Project Deliverable 4: Final Report

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Project: **Task Scheduler Program**

**Project Phase 1 Deliverable 1: Data Structure Design and Implementation**

**Objective**

The primary objective of this project is to design and implement a task scheduling system. The input data includes the task title, task deadline, task priority, and task complexity. The system efficiently manages and retrieves task priorities based on priority factors used and leverages optimized data structures in Python.

This project aims to demonstrate how theoretical knowledge of data structures and algorithmic efficiency can be applied to a realistic, command-line-based scheduling scenario.

**Application Context**

In today's world, we are overwhelmed with multiple tasks. It will be challenging to manage all the tasks simultaneously. Our job is to ensure we prioritize tasks correctly, whether at work, school, or in our personal lives, for an efficient workflow. A Scrum team or any project can utilize this, such as building a house or completing a project. We can divide smaller tasks and prioritize them according to the project milestones. If there are 100's of functions, then our job is to prioritize them to achieve ultimate efficiency.

**We believe an efficient scheduler must:**

● Prioritize urgent or high-value tasks first.

● Support dynamic updates for deadline changes in the functions (since anything can change at any moment).

● Help streamline task completion one-by-one.

**Goals**

● Implement a priority queue (min-heap) for efficiently ranking and retrieving the most urgent or highest-value tasks.

● Implement a hash table for fast O(1) lookups and updates of task details. Much more efficient.

● Design a simple command-line interface (CLI) for task addition, retrieval, and removal.

● Evaluate optimization strategies and trade-offs in terms of space and time complexity.

**Key Data Structures**

|  |  |  |  |
| --- | --- | --- | --- |
| **Data Structure** | **Purpose** | **Time Complexity** | **Description** |
| Priority Queue (Heap) | To maintain tasks sort by priority | Insert: O(log n) Remove: O(log n) | Built using Python’s inbuilt data structure to ensure efficient scheduling based on deadline. |
| Hash Table (Dictionary) | To store and retrieve tasks by ID | Lookup: O(1) Insert/Delete: O(1) | Used to store metadata (task ID, deadline, urgency). |

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### **Design Rationale**

Heap-based Priority Queue: Enables efficient retrieval of the highest-priority task (smallest deadline or highest bid) in O(\log n) time.

**Hash Table:** Provides instant access to task details, essential for quick command-line lookups.

**Tie-breaking Rule:** When multiple tasks share the same deadline, priority is determined by bid amount and, if necessary, task ID for determinism.

**Implementation Overview**

The project uses Python’s built-in heapq for priority operations and a dictionary for hash-based storage.

**CLI Commands:**

● add\_task <id> <deadline> <urgency> <description>

● get\_next\_task – retrieves the highest-priority task

● find\_task <id> – displays task info

● complete\_task <id> – marks a task as completed

### **Challenges and Limitations**

The hybrid design offers excellent performance for core operations but introduces specific complexities in dynamic data handling and inherent memory overhead.

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#### **Dynamic Priority Updates and Lazy Deletion**

Updating an existing task’s priority (e.g., changing bids or deadlines) is a non-trivial operation because Python’s native heapq implementation lacks an efficient decrease-key or increase-key function, which would allow the heap property to be locally restored in $O(\log n)$ time (Cormen et al., 2022). More complex heap structures designed for dynamic updates are known, but add implementation complexity (Ioannou & Katevenis, 2012; Sintoni et al., 2014).

Therefore, the system must rely on the Lazy Deletion workaround:

1. When a task's priority changes, the old, now-outdated entry remains in the heap. The hash table is immediately updated with the new priority values.
2. The updated task is then reinserted into the Min-Heap with its new priority key in $O(\log n)$ time.
3. During the get\_next\_task extraction phase, outdated (or "stale") entries are efficiently skipped using a validation check against the Hash Table.

This approach maintains the system's correctness and ensures an amortized $O(\log n)$ performance for updates and retrieval, but it temporarily increases the size of the heap and introduces minor, cyclical extraction overhead due to the required hash table validation.

#### **Deterministic Tie-Handling**

The system's multi-attribute priority key ((deadline, -bid\_amount, task\_id)) is crucial for ensuring predictable scheduling. Tasks with identical deadlines and bids require a final, stable sorting mechanism to guarantee a deterministic extraction order. The inclusion of the unique task\_id as the final element serves as this deterministic tiebreaker. This is vital, as arbitrary ordering in real-time or critical systems can lead to unpredictable behavior. Ensuring determinism in complex sorting scenarios is a recognized requirement in algorithmic design (Sedgewick & Wayne, 2011).

#### **Space-Time Trade-off and Memory Consumption**

The hybrid model necessitates the duplication of key data (Task ID, deadline, bid) across both core structures—metadata in the Hash Table and the priority information in the Min-Heap. This increases the overall memory footprint compared to a single, monolithic data structure. However, this is a conscious space-time trade-off that is entirely justified. The constant-time $O(1)$ access provided by the Hash Table for lookups (Knuth, 1998) and the $O(\log n)$ efficiency of the heap for priority updates (Cormen et al., 2022) ensures responsiveness. This trade-off is often favored in real-time or dynamic systems where immediate responsiveness is paramount.

### **Expected Outcomes**

The successful completion of this project is defined by the fulfillment of both functional and analytical objectives, resulting in a fully justified and operational command-line scheduler.

#### **Functional Deliverables**

● Operational CLI: A fully functional, text-based command-line interface supporting all core task management commands: add\_task, get\_next\_task, find\_task, and complete\_task.

● Hybrid Data Integrity: The final Python class (TaskScheduler) must demonstrate synchronized, concurrent management, effectively linking task metadata in the Hash Table with priority keys in the Min-Heap.

● Robust Prioritization: The system must consistently deliver accurate task ordering based on the multi-level logic: Earliest Deadline First $\rightarrow$ Highest Bid $\rightarrow$ Unique Task ID.

#### **Analytical Deliverables**

● Performance Analysis: An empirical comparison of the heap-based approach versus a list-based sorting approach for varying task volumes (e.g., 100, 1000 tasks). This analysis will provide practical validation of the theoretical $O(\log n)$ complexity for the priority queue operations.

● Trade-off Documentation: A clear written discussion documenting the precise nature of the space-time efficiency balance, justifying the chosen memory overhead against the guaranteed constant-time access benefits of the Hash Table.

● Implementation Details: Comprehensive inclusion of pseudocode for all core operations and annotated Python snippets detailing the construction of the complex heap key logic, the deterministic tie-breaking mechanism, and the implementation of the lazy deletion strategy.

**Deliverable 2: Proof of Concept Implementation**

**Hash Table (Dictionary) Proof-of-Concept Implementation**

This section provides a clear explanation of how the hash table is used within the TaskScheduler class to store and manage task metadata efficiently. The hash table serves as the primary repository for task information, playing a crucial role in ensuring rapid access and updates to task data.

The core purpose of the hash table is to support three fundamental operations: inserting new tasks, retrieving task information, and removing completed tasks. These operations are implemented through the add\_task, find\_task, and complete\_task methods in the TaskScheduler class. Because the hash table is implemented using Python’s dictionary data structure, each of these operations executes in constant time, or O(1), on average. This performance consistency is crucial, especially when managing numerous tasks in real-time environments.

In the hash table, the unique task\_id is used as the key. In contrast, the value associated with each key is a dictionary containing metadata about the task, including the deadline, urgency level, and a brief description. This design ensures that the stored metadata is well-structured, easy to understand, and simple to extend should additional attributes need to be included later.

To demonstrate the effectiveness of the hash table, a test script was used to showcase insertion, lookup, and deletion operations, including the handling of edge cases. For example, inserting tasks such as T101 and T102 confirms that data is stored correctly. A lookup for T102 returns its details instantly, highlighting the speed of the hash table. Attempts to access a non-existent task, such as T999, confirm that appropriate error messages are displayed. Additionally, deleting a task and attempting to delete it again verifies that duplicate deletions are managed gracefully.

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**Fig.** Hash Table Implementation Output

The hash table also plays a vital role in the overall design of the task scheduling system, particularly when integrating future enhancements. As the system expands to include components such as a priority queue implemented using a min-heap, the hash table will serve as the single source of truth for determining whether task entries in other structures are valid or outdated. This capability is essential for supporting a lazy deletion strategy, where tasks in other structures may not always be immediately removed.

From a development perspective, several important considerations guided this implementation. Ensuring data consistency required designating the hash table as the authoritative source for all task metadata. Structuring the stored metadata as a descriptive dictionary made the implementation more intuitive while supporting future growth. Error handling was also incorporated to help maintain system stability and provide users with meaningful feedback.

To complete the full system implementation, the following steps include integrating the hash table with a min-heap to support priority-based scheduling, implementing lazy deletion logic to manage outdated records efficiently, constructing a multi-attribute priority key to ensure accurate task ordering, and developing a command-line interface to support user interaction. By following these steps, the task management system will evolve into a robust, efficient, and user-friendly application.

**Priority Queue (Heap) Integration**

Following the initial hash table proof-of-concept, a priority queue was integrated using Python’s built-in heapq module. This enhancement enables the system to manage task prioritization efficiently based on deadlines and urgency levels. The heap ensures that the task with the earliest deadline and highest urgency is always accessible in O(1) amortized time, while insertion and removal operations maintain O(log n) performance.

Each task is represented in the heap as a tuple: (deadline, -urgency, task\_id). This composite key enforces the priority rules: earliest deadline first, highest urgency next, and finally, task ID for stability in the event of a tie.

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**Fig.** Priority Queue (Heap) and Heap TableImplementation Output

**Data Structure Summary**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Data Structure** | **Purpose** | **Insert** | **Remove** | **Lookup** |
| Priority Queue (Heap) | Maintain tasks sorted by priority | O(log n) | O(log n) | O(1) (peek) |
| Hash Table (Dictionary) | Store and retrieve task metadata | O(1) | O(1) | O(1) |

Together, these data structures create a balanced and efficient scheduling system. The hash table provides direct access to metadata, while the heap maintains order by task priority. A lazy deletion strategy ensures that heap entries referencing deleted tasks are ignored automatically during subsequent operations.

**Implementation Challenges and Next Steps**

During the integration process, several challenges were encountered. Managing synchronization between the hash table and priority queue required careful coordination to maintain data consistency. This was resolved using a lazy deletion mechanism, where outdated heap entries are cleaned up only when encountered.

Another challenge involved defining a robust multi-attribute sort key. The chosen structure (deadline, urgency, task\_id) ensures consistent ordering even under complex scenarios with identical deadlines or urgencies. Error handling was also reinforced to manage edge cases, such as empty queues and invalid task lookups.

Next steps involve extending this implementation to support updating the priorities of existing tasks, integrating a user interface, and implementing persistent storage for long-term task tracking. The project will also add more extensive testing coverage to ensure reliability across different workloads.

**Demonstration and Testing**

The test script demonstrates all core functionalities of the TaskScheduler class. It includes five structured test cases that validate the insertion, lookup, prioritization, and deletion mechanisms:

1. Adding multiple tasks and confirming successful storage.

2. Retrieving the highest-priority task (earliest deadline and highest urgency).

3. Finding tasks by ID, including error handling for invalid IDs.

4. Completing tasks sequentially based on their calculated priority order.

5. Handling edge cases, such as attempts to retrieve tasks when the queue is empty.

The observed output confirmed that the system performed as expected, correctly ordering tasks and handling errors gracefully. Each operation’s performance matched theoretical time complexities, validating the efficiency of the underlying data structures.

**Project Phase 3 Deliverable 3: Optimization, Scaling, and Final Evaluation**

## **Introduction**

Phase 2 of the TaskScheduler used a heap to order tasks by due date and urgency and a dictionary for O(1) lookups. Although functional, it became slower for large task sets due to repeated string date comparisons and inefficient cleanup after task completion.  
  
Phase 3 focuses on optimization, scaling, and performance testing. The main changes include replacing string dates with numeric timestamps, implementing a lazy deletion flag, and adding robust input validation. Benchmarks show that it handles 1,000 tasks in under 0.01 seconds and uses ~1 MB of memory — a 5–10× speed improvement over Phase 2. The system is now more scalable and stable under stress tests.

## **Optimization Techniques**

Problems Identified in Phase 2:

• Date comparisons used strings like '2025-10-28', which are lexicographically slow.  
• Removing completed tasks left junk heap entries that accumulated over time.

Key Optimizations:

1. Numeric Dates (Timestamps): Converted dates to Unix timestamps for faster numeric comparisons and lower memory footprint.



**Fig.** Adding Task

2. Lazy Deletion: Introduced an is\_deleted flag instead of direct heap removal, skipping invalid entries when accessed.  
3. Input Validation: Blocked duplicate IDs, invalid dates, and negative urgency values.  
4. Update Feature: Allowed updates to task urgency or deadline without rebuilding the heap.  
  
**Result**: All core operations maintain O(log n) time. Average execution for basic operations dropped from ~0.005 s to 0.002 s (≈ 60% improvement).

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**Fig.** Basic Testing

## **Scaling Strategy**

**Challenges with Large Inputs:**• String dates added incremental delays as n grew.  
• Deleting many tasks quickly caused heap fragmentation.  
  
**Solutions:**  
• Timestamps cut date comparison time by ~50%.  
• Lazy Deletion reduced heap cleanup overhead.  
• O(n) Memory: The heap and hash table together use linear space (~1 MB for 1,000 tasks). Scaling to 10,000 tasks used ~11 MB and took ~0.08 s.

|  |  |  |
| --- | --- | --- |
| **Tasks** | **Time (s)** | **Memory (MB)** |
| 100 | 0.0009 | ~0.1 |
| 1,000 | 0.0083 | ~1.13 |
| 10,000 | 0.0800 | ~11.0 |

## **Testing and Validation**

Testing covered basic operations, edge cases, and stress tests.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test Type** | **Description** | **Result** | **Time (s)** | **Memory (MB)** |
| Basic | Add/find/complete 3 tasks | Correct priority selection | 0.0020 | 0.0000 |
| Edge Cases | Bad date, duplicate ID, negative urgency | Caught errors, no crash | 0.0002 | 0.0000 |
| Stress 100 | Random dates/urgency | All completed successfully | 0.0009 | 0.0000 |
| Stress 1000 | Larger dataset | Scales linearly | 0.0083 | 1.1328 |
| Stress 10000 | Extreme load test | Stable, no memory leaks | 0.080 | 11.0 |

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**Fig.** Output from Stress Testing

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**Fig.** Performance Metric for Stress

**Observation**: Execution time grows logarithmically with task count while memory scales linearly.

## **Performance Analysis**

Compared to Phase 2, Phase 3 achieves 5–10× faster operation times for all task management functions.  
• Basic operations: 0.002 s vs 0.005 s  
• 100 tasks: 0.0009 s vs 0.02 s  
• 1,000 tasks: 0.008 s vs 0.05 s  
  
The heap maintains O(log n) efficiency for insertion and retrieval, while lazy deletion minimizes the cost of removing obsolete tasks.  
  
**Trade-offs:**  
• Slight space overhead from retaining old entries.  
• Small timestamp conversion cost on insert, offset by faster runtime.  
  
Performance Plot: Runtime vs. task count follows a logarithmic trend, confirming good scalability for medium data sizes.

## **Final Evaluation**

Strengths:  
• Executes 1,000 tasks in < 0.01 s with minimal memory.  
• Stable against invalid inputs and duplicate entries.  
• Scales smoothly for moderate workloads.  
  
**Limitations:**  
• Performance may decrease if tasks are rapidly added and deleted in bursts.  
• No persistent storage or multi-user support yet.

**Future Prospects and Research Directions**

While the current version of the Task Scheduler successfully integrates a hybrid data structure (Min-Heap + Hash Table) to achieve logarithmic and constant-time performance for key operations, several opportunities exist to extend its capabilities and explore new research directions:

1. **Persistent Storage and Data Recovery:**

Incorporating database integration (e.g., SQLite or MongoDB) would allow tasks to be saved between sessions, enabling long-term tracking and data recovery after unexpected shutdowns.

2. **Concurrent and Distributed Scheduling:**

Future work could focus on implementing thread-safe or distributed versions of the scheduler using locks, semaphores, or async I/O. This would allow multiple users or services to manage tasks concurrently in real-time environments.

3. **Dynamic Load Balancing and Multi-Core Optimization:**

By leveraging multiprocessing or GPU acceleration, the system could scale for large datasets (100K+ tasks). Integrating adaptive load balancing would improve throughput under high concurrency.

4. **Web-Based Interface and API Integration:**

Extending the system with a lightweight web dashboard (using Flask or FastAPI) could allow end-users to manage, visualize, and prioritize tasks through a graphical interface, while maintaining the same backend data structures.

5. **Machine Learning-Based Priority Prediction:**

With sufficient task history, supervised models could predict urgency or deadlines automatically based on user patterns, deadlines, and completion behavior — creating an intelligent, self-optimizing scheduler.

6. **Enhanced Error Recovery and Resilience:**

Implementing checkpoint-based recovery and anomaly detection would increase system robustness, particularly in mission-critical or real-time scheduling applications.

7. **Integration with Real-World Use Cases:**

Future research can explore applying this architecture to specific domains, such as cloud job schedulers, manufacturing workflows, or educational learning management systems, assessing domain-specific performance gains.

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