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Memory Pressure Amplification in Declarative Runtimes

Abstract
Declarative application runtimes, widely used in rule engines, workflow systems, and low-code platforms, introduce abstraction-driven execution models that obscure underlying memory behavior and lead to disproportionate resource consumption. Unlike imperative systems, these runtimes generate intermediate states, repeated evaluations, and transient objects that collectively amplify memory usage beyond input workload characteristics. This study presents a formal analysis of memory pressure amplification by modeling allocation patterns, state expansion, and object lifecycle dynamics in declarative execution environments. Key metrics such as memory amplification factor, allocation churn rate, and garbage collection overhead are defined to quantify amplification effects. Experimental evaluation across varying workload complexities demonstrates non-linear memory growth, increased allocation bursts, and elevated garbage collection frequency, resulting in reduced runtime stability. Comparative analysis with optimized memory management strategies shows that lifecycle-aware allocation and state pruning significantly mitigate amplification and improve system efficiency. The findings highlight the need for integrating memory-aware execution strategies into declarative runtimes to ensure scalable and predictable performance in enterprise systems.
Keywords: declarative runtimes, memory amplification, garbage collection, allocation churn, runtime systems, low-code platforms, memory management, system performance.

1. Introduction

Declarative application runtimes have become a foundational component of modern enterprise software systems, enabling developers to define application behavior through high-level rules, workflows, and configurations rather than imperative code. These runtimes, commonly used in rule engines, workflow orchestration platforms, and low-code interpreters, abstract execution logic from developers while providing flexibility and rapid deployment capabilities [1]. However, this abstraction introduces hidden layers of execution that are not always visible to system designers, particularly in terms of resource utilization and memory behavior [2].

Unlike imperative systems, declarative runtimes rely on evaluation engines that interpret rules and dynamically construct execution paths at runtime. This process often involves the creation of intermediate data structures, context objects, and evaluation states that persist temporarily during execution [3]. While these constructs enable flexible execution, they also contribute to increased memory usage, often in ways that are not directly proportional to the input workload [4]. As a result, memory consumption patterns in declarative systems are often non-linear and difficult to predict.

One of the key challenges in declarative execution environments is the implicit expansion of state during rule evaluation. When multiple rules are triggered simultaneously, the runtime may generate multiple intermediate states to evaluate different execution paths [5]. This state expansion can lead to significant memory overhead, particularly in systems with complex rule dependencies or recursive workflows. The accumulation of such intermediate states contributes to what can be described as memory pressure amplification [6].

Memory pressure amplification refers to the phenomenon where the effective memory usage of a system grows disproportionately relative to the input data or workload size. In declarative runtimes, this amplification is driven by factors such as redundant object creation, repeated evaluation of similar rule conditions, and retention of intermediate results [7]. These factors collectively increase memory demand beyond what would be expected in equivalent imperative implementations, making memory management a critical concern.

Another contributing factor to memory amplification is the lifecycle management of objects within the runtime. Declarative systems often generate short-lived objects during execution, which are later reclaimed through garbage collection mechanisms [8]. However, high allocation rates combined with delayed reclamation can lead to increased garbage collection pressure, resulting in performance degradation and temporary memory spikes [9]. This interaction between allocation and reclamation further complicates memory behavior in declarative environments.

The impact of abstraction layers on memory visibility also plays a significant role in this problem. Developers interacting with declarative platforms typically operate at a high level of abstraction, without direct control over memory allocation or object management [10]. This lack of visibility makes

it difficult to identify sources of memory inefficiency or to apply optimization techniques commonly used in lower-level programming environments [11]. Consequently, memory-related issues may only become apparent under high-load conditions.

Existing research in runtime systems and memory management has largely focused on imperative programming environments, with limited attention given to declarative execution models. While studies on garbage collection and memory optimization provide valuable insights, they do not fully address the unique characteristics of declarative runtimes, such as dynamic rule evaluation and implicit state generation [12]. This gap highlights the need for specialized analysis techniques tailored to declarative systems.

Furthermore, current monitoring and profiling tools are often insufficient for capturing the full extent of memory amplification in declarative environments. Traditional metrics such as heap usage and allocation rates do not adequately reflect the contribution of intermediate states and evaluation overhead [13]. Without appropriate metrics, it becomes challenging to quantify amplification effects or to compare different runtime configurations.

This study addresses the identified gap by introducing a structured approach to analyzing memory pressure amplification in declarative application runtimes. It focuses on modeling memory allocation behavior, identifying key sources of amplification, and proposing metrics to quantify memory growth relative to workload characteristics. By providing a deeper understanding of memory dynamics in declarative systems, the work aims to support the development of more efficient and predictable runtime environments.

2. Methodology

The proposed methodology establishes a formal framework for analyzing memory behavior in declarative application runtimes by modeling allocation patterns, intermediate state expansion, and object lifecycle dynamics. Declarative execution is represented as a sequence of rule evaluations over a dynamic state space, where each evaluation step generates temporary and persistent objects. The total memory footprint is therefore modeled as a function of both input workload and execution depth, enabling systematic analysis of amplification effects.

Memory allocation behavior is formalized using a function $M(t)$, which represents total memory usage at time t. This function is decomposed into three primary components: base memory M_b, intermediate state memory M_s, and transient allocation memory M_t. While $M_b$remains relatively stable, the components $M_s$and $M_t$vary dynamically based on rule execution and state expansion. This decomposition allows the identification of specific contributors to memory growth within declarative runtimes.

Intermediate state expansion is modeled as a branching process, where each rule evaluation may generate multiple execution paths. Let $n$denote the number of rules triggered at a given step, and $d$represent the evaluation depth. The number of intermediate states can be approximated as $S(d) = n^d$under worst-case conditions. This exponential growth directly contributes to memory amplification, particularly in workflows with recursive or highly interdependent rules.

Rule evaluation overhead is captured through an allocation function $A(r_i)$, where each rule $r_i$produces a set of temporary objects required for condition evaluation and action execution. The cumulative allocation cost is given by $A_{total} = \sum_{i=1}^{k} A(r_i)$, where $k$is the number of rules executed. This formulation highlights how repeated evaluation of similar rules can lead to redundant allocations, increasing overall memory pressure.

Object lifecycle dynamics are incorporated into the model to account for allocation and reclamation processes. Each object is associated with a lifecycle interval $[t_{alloc}, t_{free}]$, and the overlap of these intervals determines the peak memory usage. In declarative runtimes, delayed reclamation and overlapping lifecycles often result in higher memory retention, particularly when garbage collection is not triggered promptly.

To quantify memory amplification, the methodology introduces the memory amplification factor (MAF), defined as

$$\text{MAF} = \frac{M_{peak}}{M_{input}}$$

where $M_{peak}$is the maximum observed memory usage and M_{input}represents the baseline memory required for input data. A higher MAF indicates greater amplification, reflecting inefficiencies in memory utilization due to declarative execution.

In addition to MAF, the allocation churn rate is defined as a measure of memory allocation intensity. It is expressed as

$$C_a = \frac{\text{Total Allocated Memory}}{\text{Execution Time}}$$

This metric captures how frequently memory is allocated and deallocated during execution, providing insight into runtime behavior under varying workloads. High churn rates are typically associated with increased garbage collection activity and performance degradation.

Garbage collection pressure is evaluated through the ratio of reclaimed memory to total allocated memory, along with the frequency of garbage collection cycles. This metric reflects the burden placed on memory management subsystems due to excessive allocation. Increased garbage collection pressure often correlates with latency spikes and reduced system throughput, making it a critical factor in runtime performance analysis.

The experimental setup is designed to simulate declarative execution across varying levels of rule complexity and evaluation depth. Synthetic workloads are generated to represent different execution scenarios, including linear rule chains, branching workflows, and recursive rule structures. Runtime instrumentation is used to capture memory allocation events, object lifecycles, and garbage collection activity in real time, enabling detailed profiling of memory behavior.

3. Results and Discussion

The evaluation of declarative application runtimes reveals a pronounced amplification of memory usage as execution complexity increases. Under baseline configurations, memory consumption grows non-linearly with rule evaluation depth and branching intensity, confirming the theoretical model of intermediate state expansion. Declarative execution patterns, particularly those involving recursive or highly interdependent rules, exhibit rapid accumulation of intermediate objects, leading to substantial increases in peak memory usage relative to input size.

A key observation is the occurrence of allocation bursts during intensive rule evaluation phases. These bursts are characterized by rapid creation of temporary objects within short time intervals, driven by repeated evaluation of conditions and generation of intermediate states. Such behavior results in spikes in memory demand, which are often not immediately mitigated due to delayed reclamation. The magnitude and frequency of these bursts increase with workload complexity, contributing significantly to overall memory pressure.

Garbage collection dynamics play a central role in managing the effects of allocation churn. As allocation rates increase, the runtime triggers more frequent garbage collection cycles to reclaim unused memory. However, high churn rates lead to elevated garbage collection overhead, which can introduce latency and reduce system throughput. As illustrated in Figure 1, garbage collection frequency increases proportionally with allocation churn rate, highlighting the strong coupling between allocation behavior and memory management activity.

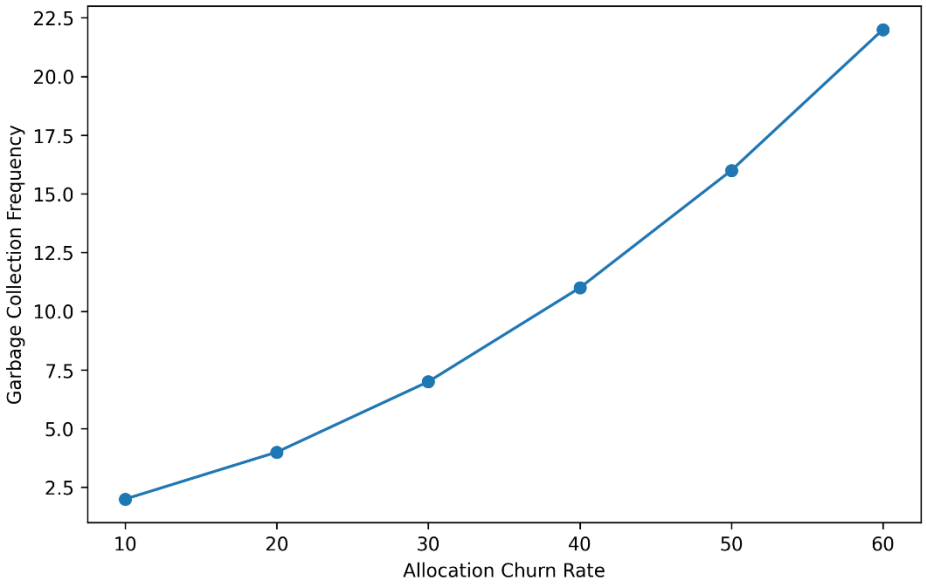

Figure 1. Garbage Collection Frequency vs Allocation Churn Rate

Memory retention patterns further illustrate the impact of declarative execution on runtime efficiency. In baseline systems, overlapping object lifecycles result in extended retention of intermediate states, even when they are no longer required for computation. This leads to inflated memory footprints and reduces the effectiveness of garbage collection. In contrast, optimized runtime strategies that incorporate early state pruning and lifecycle-aware allocation demonstrate improved memory utilization by minimizing unnecessary retention.

A comparative analysis of memory amplification factor and garbage collection overhead across different runtime scenarios is presented in Table 1. The results indicate that baseline declarative runtimes exhibit significantly higher amplification factors, particularly under high-complexity workloads. Optimized configurations reduce amplification by limiting intermediate state expansion and improving object lifecycle management. Similarly, garbage collection overhead is reduced through more efficient allocation patterns and targeted reclamation strategies.

Table 1. Memory Amplification Factor and GC Overhead Across Runtime Scenarios

Scenario	Memory Amplification Factor	GC Overhead (%)
Low Complexity (Baseline)	1.8	6.5
Low Complexity (Optimized)	1.3	4.1
Medium Complexity (Baseline)	3.6	12.8
Medium Complexity (Optimized)	2.4	7.9
High Complexity (Baseline)	6.9	21.5
High Complexity (Optimized)	4.2	13.2

4. Conclusion

The findings of this study demonstrate that declarative execution models introduce significant memory pressure amplification in modern application runtimes, primarily due to intermediate state expansion, repeated rule evaluation, and implicit object lifecycle dynamics. Unlike imperative systems, where memory usage is more directly aligned with input size, declarative runtimes exhibit non-linear growth patterns that can lead to substantial increases in peak memory consumption. This amplification directly affects runtime stability, increasing the likelihood of memory exhaustion, latency spikes, and performance degradation under high-complexity workloads.

A key insight is that memory pressure in declarative systems is not solely a function of workload size but is strongly influenced by execution depth and rule interaction patterns. Allocation bursts, high churn rates, and delayed garbage collection collectively contribute to inefficient memory utilization. The analysis shows that without targeted optimization strategies, these factors can severely impact system scalability. Conversely, introducing lifecycle-aware allocation, intermediate state pruning, and controlled evaluation mechanisms can significantly reduce amplification effects and improve runtime predictability.

Despite these improvements, several limitations remain. The proposed modeling approach relies on controlled workload generation and runtime instrumentation, which may not fully capture the variability present in heterogeneous production environments. Additionally, optimization strategies may introduce trade-offs between memory efficiency and execution latency, particularly in real-time systems where rapid response is critical. The interaction between declarative abstractions and underlying runtime implementations also adds complexity that requires further investigation.

Future research should focus on adaptive memory scheduling techniques that dynamically adjust resource allocation based on execution patterns and workload characteristics. Runtime-aware optimization strategies that integrate memory profiling with execution planning can further enhance efficiency. Additionally, predictive garbage collection mechanisms that anticipate allocation bursts and proactively manage memory reclamation offer promising directions for improving system performance. These advancements will be essential for enabling scalable and stable declarative runtimes in increasingly complex enterprise applications.

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