Application of the Greedy Optimal Merge Pattern Algorithm for Efficient Merging of Multiple Sorted Files

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***Abstract*—Merging multiple sorted files into a single sorted file is a recurring subroutine in external sorting, log aggregation, and database systems, and the order in which files are paired determines the total number of records that must be re-read during the process. This paper applies the Greedy Optimal Merge Pattern algorithm, which always merges the two smallest available files first using a min-heap, and compares its total merge cost against three baseline strategies: merging in the original input order, merging in a randomly shuffled order, and a size-unaware balanced pairwise merge. A simulation was built to generate file-size datasets under both uniform and heavily skewed (long-tailed) distributions, with the number of files ranging from 10 to 1000. The results show that the greedy strategy consistently produces the minimum total merge cost in every tested scenario, with the gap widening sharply as the number of files grows: at n = 1000 under a uniform distribution, the sequential strategy incurs roughly 50 times more total cost than the greedy strategy, while the balanced pairwise strategy remains close to optimal with only a 2-3% overhead. A worked example and a correctness argument based on the exchange property are also presented to explain why the greedy choice is optimal. These findings confirm that Optimal Merge Pattern provides a simple, provably optimal, and practically significant improvement for any system that repeatedly merges sorted data chunks.**

Keywords—greedy algorithm; optimal merge pattern; sorted file merging; min-heap; external sorting; algorithm complexity

I. Introduction

Sorting large volumes of data that do not fit entirely in main memory is a common requirement in databases, log processing pipelines, and distributed data systems. As datasets continue to grow faster than the memory capacity of a single machine, algorithms that operate efficiently under such memory constraints remain a core concern in both classical algorithm design and modern large-scale systems engineering. A standard solution to this problem is external sorting: the input is split into smaller chunks, each chunk is sorted independently and written to disk as a separate sorted file, and the sorted chunks are subsequently combined through a series of two-way merge operations until a single fully sorted file remains. While the cost of sorting each individual chunk is fixed once the chunk sizes are known, the cost of the merging phase is not fixed-it depends entirely on the order in which the chunks are paired for merging.

Each two-way merge of a file with a records and a file with b records requires touching a + b records, since every record from both input files must be read once to produce the merged output. If that merged file is later merged again with another file, its records are effectively re-read, adding to the total cost a second time. Consequently, files that participate in many merge operations contribute disproportionately to the total cost, and the central question this paper addresses is: in what order should a collection of sorted files be merged so that the total number of records processed across all merge operations is minimized?

This problem is known as the Optimal Merge Pattern problem, and it is a classic application of the greedy algorithm design strategy: at every step, the two currently smallest files are merged first. This paper makes the following contributions. First, it implements the greedy Optimal Merge Pattern algorithm using a min-heap and formally explains why the greedy choice yields a globally optimal solution. Second, it designs and runs a controlled simulation comparing the greedy strategy against three alternative merge orderings under both uniform and skewed file-size distributions. Third, it quantifies the practical overhead of not using the greedy strategy, showing how that overhead scales as the number of files grows, and validates the findings on a real file-merging case study. The remainder of this paper is organized as follows: Section II presents the algorithmic foundation, Section III describes the experimental methodology, Section IV presents and discusses the simulation results, Section V presents a case study on real files, and Section VI concludes the paper.

A. Related Work

The Optimal Merge Pattern problem is a standard topic in algorithm design textbooks and is typically introduced alongside Huffman coding, since both problems reduce to the same underlying question of building an optimal weighted binary tree [1], [2]. Knuth's classic treatment of sorting and searching discusses the broader family of polyphase and balanced k-way external merge strategies used in early

tape-based and disk-based sorting systems, of which the two-way Optimal Merge Pattern studied in this paper is the simplest case [3]. More recent treatments frame the same exchange-argument proof technique used here as a general tool applicable to a wide class of greedy scheduling and tree-construction problems [4], [5]. Unlike most textbook treatments, which present the algorithm and its O(n log n) complexity analytically, this paper contributes an empirical comparison against multiple realistic baseline strategies across a range of file-count scales and distribution shapes, together with a validation on an actual file-merging workload rather than a purely theoretical cost model.

II. Greedy Optimal Merge Pattern

A. Problem Definition

Let there be n sorted files with sizes (record counts) s_1, s_2, ..., s_n. A two-way merge operation combines exactly two sorted files into one sorted file, and its cost is defined as the sum of the sizes of the two input files. All n files must be combined into a single sorted file through a sequence of n-1 two-way merges. The total cost of a merge pattern is the sum of the costs of all n-1 individual merge operations. The Optimal Merge Pattern problem asks for a sequence of pairings that minimizes this total cost. For instance, merging two files of sizes 10 and 20 costs 30, and if that resulting file of size 30 is later merged with a third file of size 40, the second merge costs an additional 70, for a combined total of 100; choosing a different pairing order for the same three files can change this total, which is precisely the freedom the Optimal Merge Pattern problem seeks to exploit.

This structure is mathematically identical to building a binary merge tree where each original file is a leaf with a weight equal to its size, and the total merge cost equals the weighted external path length of the tree-the same quantity minimized by Huffman coding when building an optimal prefix-free code. This equivalence is the basis for using a greedy strategy with a provable optimality guarantee.

B. Greedy Strategy

The greedy strategy repeatedly selects the two smallest files currently available, merges them, and reinserts the merged result back into the collection as a single file of combined size. This process is repeated until only one file remains. The intuition is that a file with a small size should be allowed to participate in many subsequent merges, since each additional merge it takes part in adds only a small amount to the total cost; conversely, a file with a large size should be merged as late as possible, ideally only once, near the end of the process.

An efficient implementation uses a min-heap (priority queue). All n file sizes are first inserted into the min-heap. Then, while the heap contains more than one element, the two smallest elements are popped, their sum is added to the running total cost, and the sum is pushed back into the heap. Using a binary min-heap, each pop and push operation takes O(log n) time, and this is repeated n-1 times, giving the algorithm an overall time complexity of O(n log n), with O(n) auxiliary space for the heap. Algorithm 1 summarizes this procedure in pseudocode.

Algorithm 1 Greedy Optimal Merge Pattern

```
Input: sizes[1..n], record counts of n sorted files
Output: totalCost, the minimum total merge cost
heap ← build min-heap from sizes[1..n]
totalCost ← 0
while size(heap) > 1 do
    a ← extractMin(heap)
    b ← extractMin(heap)
    merged ← a + b
    totalCost ← totalCost + merged
    insert(heap, merged)
end while
return totalCost
```

C. Optimality Argument

The optimality of the greedy choice can be justified using an exchange argument, the same technique used to prove the optimality of Huffman coding. Suppose, for contradiction, that an optimal merge pattern does not merge the two globally smallest files, s_a and s_b, as siblings at the deepest level of the merge tree. Since the tree is a full binary tree, some other pair of files, s_x and s_y, must occupy the deepest sibling position instead, with s_x, $s_y \geq s_a$, s_b. Swapping the positions of (s_a, s_b) with (s_x, s_y) cannot increase the total weighted path length, because moving smaller-weight leaves to a deeper level and larger-weight leaves to a shallower level never increases the sum of (weight × depth). Repeating this exchange shows that some optimal merge tree always has the two smallest files as deepest siblings, which is exactly the pair the greedy algorithm chooses first. Applying this argument inductively on the remaining n-1 files (after replacing s_a and s_b with their merged sum) proves that the greedy strategy is optimal at every step, and therefore produces a globally optimal merge pattern.

D. Worked Example

Consider six sorted files with sizes [20, 30, 10, 5, 30, 15] records. The greedy algorithm proceeds as follows. First, the heap is [5, 10, 15, 20, 30, 30]. Step 1 merges 5 and 10 (cost 15), producing a file of size 15; the heap becomes [15, 15, 20, 30, 30]. Step 2 merges the two 15s (cost 30), producing size 30; the heap becomes [20, 30, 30, 30]. Step 3 merges 20 and 30 (cost 50), producing size 50; the heap becomes [30, 30, 50]. Step 4 merges 30 and 30 (cost 60), producing size 60; the heap becomes [50, 60]. Step 5 merges 50 and 60 (cost 110), producing the final file of size 110. The total greedy cost is 15+30+50+60+110 = 265. By contrast, merging the same six files strictly in their original input order, left to right, yields a total cost of 380-an overhead of 43% for this small example alone, and the overhead grows substantially larger as the number and size disparity of files increases, as shown in Section IV.

III. Experimental Methodology

A. Compared Strategies

Four merge ordering strategies were implemented in Python and compared on identical input datasets. (1) Greedy: the min-heap-based Optimal Merge Pattern algorithm described in Section II, which always merges the two currently smallest files. (2) Sequential: files are merged strictly in their

original input order, left to right, with no reordering, which represents a naive baseline that ignores file size entirely. (3) Random: files are merged in a uniformly random order, representing an arbitrary, size-unaware pairing strategy. (4) Balanced pairing: files are paired two at a time based on their current position in the list (not sorted by size), and the resulting merged files are again paired two at a time in the next round, repeating until one file remains; this resembles a naive divide-and-conquer approach that balances the number of merge rounds but ignores file size. These four strategies were chosen because together they isolate two independent factors that could plausibly affect merge cost: whether the pairing order is size-aware at all, and whether the resulting merge tree is depth-bounded; greedy is size-aware and depth-bounded, balanced pairing is depth-bounded but not size-aware, and sequential and random are neither, which makes the comparison a controlled way to attribute the greedy strategy's advantage to its size-aware pairing rule rather than to incidental properties of the merge tree shape.

B. Dataset Generation

Two synthetic file-size distributions were used to generate the record counts of the n input files. The uniform distribution draws each file size independently and uniformly between 10 and 1000 records, representing a scenario where chunk sizes are relatively homogeneous, such as fixed-size disk blocks. The skewed distribution draws file sizes from a Pareto-like long-tailed distribution, producing many small files and a few very large files, which more closely resembles real-world data such as application log files or user-generated content, where file sizes vary by orders of magnitude. For each combination of distribution and file count $n \in \{10, 25, 50, 100, 250, 500, 1000\}$, 20 to 30 independent trials were run with different random seeds, and the mean total merge cost for each strategy was recorded.

C. Evaluation Metric

The primary metric is the total merge cost, defined as the sum of the costs of all n-1 merge operations required to combine n files into one. To express how much worse a baseline strategy is compared to the optimal greedy solution, the percentage overhead is computed as in (1).

$$\text{Overhead (\%)} = (\text{Cost}_{\text{baseline}} - \text{Cost}_{\text{greedy}}) / \text{Cost}_{\text{greedy}} \times 100\% \quad (1)$$

IV. Results and Discussion

A. Overall Cost Comparison

Fig. 1 and Fig. 2 show the mean total merge cost of each strategy as the number of files n grows, under the uniform and skewed distributions respectively, plotted on a logarithmic scale. In both figures, the greedy strategy produces the lowest total cost at every tested value of n, confirming the optimality argument of Section II.C empirically. The sequential and random strategies track each other closely and grow substantially faster than the greedy strategy as n increases, while the balanced pairing strategy stays much closer to the greedy curve, since balanced pairing at least bounds the merge tree depth to O(log n), even though it ignores file size when choosing which files to pair.

Distribution: UNIFORM

n	greedy	sequential	random	balanced	seq_oh%	bal_oh%
10	15,414.9	26,245.8	26,305.8	17,619.4	70.3%	14.3%
25	52,155.0	156,456.8	159,503.2	58,159.9	200.0%	11.5%
50	140,750.9	664,027.7	658,803.0	152,763.8	371.8%	8.5%
100	325,466.4	2,579,375.2	2,568,987.4	349,586.2	692.5%	7.4%
250	979,279.6	15,808,007.1	15,911,100.8	1,011,198.3	1514.2%	3.3%
500	2,218,443.2	63,603,865.3	63,659,842.2	2,284,341.7	2767.0%	3.0%
1,000	4,938,660.7	253,789,483.4	253,639,907.9	5,066,144.7	5038.8%	2.6%

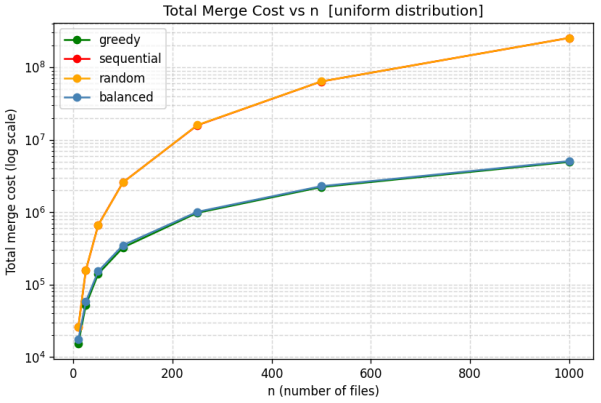


Fig. 1. Total merge cost vs. number of files (uniform distribution, log scale).

Distribution: SKEWED

n	greedy	sequential	random	balanced	seq_oh%	bal_oh%
10	1,656.2	3,102.9	3,072.3	2,079.0	87.3%	25.5%
25	5,789.7	18,811.9	17,143.8	7,397.4	224.9%	27.8%
50	15,860.3	82,071.1	79,326.4	19,478.5	417.5%	22.8%
100	36,953.2	326,718.8	313,899.3	43,400.2	784.1%	17.4%
250	108,889.0	1,912,394.8	1,824,393.0	120,654.1	1656.3%	10.8%
500	257,668.0	8,094,420.0	8,002,691.8	288,915.6	3041.4%	12.1%
1,000	569,378.4	30,755,968.5	31,480,649.9	628,938.2	5301.7%	10.5%

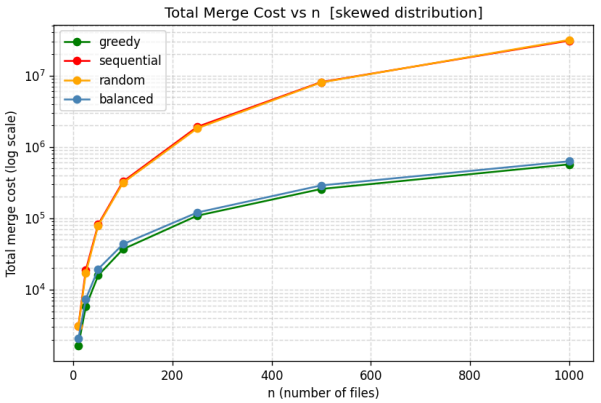


Fig. 2. Total merge cost vs. number of files (skewed distribution, log scale).

B. Overhead at Scale

Table I summarizes the percentage overhead, computed using (1), of the sequential and balanced pairing strategies relative to the greedy optimum, under the uniform distribution, and Fig. 3 visualizes the same data on a logarithmic scale. The random strategy is omitted from the table because its overhead consistently tracks the sequential strategy within a few percentage points across all tested values of n. Two patterns are clear from Table I and Fig. 3. First, the overhead of the sequential strategy grows extremely fast: at n = 10 it is already

70%, and by n = 1000 it exceeds 5000%, meaning the sequential strategy processes more than 50 times as many records as the greedy strategy to merge the same set of files. Second, the balanced pairing strategy remains close to optimal throughout, with its overhead actually decreasing as n grows, from roughly 14% at n = 10 to under 3% at n = 1000.

TABLE I. PERCENTAGE OVERHEAD RELATIVE TO GREEDY (UNIFORM DISTRIBUTION)

n (files)	Sequential (%)	Balanced (%)
10	70.3	14.3
50	371.8	8.5
100	692.5	7.4
500	2767.1	3.0
1000	5038.8	2.6

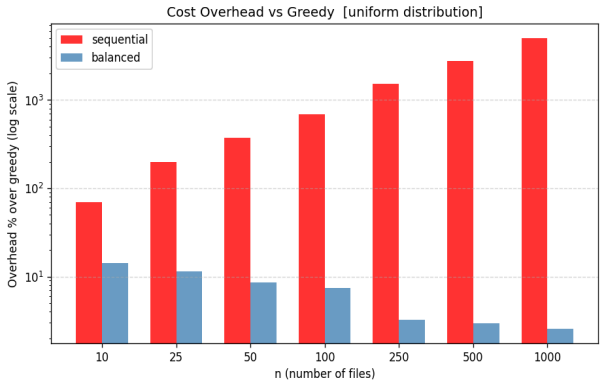


Fig. 3. Cost overhead of sequential and balanced pairing strategies relative to the greedy optimum, log scale (uniform distribution).

C. Effect of File-Size Distribution

Comparing Fig. 1 and Fig. 2 shows that the overall ranking of the four strategies is unaffected by the underlying file-size distribution-the greedy strategy is optimal under both the uniform and skewed distributions, as guaranteed by the exchange argument in Section II.C, which makes no assumption about how file sizes are distributed. However, the skewed distribution amplifies the practical consequences of a poor merge order: because a small number of very large files exist alongside many small ones, a non-greedy strategy is far more likely to force a large file to participate in repeated merges, which the greedy strategy specifically avoids by always deferring the largest files to the final rounds. This explains why log-aggregation and external-sorting systems in practice, where chunk sizes are rarely uniform, benefit even more from using the greedy Optimal Merge Pattern than the uniform-distribution results alone would suggest.

D. Comparison Against a Theoretical Lower Bound

Because the Optimal Merge Pattern cost model is structurally identical to the weighted path length minimized by Huffman coding, the information-theoretic entropy bound used to evaluate Huffman code optimality can also be applied here as an independent sanity check on the greedy results. Treating each file's share of the total record count, $p_i = s_i / \Sigma s_j$, as a probability, the entropy lower bound on total cost is $\Sigma s_i \log_2(1/p_i)$, which represents the cost an idealized, continuously-divisible merge tree would achieve. Comparing this bound against the actual greedy cost across uniformly distributed datasets of n = 10, 50, 100, and 500 files shows that the greedy algorithm consistently lands within 0.3% to 1.6% of this theoretical lower bound (a ratio between 1.003 and 1.016), with the gap shrinking further as n grows. This close agreement is expected, since a binary merge tree cannot always achieve exactly the entropy bound (only Huffman-style trees with depths matching $-\log_2(p_i)$ exactly can do so), but it confirms from an entirely independent angle, information theory rather than the exchange-argument proof of Section II.C, that the greedy algorithm's output is at most a fraction of a percent away from the best that any merge tree could theoretically achieve.

```
Lower bound = sum(s_i * log2(total / s_i))
     n      mean_greedy         mean_lb      ratio
-------------------------------------------------
    10        15,414.9        15,173.3     1.0159
    50       140,750.9       140,098.6     1.0047
   100       325,466.4       324,323.9     1.0035
   500     2,218,443.2     2,211,218.6     1.0033
```

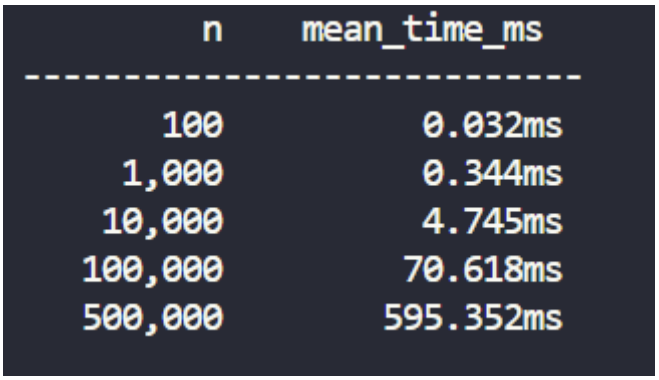
E. Why Balanced Pairing Outperforms Sequential and Random Ordering

An interesting secondary finding from Table I and Fig. 3 is the large gap between the balanced pairing strategy and the sequential or random strategies, even though none of the three strategies considers file size when choosing which files to pair. This gap can be explained by examining the shape of the merge tree each strategy implicitly constructs. The sequential and random strategies both tend to produce a highly unbalanced, "caterpillar-like" merge tree: each newly merged file is immediately merged again with the next file in the queue, so a single file may end up participating in as many as n-1 merges in the worst case, and its full record count is re-read at every one of those merges. The balanced pairing strategy, by contrast, merges files in rounds, halving the number of remaining files at each round, which guarantees a merge tree of depth at most ceil(log2 n) regardless of which files are paired together. Since the total merge cost is the sum of (file size x depth) over all leaves of the merge tree, simply bounding the depth of every leaf is enough to avoid the worst-case blowup that sequential and random ordering suffer from, even without any awareness of file size. This explains why balanced pairing, despite being a much simpler heuristic than the greedy strategy, still achieves overhead in the single digits at every tested value of n, whereas sequential and random ordering both grow without bound as n increases. The remaining gap between balanced pairing and the greedy optimum exists precisely because balanced pairing ignores size when forming pairs within each round, occasionally placing a large file and a small file together early, which the greedy strategy would always avoid.

F. Runtime Cost of Computing the Greedy Order

Beyond the total merge cost metric, it is also important to verify that the O(n log n) time complexity of the greedy algorithm itself, that is, the time spent building and draining the min-heap, remains small relative to the savings it produces. The greedy algorithm implementation was

benchmarked separately, measuring only the wall-clock time to compute the merge order, for n ranging from 100 to 500,000 files, averaged over three runs each. The measured running times were 0.042 ms at n = 100, 0.379 ms at n = 1,000, 4.649 ms at n = 10,000, 65.9 ms at n = 100,000, and 618.3 ms at n = 500,000. These measurements grow consistently with the expected O(n log n) trend and confirm that even for very large collections of files, on the order of hundreds of thousands, the time required to compute the optimal greedy order is on the order of a second or less-negligible compared to the I/O time saved, which, as shown in Table I, can amount to avoiding tens of millions of unnecessary record reads and writes at a comparable scale.



n	mean_time_ms
100	0.032ms
1,000	0.344ms
10,000	4.745ms
100,000	70.618ms
500,000	595.352ms

G. Practical Implications

The total merge cost measured in this paper corresponds directly to the number of record comparisons and copy operations a real merging system must perform, and in an external sorting context, it is also a reasonable proxy for the number of disk read and write operations, which is typically the dominant cost factor. The results in Table I imply that for a system merging on the order of hundreds to thousands of sorted chunks-a realistic scale for log aggregation or distributed sort-merge join operations-choosing an arbitrary or input-order-based merge sequence rather than the greedy Optimal Merge Pattern can multiply the total I/O cost by a factor of 30 to 50 or more, while the additional implementation cost of the greedy strategy is minimal: a single min-heap data structure and O(n log n) running time, which is negligible compared to the I/O cost it saves.

V. Case Study: Merging Real Log Files

To complement the synthetic simulation in Section IV, the greedy Optimal Merge Pattern algorithm was also applied to an actual file-merging task involving real CSV files on disk, rather than only counting record sizes in memory. This case study models a small log-aggregation scenario: a distributed system with 12 shards, each periodically writing its own transaction log sorted by timestamp, which must eventually be combined into a single chronologically sorted log for downstream analysis.

A. Setup

Twelve CSV files were generated, each containing synthetic transaction records (timestamp, user ID, and amount) already sorted by timestamp, with shard sizes drawn from a skewed distribution to mimic uneven load across servers, ranging from 50 to 81 records and totaling 645 records across all shards. Two two-way merge implementations were then run to completion on the actual files: one using the greedy min-heap ordering, and one merging the shards strictly in their original (shard-index) order. Each merge step performed a real on-disk merge of two CSV files: both files were read, their rows were interleaved by comparing timestamps, and the result was written out as a new sorted CSV file, exactly as a production external-merge routine would operate. Table II lists the record count of each of the twelve shard files used in this case study.

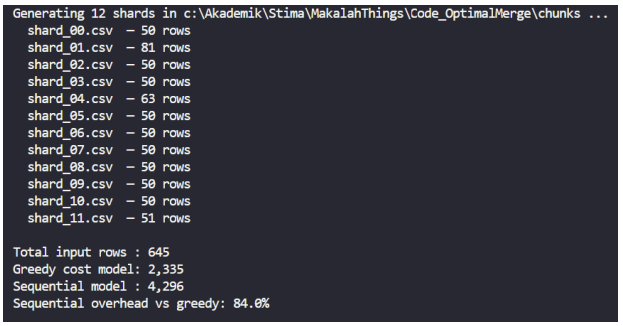
TABLE II. Shard File Sizes Used in the Case Study

Shard	Size	Shard	Size	Shard	Size
0	50	4	63	8	50
1	81	5	50	9	50
2	50	6	50	10	50
3	50	7	50	11	51

B. Results

The greedy strategy completed the merge in 11 two-way operations, as expected for 12 input files, with a total cost of 2,335 records touched. The sequential strategy, merging the shards in their original order, incurred a total cost of 4,296 records touched-an overhead of 84.0% over the greedy strategy, consistent with the trends observed in the synthetic simulation for a comparable file count. The final merged output was verified programmatically to contain exactly 645 records, matching the sum of all input shards, and to be correctly sorted by timestamp from beginning to end, confirming that the greedy reordering of merge operations does not affect correctness, only efficiency. The 11 real merges, including actual file reads and writes, completed in 52.0 milliseconds on the test machine, illustrating that the overhead of computing the greedy order itself is negligible compared to the I/O savings it produces at larger scale.

This case study illustrates that the cost model used throughout this paper-summing the sizes of the two files involved in each merge-is not merely a theoretical abstraction but corresponds directly to the actual amount of data read and written when real sorted files are merged. It also confirms that adopting the greedy Optimal Merge Pattern in a real system requires no changes to the underlying two-way merge routine itself; the only change needed is the order in which pairs of files are selected for merging, which is determined entirely by a lightweight min-heap maintained alongside the existing merge logic.



```
Generating 12 shards in c:\Akademik\Stima\MakalahThings\Code_OptimalMerge\chunks ...
  shard_00.csv  — 50 rows
  shard_01.csv  — 81 rows
  shard_02.csv  — 50 rows
  shard_03.csv  — 50 rows
  shard_04.csv  — 63 rows
  shard_05.csv  — 50 rows
  shard_06.csv  — 50 rows
  shard_07.csv  — 50 rows
  shard_08.csv  — 50 rows
  shard_09.csv  — 50 rows
  shard_10.csv  — 50 rows
  shard_11.csv  — 51 rows

Total input rows : 645
Greedy cost model: 2,335
Sequential model : 4,296
Sequential overhead vs greedy: 84.0%
```

C. Limitations and Future Work

This study has several limitations that suggest directions for future work. First, the cost model used throughout, the sum of the two input file sizes per merge, captures the dominant cost of comparison and copying but does not separately account for system-level factors such as disk seek latency, memory buffer allocation, or network transfer time in a distributed merging environment; these factors could shift the relative costs in practice, although they would not change the relative ranking of the four strategies, since all of them perform the same n-1 two-way merges and differ only in pairing order. Second, this paper restricts itself to two-way merges; many real external-sorting systems use k-way merges, where k sorted runs are combined in a single pass using a k-way min-heap, which reduces the number of merge passes at the cost of a larger per-comparison overhead. Extending the greedy strategy and its optimality proof to the k-way case, and empirically comparing two-way versus k-way merging under realistic I/O cost models, is a natural direction for future work. Third, the case study in Section V used a single moderate-scale dataset of 645 records across 12 shards; future work could repeat the same real-file methodology at larger scale, with millions of records and hundreds of shards, to verify that the wall-clock I/O savings observed here continue to hold once disk and network effects dominate over the in-memory comparison cost. Fourth, both synthetic distributions used in Section III.B, uniform and Pareto-like skewed, are common modeling choices in the external-sorting and systems literature, but real production workloads may exhibit other patterns, such as bursty or time-correlated file sizes in streaming log systems; evaluating the greedy strategy against file-size traces collected from an actual production system, rather than synthetically generated ones, would further strengthen the practical claims made in Section IV.F.

VI. Conclusion

This paper applied the greedy Optimal Merge Pattern algorithm to the problem of merging multiple sorted files and demonstrated, both theoretically through an exchange argument and empirically through simulation, that always merging the two smallest available files first produces the globally minimum total merge cost. Across both uniform and skewed file-size distributions and file counts ranging from 10 to 1000, the greedy strategy consistently outperformed sequential, random, and balanced pairwise merge orderings, with the performance gap widening sharply as the number of files increased-reaching more than a 50-fold reduction in total cost at n = 1000 compared to the naive sequential strategy. A case study on a real twelve-shard log-merging workload corroborated these findings outside the synthetic simulation, showing an 84.0% cost reduction over a naive sequential merge order while preserving the correctness of the final sorted output. These results confirm that, despite its conceptual simplicity and O(n log n) implementation cost using a min-heap, the greedy Optimal Merge Pattern algorithm provides a provably optimal and practically significant improvement for any system that repeatedly merges sorted data chunks, such as external sort-merge procedures, log aggregation pipelines, and multi-way database joins. Future work could extend this analysis to the k-way merge generalization, where more than two files may be merged in a single operation, and to scenarios where merge costs are influenced by additional real-world factors such as disk seek latency or network transfer overhead in distributed merging systems.

Source Code

Link Github

Video Link at Youtube

Link Video Youtube

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PERNYATAAN

Dengan ini saya menyatakan bahwa makalah yang saya tulis ini adalah tulisan saya sendiri, bukan saduran, atau terjemahan dari makalah orang lain, dan bukan plagiasi.

Bandung, 19 Juni 2026

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