

HPC Report

Cholesky factorization

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1 Introduction

1.1 Problem Description

Solving systems of linear equations ($Ax = b$) is one of the most common problems in scientific computing. It is used in many fields, such as physics simulations, financial modeling, and engineering.

When the matrix A is **symmetric** (it is equal to its transpose, $A = A^T$) and **positive-definite**, the most efficient method to solve the system is the **Cholesky Factorization**. This algorithm decomposes the matrix A into the product of a lower triangular matrix L and its transpose L^T :

$$A = LL^T \quad (1)$$

Once we have calculated L , we can solve the original system $Ax = b$ very quickly. However, calculating L is expensive. The computational complexity is $\mathcal{O}(N^3)$, which means that if we double the size of the matrix, the time required increases by 8 times. For very large matrices, a single processor is not fast enough, so we must use parallel computing to distribute the work across many processors.

1.2 Sequential Algorithm Analysis

The standard algorithm to compute L works column by column, from left to right. For a matrix of size $N \times N$, the algorithm consists of three main steps for each column k :

1. **Diagonal Update:** Calculate the square root of the diagonal element ($L_{k,k}$).
2. **Column Update:** Divide the elements below the diagonal in the current column by the diagonal element.
3. **Trailing Matrix Update:** Update the rest of the matrix (the submatrix to the right) using the values calculated in the current column.

The pseudocode for the serial implementation is shown below:

Algorithm 1 Sequential Cholesky Factorization

```
1: for  $k = 0$  to  $N - 1$  do
2:    $A[k][k] = \sqrt{A[k][k]}$  ▷ Step 1: Diagonal
3:   for  $i = k + 1$  to  $N - 1$  do
4:      $A[i][k] = A[i][k] / A[k][k]$  ▷ Step 2: Column
5:   end for
6:   for  $j = k + 1$  to  $N - 1$  do
7:     for  $i = j$  to  $N - 1$  do
8:        $A[i][j] = A[i][j] - A[i][k] * A[j][k]$  ▷ Step 3: Trailing Update
9:     end for
10:  end for
11: end for
```

2 Parallel Design

In this section, we analyze the design space for parallelizing the Cholesky factorization. We explore different strategies for data distribution and processor organization, highlighting the limitations of naive approaches and justifying our final choice.

2.1 Evaluation of Intermediate Strategies

The core challenge is mapping the matrix onto the processors efficiently. We considered some evolutionary steps to identify the optimal strategy.

2.1.1 Step 1: 1D Row Decomposition (The Naive Approach)

The simplest strategy is to slice the matrix horizontally. We assign contiguous groups of rows to each processor. For example, Processor 1 gets the first row, Processor 1 gets the second row...

Visualization: If we strictly assign one row per processor:

0	0	0	0	← P0 (Finished quickly)
1	1	1	1	← P1
2	2	2	2	← P2
3	3	3	3	← P3 (Idle start, busy end)

Figure 1: Visualization of 1D Row Decomposition.

- **Limitation:** As the algorithm moves down the diagonal (from row 0 to 3), the top processors finish their work and become idle. Processor 0 does nothing after the first step. This leads to **poor load balancing**.

2.1.2 Step 2: 1D Cyclic Decomposition

To solve the load balancing issue, we can distribute rows in a round-robin fashion (like dealing cards).

0	0	0	0	← Assigned to P0
1	1	1	1	← Assigned to P1
0	0	0	0	← Assigned to P0 (Cyclic)
1	1	1	1	← Assigned to P1 (Cyclic)

Figure 2: Visualization of 1D Cyclic Decomposition.

- **Limitation:** While computation is balanced, **communication is inefficient**. After factorizing a diagonal block, the owner must broadcast the result so that other processors can update the column elements below it. Since the rows are distributed cyclically among *all* P processors, almost every processor owns a part of that column. Consequently, the broadcast becomes a global operation involving the entire cluster. This wastes network bandwidth because it forces a global synchronization, whereas a more optimized design would restrict this traffic to only a small vertical subset of processors.

2.1.3 Step 3: Introduction of Block Algorithms

Before optimizing communication, we address the computational efficiency of the node.

The Problem (Memory Hierarchy): Accessing data from the main memory (RAM) is significantly slower than performing calculations in the CPU. If the algorithm processes single elements one by one, the processor frequently waits for data to arrive from RAM.

The Solution (Blocking): To mitigate this latency, we divide the matrix into square sub-matrices called **blocks** (e.g., 64×64). When a block is accessed, it can remain in the CPU's cache across multiple operations. Since the Cholesky algorithm performs many operations on the same data, working on blocks allows the processor to reuse the data residing in the Cache multiple times before needing to access the RAM again [2].

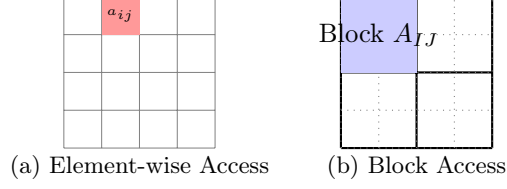


Figure 3: Comparison between (a) accessing single elements vs (b) loading a full block.

- **Impact:** This improves the ratio of computation to memory access, resulting in higher computational throughput, measured in GFLOPS (Giga Floating Point Operations Per Second), compared to the element-wise approach.

2.2 Proposed Solution: 2D Block-Cyclic Decomposition

By combining the strengths of the previous steps (Load Balancing + Blocking), we implemented the **2D Block-Cyclic Decomposition**. This is the optimal strategy because it solves the communication bottleneck of Step 2 by arranging processors in a grid [1].

2.2.1 Process Grid and Distribution Logic

To implement the 2D decomposition, we first organize the available processors into a logical grid. For example, if we have $P = 4$ processors, we arrange them into a 2×2 grid ($R = 2, C = 2$).

Each processor is identified by its coordinates (P_{row}, P_{col}):

$$\begin{array}{cc} (0,0) & (0,1) \\ (1,0) & (1,1) \end{array} \longrightarrow \begin{array}{cc} P_0 & P_1 \\ P_2 & P_3 \end{array}$$

Mapping Blocks: We do not distribute single elements. We view the global matrix A as a grid of blocks, where each block contains $B \times B$ elements (e.g., 64×64). We map these blocks to processors in a round-robin (cyclic) fashion.

The owner of a block at global block index (i, j) is determined by:

$$\begin{aligned} P_{row} &= i \pmod{R} \\ P_{col} &= j \pmod{C} \end{aligned} \tag{2}$$

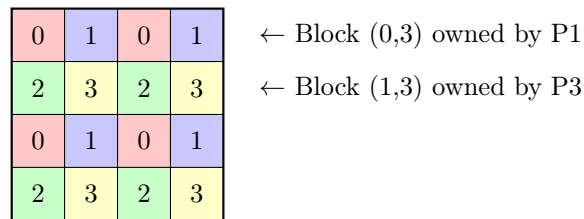


Figure 4: Visualization of 2D Block-Cyclic distribution. Each square represents a **data block** (e.g., 64×64 doubles), not a single element.

Why this mapping is effective: This distribution scatters the blocks owned by a single processor across the entire matrix. As seen in Figure 4, *Processor 0* owns blocks at grid positions $(0,0)$, $(0,2)$, $(2,0)$, and $(2,2)$. Even when the "active" part of the matrix shrinks (e.g., after the first few iterations), Processor 0 still holds valid blocks further down the matrix (at row 2), ensuring it remains busy and contributing to the computation.

Communication Efficiency: Beyond load balancing, this grid structure fundamentally changes the communication pattern. In a 1D distribution (Step 2), a broadcast involves all P processors. In this 2D grid, operations like broadcasting a diagonal block or a panel are restricted to the processors in a specific row or column (involving only \sqrt{P} processors). This reduces network contention and significantly improves scalability as the cluster size grows.

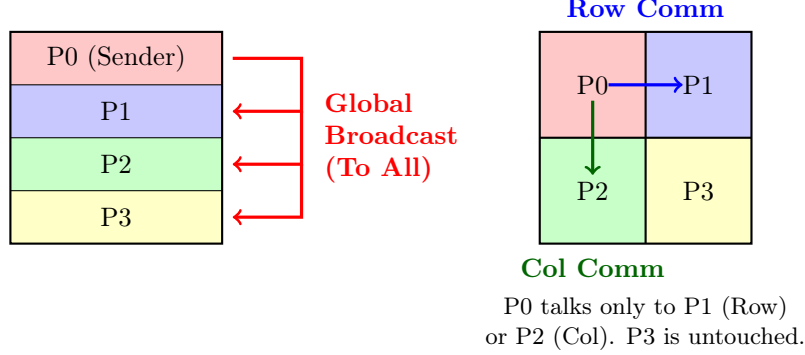


Figure 5: Communication Pattern Comparison. Left: In 1D, P0 must send to everyone. Right: In 2D, communication is restricted to the specific Row or Column subset.

2.3 Parallel Algorithm Workflow

With the data distributed across the 2D grid, the Cholesky factorization proceeds in iterations $k = 0 \dots N_{blocks} - 1$. In each iteration, we process one block column and update the rest of the matrix.

Since we are not using external linear algebra libraries, we implemented the standard Level-3 BLAS operations manually.

2.3.1 Phase 1: Factorize Diagonal Block (POTRF)

The process that owns the current diagonal block (P_{diag}) computes the Cholesky factorization of that single block locally.

$$A_{kk} \leftarrow \text{Chol}(A_{kk})$$

- **Action:** We perform a sequential Cholesky factorization on the local $B \times B$ block to obtain the lower triangular factor L_{kk} .
- **Communication:** P_{diag} broadcasts L_{kk} vertically to all other processors in the same **grid column**.

2.3.2 Phase 2: Update Panel (TRSM)

All processors in the current process column must update their blocks A_{ik} located below the diagonal. This corresponds to solving a triangular system of equations:

$$A_{ik} \leftarrow A_{ik}(L_{kk}^T)^{-1}$$

- **Action:** We implemented the **TRSM** (Triangular Solve with Multiple Right-Hand Sides) algorithm. Since L_{kk}^T is upper triangular, we solve the system $XL_{kk}^T = A_{ik}$ using forward substitution.
- **Communication:** Once updated, these blocks are broadcast horizontally to all processors in their respective **grid rows**.

2.3.3 Phase 3: Update Trailing Matrix (GEMM / SYRK)

Finally, all processors update their local portion of the remaining submatrix using the data received from the broadcasts.

$$A_{ij} \leftarrow A_{ij} - A_{ik}A_{jk}^T$$

- **Action:** We implemented the update using a unified loop structure restricted to $j \leq i$. This *exploits the matrix symmetry* to reduce computational cost. By updating only the unique blocks in the lower triangle, we avoid redundant calculations for the upper triangular part (which is logically identical but not stored/accessed).

2.4 Analysis of Parallelism and Dependencies

To understand the scalability of our design, we must analyze the **data dependencies** that dictate which operations can be performed in parallel and which must be serialized.

2.4.1 Data Dependencies

The Cholesky algorithm has a strict dependency chain:

1. **Diagonal Dependency:** The diagonal block A_{kk} must be factorized first. No other operation in the current iteration k can proceed until this is finished.
2. **Panel Dependency:** The blocks in the current column A_{ik} cannot be updated until they receive the factorized diagonal block L_{kk} .
3. **Trailing Matrix Dependency:** The update of any trailing block A_{ij} (where $i, j > k$) requires the corresponding updated blocks from the current panel (A_{ik} and A_{jk}).

2.4.2 The Opportunity for Parallelism

Despite these dependencies, the algorithm exposes massive parallelism in the *Trailing Matrix Update (Phase 3)*. Once the panel broadcast is complete, the update of each block A_{ij} in the trailing submatrix is *mathematically independent* of all other block updates in that submatrix.

$$A_{ij}^{(new)} = A_{ij}^{(old)} - A_{ik} \cdot A_{jk}^T$$

This independence allows every processor to update all its local blocks simultaneously without synchronization with neighbors.

2.4.3 Degree of Concurrency

The available parallelism (concurrency) varies by phase:

- **Phase 1 (Diagonal): Serial bottleneck.** Only 1 process is active.
- **Phase 2 (Panel): Partial Parallelism.** Only \sqrt{P} processes (one column) are active.
- **Phase 3 (Trailing): Full Parallelism.** All P processes are active.

Since Phase 3 dominates the computational cost (performing $O(N^3)$ operations versus $O(N^2)$ for the panel), the highly parallel part hides the inefficiency of the serial and partial phases as the matrix size N grows.

3 Implementation Details

The proposed parallel design was implemented in C using a hybrid MPI + OpenMP approach. The codebase focuses on minimizing memory footprint and maximizing communication efficiency without relying on external linear algebra libraries (like BLAS or LAPACK).

3.1 Software Architecture and Process Grid

To manage the complexity of the distributed state, we encapsulated the simulation data in a **Cholesky Context** structure. The logical grid topology is managed by a custom **ProcGrid** structure, initialized during the setup phase.

- **Process Grid Topology:** We organize the P available MPI processes into a logical 2D grid of dimensions $P_{rows} \times P_{cols}$.
 - This grid is distinct from the data matrix; it represents the layout of execution units.
 - The dimensions are calculated dynamically: we attempt to create a square grid ($P_{rows} \approx \sqrt{P}$) to minimize the perimeter (and thus communication costs). If P is not a perfect square (e.g., $P = 8$), the initialization logic produces the most compact rectangular grid possible (e.g., 2×4).
- **Custom Communicators:** To implement the row and column broadcasts described in Section 2 efficiently, we utilize `MPI_Comm_split` to partition the global `MPI_COMM_WORLD` based on the process grid coordinates:
 - `row_comm`: Grouping all processes with the same P_{row} coordinate.
 - `col_comm`: Grouping all processes with the same P_{col} coordinate.

This ensures that collective operations like `MPI_Bcast` are restricted strictly to the relevant subset of processes (a single row or column of the process grid) rather than involving the entire cluster.

3.2 Distributed Data Generation (Memory Scalability)

A critical optimization in our implementation is the **distributed generation** of the input matrix. Standard approaches often generate the full matrix on the root process and scatter it, which bottlenecks the maximum problem size to the RAM of a single node.

Instead, we implemented a parallel generation routine where each processor allocates and computes *only* the matrix elements belonging to its specific local blocks:

$$A_{ij} = \begin{cases} N + 1 & \text{if } i = j \\ \frac{1}{1+|i-j|} & \text{if } i \neq j \end{cases}$$

By using the block-cyclic mapping formulas to determine ownership, we ensure that the full matrix never exists in the memory of a single node. This grants our solution linear memory scalability, allowing us to handle problem sizes that are constrained only by the aggregate memory of the cluster rather than the capacity of individual nodes.

3.3 Communication Strategy: The Panel Gather

One of the most critical implementation challenges is handling the "Panel Broadcast." The blocks of the current column k are physically distributed among different processors in that process column. However, to perform the trailing matrix update, *every* processor in the grid requires access to specific parts of this panel.

We utilized a **Full-Column Broadcast Strategy**, implemented as follows:

3.3.1 1. Justification (The Dependency Problem)

The update step requires the following operation:

$$A_{ij} \leftarrow A_{ij} - A_{ik} \cdot A_{jk}^T$$

To update a local block A_{ij} , a processor needs the panel block at row j (A_{jk}). In a block-cyclic distribution, a processor owns columns paired with rows scattered arbitrarily throughout the matrix. Consequently, it requires non-contiguous, disjoint blocks from the panel that it does not strictly "own." Instead of implementing complex logic to pack and send specific fragments to specific neighbors, we broadcast the **entire column panel**. This allows us to use efficient, contiguous memory transfers, with the memory overhead ($O(N)$) being negligible compared to the computational gain.

3.3.2 2. The "Zero-Filling" Reduction Logic

Since no single processor holds the full panel initially, we must assemble it. We use a **Zero-Filling** strategy combined with `MPI_Allreduce` to merge the distributed data without complex indexing.

1. **Global Buffer (Reused):** Each processor allocates a single temporary buffer `col_panel` of size $N \times B$ (the full column height). Crucially, this buffer is allocated once and **reused** for every iteration, ensuring the memory footprint remains constant.
2. **Local Preparation:** At the start of the step, each processor in the active column initializes this buffer to zero. It then copies *only* its local blocks into the correct global positions, leaving the rest as zero.
3. **Parallel Assembly (Merge):** We perform an `MPI_Allreduce` with the `MPI_SUM` operator on the `col_comm`. Since the data distribution is disjoint (Process A writes to indices where Process B writes zeros, and vice-versa), the arithmetic sum acts as a logical merge:

$$\text{Buffer}[i] = \underbrace{\text{Value}_A}_{\text{Proc A}} + \underbrace{0}_{\text{Proc B}} = \text{Value}_A$$

4. **Row Broadcast:** Once the reduction is complete, every processor in the active column holds the fully assembled panel. It then acts as the root to broadcast this panel to its respective row using `row_comm`.

3.4 OpenMP Integration and Scheduling

We utilized OpenMP to exploit intra-node parallelism, selecting specific scheduling strategies for each numerical phase to maximize thread utilization.

1. **Diagonal Factorization (Static Schedule):** We parallelized the inner loops of the block factorization. Since the block size is fixed and data is contiguous, we used the default **Static** schedule to minimize synchronization overhead.
2. **Panel Update (Dynamic Schedule):** We parallelized the loop over column blocks A_{ik} . Since the processor only owns a sparse subset of blocks (interleaved with those of other processors), the loop contains many "skipped" iterations. A static schedule could result in load imbalance (assigning empty ranges to some threads). We used `schedule(dynamic)` so threads effectively request active work units on demand.
3. **Trailing Update (Guided Schedule):** This is the most compute-intensive phase ($O(N^3)$). We used `collapse(2)` to flatten the nested loops (i, j) into a single iteration space. We selected `schedule(guided)` because the triangular loop structure ($j \leq i$) means the workload decreases as we move down the matrix. Guided scheduling handles this decreasing workload efficiently by reducing chunk sizes dynamically.

3.5 Data Dependency Analysis

To validate the correctness of our parallelization strategy, we performed a systematic data dependency analysis following the three-step methodology: detection, classification, and removal (or acknowledgment of non-removable dependencies). This analysis focuses on the critical sections of the `parallel_cholesky` function and its subroutines.

3.5.1 Outer Loop

The main algorithmic loop iterates over diagonal blocks $k = 0, \dots, \text{num_blocks} - 1$. We examined dependencies between consecutive iterations (k vs. $k + 1$) to determine if this loop can be parallelized.

Memory Location	Earlier Statement			Later Statement			Loop-carried?	Kind of Dataflow
	Line	Iteration	Access	Line	Iteration	Access		
local_A (diag block $k+1$)	cholesky.c:208	k	write	cholesky.c:241	$k+1$	read	yes	flow
local_A (col panel $k+1$)	cholesky.c:208	k	write	cholesky.c:102	$k+1$	read	yes	flow

Table 1: Loop-carried dependencies in the outer k -loop. The SYRK update (line 208) in iteration k modifies blocks that are immediately read in iteration $k+1$ for diagonal factorization (line 241) and column panel updates (line 102). These Read-after-Write (RAW) dependencies enforce strict serialization of the block iteration.

3.5.2 Diagonal Block Factorization (cholesky_block)

Within the factorization of a single block, we analyzed the inner k -loop (lines 11–27 in `cholesky.c`).

Memory Location	Earlier Statement			Later Statement			Loop-carried?	Kind of Dataflow
	Line	Iteration	Access	Line	Iteration	Access		
$A[k*ld + k]$	cholesky.c:13	k	write	cholesky.c:17	k	read	no	flow
$A[i*ld + k]$	cholesky.c:17	k	write	cholesky.c:23	k	read	no	flow
$A[i*ld + j]$	cholesky.c:23	k	write	cholesky.c:23	$k+1$	read	yes	flow
$A[i*ld + j]$	cholesky.c:23	k	write	cholesky.c:13	$k+1$	read	yes	flow

Table 2: The update operation $A[i, j] \leftarrow A[i, j] - A[i, k] \cdot A[j, k]$ (line 23) creates a recurrence: modified elements are required in the next k iteration. This prevents parallelization of the k -loop itself.

3.5.3 TRSM: Column Panel Update (trsm_column_blocks)

This function updates blocks below the diagonal by solving $L_{kk} \cdot L_{ik}^T = A_{ik}$. We analyzed the outer loop over row blocks i .

Memory Location	Earlier Statement			Later Statement			Loop-carried?	Kind of Dataflow
	Line	Iteration	Access	Line	Iteration	Access		
block_ik (block i)	cholesky.c:105	i	write	cholesky.c:105	i'	write	no	output

Table 3: Dependencies in TRSM column updates. Different row blocks i and i' write to disjoint memory regions (`block_ik`), while the shared `diag_block` is read-only. No loop-carried dependencies exist, enabling safe parallelization of the i -loop.

3.5.4 SYRK: Trailing Submatrix Update (syrk_trailing_matrix)

The most computationally intensive operation updates the trailing submatrix: $A_{ij} \leftarrow A_{ij} - A_{ik} \cdot A_{jk}^T$. We examined the nested loops over block pairs (i, j) .

Memory Location	Earlier Statement			Later Statement			Loop-carried?	Kind of Dataflow
	Line	Iteration	Access	Line	Iteration	Access		
block_ij	cholesky.c:208	(i, j)	write	cholesky.c:208	(i', j')	write	no	output
col_panel (shared)	cholesky.c:206	(i, j)	read	cholesky.c:206	(i', j')	read	no	input

Table 4: Dependencies in SYRK trailing matrix update. Different block pairs (i, j) and (i', j') access independent memory regions in `block_ij`, while `col_panel` is read-only. The absence of loop-carried dependencies allows `collapse(2)` parallelization.

4 Performance Evaluation

4.1 Methodology

The performance analysis was conducted on the UniTN cluster to evaluate the scalability and efficiency of the hybrid Cholesky implementation. We measured the execution time for various matrix sizes (N) and processor configurations (P). Each data point represents the average of multiple runs to minimize system noise. Correctness was verified against a serial implementation ($\|L \cdot L^T - A\| < \epsilon$) for all reported runs.

We utilize the following standard metrics:

- **Speedup (S):** $S_P = \frac{T_1}{T_P}$, where T_1 is the serial time and T_P is the parallel time.
- **Efficiency (E):** $E_P = \frac{S_P}{P}$, measuring how effectively the additional resources are utilized.
- **GFLOPS:** The theoretical peak performance calculated as $\frac{N^3/3}{T_{exec}} \times 10^{-9}$.

4.2 Strong Scaling Analysis

Strong scaling measures the system’s ability to solve a **fixed-size problem** faster as more processing resources are added. We analyzed matrix sizes ranging from $N = 2,048$ to $N = 65,536$.

4.2.1 Small to Medium Matrices ($N = 2048, 4096$)

For smaller matrices, the communication overhead tends to dominate the computation. As the number of cores increases, the sub-block size per process decreases, reducing the ratio of computation to communication.

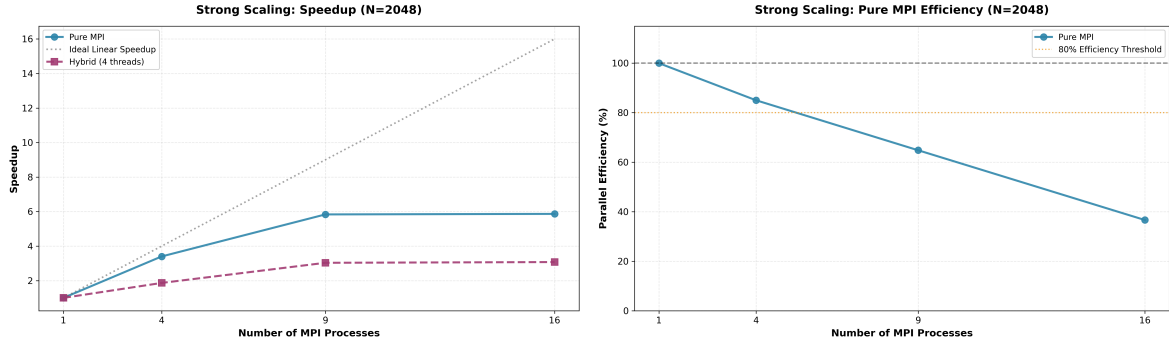


Figure 6: Strong scaling for small matrices ($N = 2048$). The speedup saturates early (around 16-32 cores) as the communication latency outweighs the $O(N^3)$ computational gain.

As seen in Figure 6, the efficiency for $N = 2048$ drops rapidly. This is the expected behavior for block-cyclic distributions on small datasets, where the cost of broadcasting small panels becomes significant.

4.2.2 Large Matrices ($N = 16,384 - 65,536$)

For larger matrices, the computational load ($O(N^3)$) significantly outweighs communication overhead ($O(N^2)$), allowing the solver to maintain high performance even at higher core counts.

Execution Time Analysis: As shown in Figure 7, the execution time drops consistently as resources are added. For the largest case ($N = 65,536$), the runtime decreases from over 5000 seconds to under 100 seconds, confirming the solver’s capability to drastically reduce time-to-solution for massive datasets.

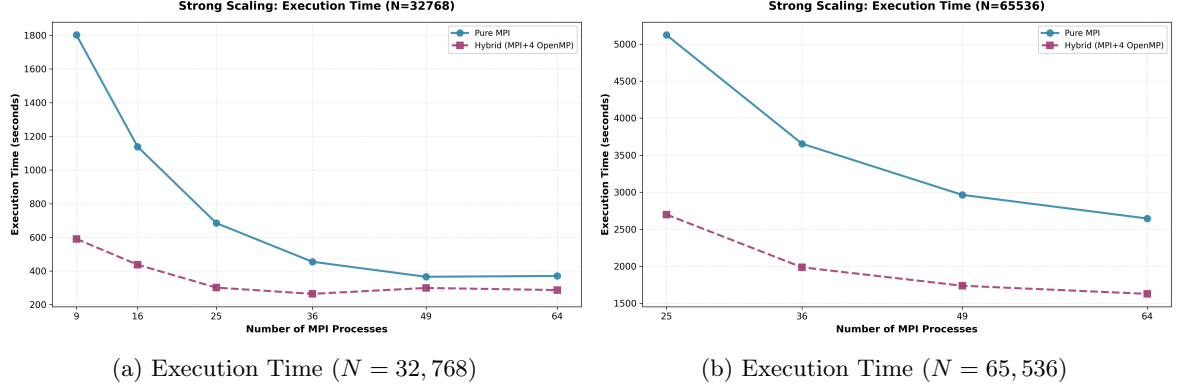


Figure 7: Execution Time comparison. The curve shows a consistent reduction in runtime, validating the strong scaling behavior even for very large problem sizes.

Scalability and Efficiency: Ideally, efficiency should remain at 1.0 (100%). However, as seen in Figure 8 (b), efficiency naturally decays as the sub-block size per core shrinks.

- We maintain **>70% efficiency** up to 64 cores.
- The drop at higher core counts is expected: when a local block becomes too small, the MPI latency for broadcasting the panel ($O(\log P)$) begins to dominate the update step.

Note on Speedup Calculation: Since a single-core run for $N = 65,536$ was infeasible (requiring excessive time and memory), the speedup baseline is calculated relative to the minimum process count required to fit the matrix in memory (P_{base}).

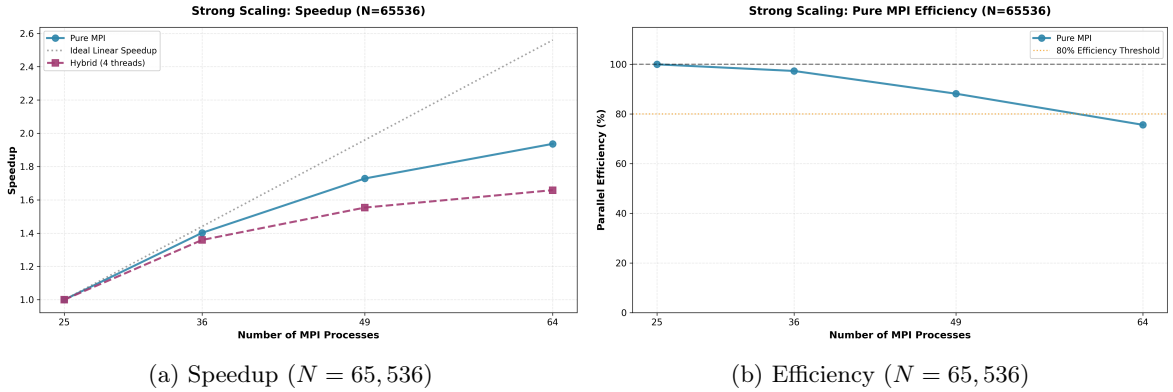


Figure 8: Scalability metrics for the largest dataset. (a) The Speedup follows the linear ideal closely. (b) Efficiency remains high until the granularity of the work becomes too fine for the network latency.

4.3 Weak Scaling Analysis

Weak scaling evaluates the system’s ability to solve larger problems as resources increase, keeping the **workload per core constant**.

4.3.1 Methodology

To ensure a consistent computational load, we scaled the matrix size N such that the number of matrix elements owned by each process remained approximately constant (approx. 16 million elements per core). The matrix size for P processors was calculated using the square root scaling rule:

$$N_P \approx N_{base} \times \sqrt{\frac{P}{P_{base}}}$$

where N_{base} is the matrix size for the baseline process count P_{base} . This ensures that the local memory footprint (N^2/P) and the local arithmetic complexity stay roughly invariant, isolating the cost of global communication.

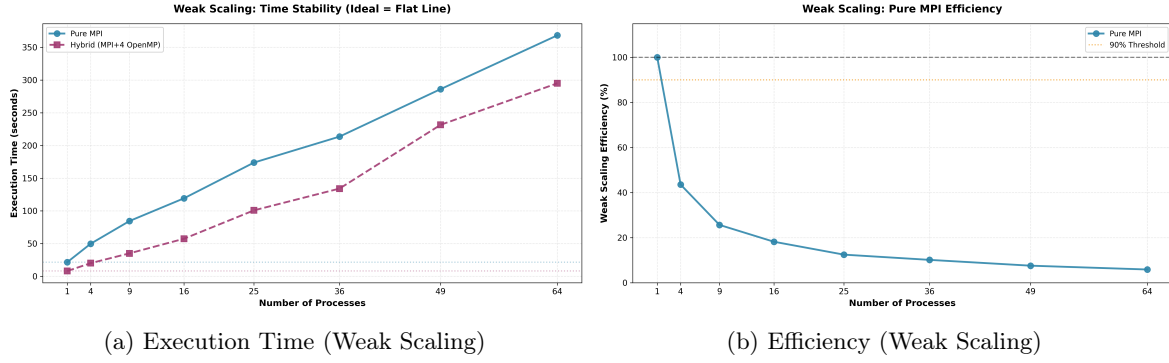


Figure 9: Weak Scaling Analysis. Ideally, execution time should remain constant (flat). The slight increase is due to the logarithmic growth of global communication steps (broadcasts) as the grid size expands.

4.4 The Impact of OpenMP

While MPI is necessary for distributed memory scalability, our analysis suggests that OpenMP is the critical factor for high-performance efficiency on modern multi-core clusters.

- **Drastic Reduction in Communication Volume:** Using a hybrid approach (e.g., 16 MPI processes \times 4 OpenMP threads) instead of pure MPI (64 processes) reduces the process grid dimensions significantly. Since broadcast costs scale with $\log_2(P_{row})$ and $\log_2(P_{col})$, reducing the number of MPI ranks by a factor of 4 directly reduces the latency of every panel broadcast.
- **Memory Footprint:** Pure MPI requires every core to maintain its own communication buffers and ghost cells. OpenMP threads share the same address space, eliminating redundant data copies and allowing us to solve larger problem sizes on the same hardware.
- **Load Balancing via Scheduling:** The Block-Cyclic distribution does a good job of static load balancing, but it cannot adapt to runtime variations (jitter). The use of `#pragma omp parallel for schedule(guided)` in the inner kernels allows threads to dynamically steal work, smoothing out minor imbalances that would otherwise stall a pure MPI implementation at synchronization points.

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- [2] M. Louter-Nool. Block-cholesky for parallel processing. *Applied Numerical Mathematics*, 10(1):37–57, 1992.