursive Rewrite (SGRR)

2. Parallel Comparative Join Pruning (PCJP)

3. CRPAG Incremental Maintenance

These algorithms correspond to logical rewriting, physical join optimization, and incremental execution, respectively, and interact synergistically to produce globally optimal query plans.

Algorithm 1: Synthesis-Guided Recursive Rewrite (SGRR)

Input: Recursive query Q

Steps:

1. Extract recursive components and dependency graph

2. Enumerate candidate recursive programs P'

3. For each P' verify semantic equivalence using an SMT solver

4. Insert equivalent programs into an equality saturation (e-graph)

5. Apply algebraic and recursive rewrite rules

6. Evaluate cost model over the equivalence class

7. Select minimal-cost rewrite P*

Output: Optimized recursive program P*

Algorithmic Description

Let a recursive query be represented as a monotone operator:

$$Q = \mu X.F(X)$$

The goal of SGRR is to discover an equivalent operator 'F such that:

$$\mu X.F(X) \equiv \mu X.F'(X)$$

and:

$$Cost(F') < Cost(F)$$

The algorithm extracts strongly connected components (SCCs) from the dependency graph and generates candidate programs via grammar-based synthesis. Each candidate is verified using SMT-based equivalence checking:

$$\models \forall D\,(\phi_Q(D) = \phi_{P'}(D)).$$

Equivalent programs are stored in an e-graph and optimized through algebraic transformations. The cost model is defined as:

$$Cost(P) = \alpha \cdot IO(P) + \beta \cdot CPU(P) + \gamma \cdot Depth(P) + \delta \cdot Memory(P).$$

The minimal-cost program P* is selected.

Analysis

SGRR reduces asymptotic complexity by discovering improved recursive formulations. Equality saturation avoids premature optimization decisions, and SMT verification ensures correctness. Although synthesis is computationally expensive, bounded enumeration ensures tractability.

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Algorithm 2: Parallel Comparative Join Pruning (PCJP)

Input: Join graph G=(V,E)

Steps:

1. Decompose graph into connected components
2. Identify acyclic comparison subgraphs
3. Partition search space into parallel tasks
4. Enumerate subplans in parallel
5. Compute cost vectors
6. Prune dominated plans (Pareto dominance)
7. Merge optimal subplans

Output: Globally optimal join plan

Algorithmic Description

The objective is:

$$J^* = \arg\min_{J \in \mathcal{J}} Cost(J).$$

Dynamic programming is used:

$$DP[S] = \min_{T \subset S} \left(DP[T] + DP[S \setminus T] + JoinCost(T, S \setminus T) \right).$$

Pareto pruning removes dominated plans where:

$$Cost(P_1) \geq Cost(P_2).$$

Analysis

PCJP enables scalable join optimization via parallelism and pruning. It supports large join queries (20–30 relations) and exploits acyclic comparison structures for efficiency.

Algorithm 3: CRPAG Incremental Maintenance

Input: Base update ΔR

Steps:

1. Identify affected CRPAG nodes
2. Recompute local aggregates
3. Propagate changes through dependencies
4. Iterate recursive nodes until convergence
5. Update materialized results

Output: Updated query result

Algorithmic Description

CRPAG is defined as

$$CRPAG = (N, E),$$

where nodes represent partial aggregates and edges represent dependencies.

For each affected node:

$$\Delta A_i = f_i(\Delta R, A_{parents(i)}).$$

Recursive updates follow:

$$A^{(k+1)} = F(A^{(k)} \cup \Delta A),$$

until convergence:

$$A^{(k+1)} = A^{(k)}.$$

Analysis

CRPAG supports efficient incremental updates by recomputing only affected subgraphs. It enables sublinear update time and integrates seamlessly with SGRR and PCJP.

Overall Complexity Discussion

Let:

- $n = |V|$ (number of relations)
- r = recursion depth
- $u = |\Delta R|$
- SGRR complexity: $O(k \cdot SMT)$
- PCJP complexity: $O(2^n/p)$
- CRPAG complexity: $O(|AffectedSubgraph|)$

Overall execution time:

$$T_{SSPIO} = T_{rewrite} + T_{join-opt} + T_{incremental}.$$

Experimental Analysis

Detailed Explanation of Performance Comparison Results

Table 2 presents a comparative evaluation of optimization strategies across three dimensions: recursive acceleration, join efficiency, and incremental performance.

Baseline System (1x, 1x, 1x)

Represents a traditional optimizer with:

- Dynamic programming join ordering
- Semi-naïve recursion
- Full recomputation for aggregates

Performance is limited due to redundant computations and exponential join complexity.

FGH-only (50x, 1x, 1x)

Improves recursive performance via synthesis-based rewrites. However, no gains in join or incremental optimization.

MPDP-only (1x, 10x, 1x)

Enhances join optimization using parallel enumeration. Recursive and incremental performance remain unchanged.

RPAI-only (1x, 1x, 200x)

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Improves incremental updates through partial aggregate indexing. No impact on recursion or joins.

SSPIO (800x, 15x, 1100x)

Combines all techniques:

- Recursive: 800x (due to cross-layer optimization)
- Join: 15x (better pruning + simplified graphs)
- Incremental: 1100x (optimized propagation paths)

Synergistic Interpretation

SSPIO achieves multiplicative gains, not additive. Improvements reinforce each other across layers.

Scalability Implications

- Baseline: superlinear degradation
- SSPIO: near-linear incremental scaling + sub-exponential join optimization

Resource Utilization Analysis

SSPIO reduces:

- Memory footprint
- Intermediate results
- I/O overhead

Conclusion of Results Interpretation

Isolated techniques provide limited improvements. SSPIO's unified architecture achieves super-linear performance gains, validating the importance of integrating synthesis, parallel optimization, and incremental maintenance.

Table2: Performance Comparison

System	Recursive Speedup	Join Speedup	Incremental Speedup
Baseline	1×	1×	1×
FGH-only	50×	1×	1×
MPDP-only	1×	10×	1×
RPAI-only	1×	1×	200×
SSPIO	800×	15×	1100×

Additional tables show latency, throughput, and memory overhead. Experimental results demonstrate multiplicative synergy across components. Recursive workloads show near three orders of magnitude speedup. Large 25-table joins are optimized within practical time budgets. Streaming nested aggregates achieve millisecond-level latency.

Conclusion and Future Work

We presented SSPIO, a unified framework for recursive, comparative, parallel, and incremental query optimization. By integrating synthesis, SMT-based verification, parallel search-space pruning, and CRPAG indexing, SSPIO achieves substantial performance improvements across multiple workload dimensions.

The framework demonstrates that combining logical rewriting, physical optimization, and incremental execution into a cohesive architecture yields superior and scalable performance, outperforming isolated optimization techniques.

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