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Exploration by model-checking of timing anomaly cancellation in a processor

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Abstract

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Acknowledgement

I would like to express my sincere gratitude to .. for his invaluable assistance and comments in reviewing this report... Good luck :)

Résumé

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Introduction

In critical systems such as airplanes and cars, it is important that tasks running on the hardware meet their deadlines. For example, in a car's braking system, missing a program deadline can lead to loss of control over the vehicle. Therefore, it is crucial to have a rigorous analysis that can provide an upper bound for the program's execution time on a given hardware platform. In non-critical real-time applications, the execution time bound can be estimated by measuring the execution time for many input values. This gives the maximum observed execution time, which usually underestimates the real *worst-case execution time (WCET)*.

In critical real-time systems, this approach is not enough because some cases may be missed during observation, as shown in Figure 1.1. The real WCET can only be found by testing the program on all possible inputs, which is usually not possible due to the large number of cases. Therefore, methods to estimate WCET bounds use abstractions of the program and hardware. These methods may overestimate the WCET because of simplifications, but they are more scalable.

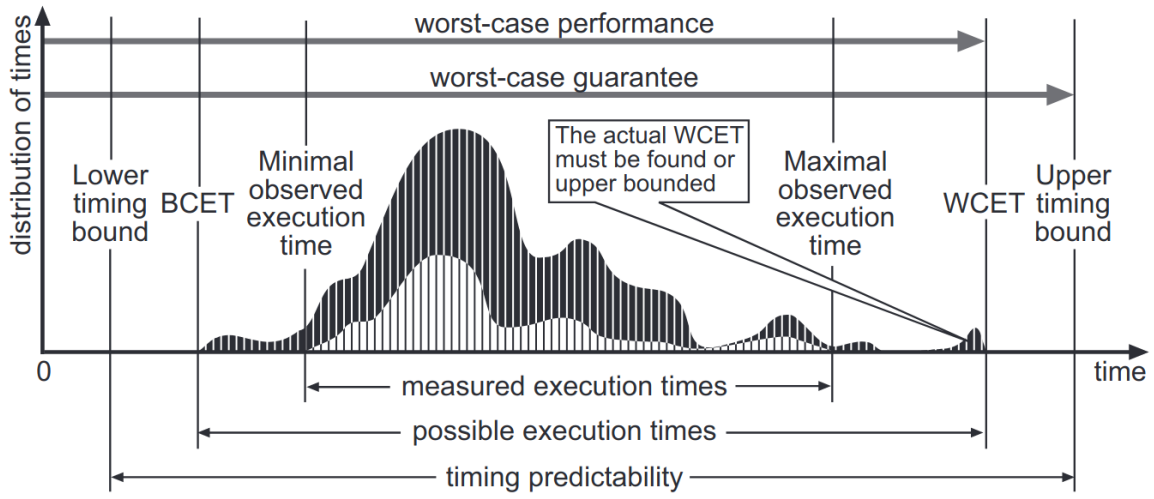


Figure 1.1: Timing analysis notations. The lower curve shows a subset of measured executions. The darker curve, an envelope of the former, shows the times of all executions (from [3]).

Usually, WCET analysis is divided into several phases, each focusing on a part of the hardware or software. For example, in the software part, memory analysis assigns address bounds

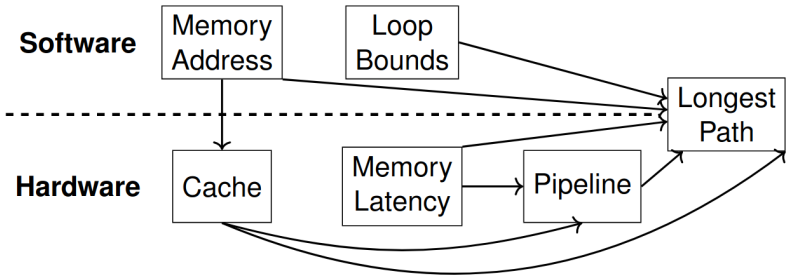


Figure 1.2: WCET analysis phases and their dependencies. ()

for each instruction [7], and loop bounds analysis finds the bounds for loop iterations as constants or formulas [8]. On the hardware side, there are analyzes for cache, main memory access latency, and pipeline. Together, these analyzes help to find the longest path of a program, which gives the WCET bound.

Dividing WCET analysis into phases creates the phase ordering problem: one phase may need information from another. Sometimes, these dependencies are circular. For example, in Out-of-Order (OoO) processors, the instruction order depends on the architecture state, which also affects cache access. This means cache analysis needs pipeline analysis. For timing analysis, it is desirable to have composable systems [14].

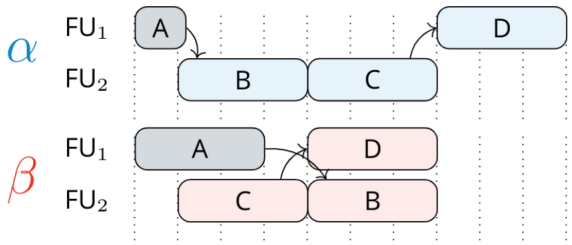
However, most architectures are not composable and have so-called *timing anomalies (TA)*. A TA happens when local worst cases do not lead to a global worst case. TAs are seen in pairs of execution traces where the initial hardware state is different, but the instruction sequences are the same. Different cache states can cause variations in timing because of a miss in one trace and a hit in another.

Example 1:

Figure 4.3 shows an example of such an anomaly. The assembly sequence has 4 instructions (A, B, C, D) with data dependencies $A \rightarrow B$ and $C \rightarrow D$. Figure 1.3b shows two traces (α, β) from running the program. There is a difference in the latency of instruction A (1 in α and 2 in β). In trace α, the variation seems better, but the total execution time is higher, which shows an anomaly.

```
LD   r1, 0(r2)   ; A
ADD  r3, r1, r4  ; B
ADD  r5, r6, r7  ; C
LD   r8, (0)r5   ; D
```

(a) Input assembly sequence



(b) Scheduling on functional units comparison

Figure 1.3: TA caused by variation in latency of instruction A (from [1])

Timing anomalies are a serious problem for timing predictability. Understanding their na-

ture is important to estimate their impact on global execution time or to design hardware without TAs. Many hardware features can cause TAs, such as caches and memory buses. In this work, we focus on branch prediction. We start by explaining the microarchitecture context, then review existing definitions, and finally present our framework to find branch-related TAs and propose a formal definition for them.

— 2 —
Processor architecture

2.1 Instruction Set architecture

Instruction Set Architecture (ISA) defines the set of instructions and the registers on which they operate. From ISA-perspective all instructions are executed atomically, and their result is visible only after an execution is complete. ISA serves as an interface between software and actual hardware microarchitecture which implements the ISA. This abstraction allows software to reason about program behavior independently of the underlying microarchitectural implementation, which may use additional internal registers or buffers and update state at finer (cycle-level) granularity.

ISA defines binary format of instructions which are stored in memory and accessed by the processor through cache mechanisms. Often, fixed length instructions are used (for example, RISC architectures), while variable-length also exist (in CISC architectures). Processor is a cycled device that performs fetching instructions from memory and their subsequent execution, we call the microarchitectural state the state of all hardware registers of the processor. Unlike in ISA, states are defined at clock-cycle granularity, so an instruction may take several clock-cycles to finish.

2.2 Processor Pipeline Stages

Early processors executed instructions sequentially, completing one instruction before starting the next. This approach, known as non-pipelined or single-cycle execution, resulted in lower throughput because each instruction had to wait for the previous one to finish all processing steps. Modern processors, in contrast, employ pipelining, which overlaps the execution of multiple instructions by dividing the process into discrete stages. This significantly improves instruction throughput and overall performance by utilizing hardware resources more efficiently.

Although the exact decomposition into stages may vary across architectures, a typical processor pipeline consists of five fundamental stages. More advanced processors may further subdivide these stages to enhance performance.

We start by describing the fundamental pipeline stages and then introduce some optimizations such as superscalar pipelines, out-of-order execution and branch prediction.

1. **Instruction Fetch (IF)**: The processor retrieves the next instruction from memory by the address from the program counter (PC). This access typically leverages the instruction

cache to reduce latency.

2. **Instruction Decode (ID)**: The fetched instruction, represented in binary format, is decoded to determine its type and the registers it operates on. During this stage, the required operands are read from the register file, and control signals are generated for subsequent pipeline stages depending on the instruction type.

3. **Execute (EX)**: The instruction is executed in this stage. Arithmetic and logic operations are performed by dedicated *functional units* (FUs), which are selected based on the decoded instruction type. For memory access or control flow instructions, the effective address or branch target is computed during this stage.

4. **Memory Access (MEM)**: If the instruction involves a memory operation (load or store), this stage accesses the memory hierarchy to read or write data. Non-memory instructions are not affected by this stage.

5. **Writeback (WB) or Commit (COM)**: The final stage writes the result of the instruction back to the register file, making it visible at the architectural (ISA) level. Only after this stage does the instruction's result become accessible to subsequent instructions.

2.3 Hazards

Although pipelining significantly improves throughput, it is still susceptible to stalls – situations where instruction progress is temporarily halted for one or more clock cycles. These stalls often result from dependencies and interactions among instructions within the program.

In this section, we provide an overview of these hazards and later we discuss hardware mechanisms designed to mitigate their impact.

2.3.1 Data Hazards

Pipeline stalls can arise due to dependencies between instructions that access the same registers. There are three primary types of register dependencies:

Read-After-Write (RAW) dependencies, also known as true data dependencies, occur when an instruction requires a value that is produced by a preceding instruction. For example, in the expression $(1+2*3)$, the addition depends on the result of the multiplication, creating a RAW dependency between the two operations.

Write-After-Write (WAW) dependencies occur when two instructions write to the same register. To preserve program correctness, the writes must occur in program order, ensuring that the final value in the register corresponds to the last write.

Write-After-Read (WAR) dependencies arise when a younger instruction writes to a register that a previous instruction still needs to read. If the write occurs before the read, the earlier instruction may read an incorrect value.

RAW hazards are inherent to all architectures and must be handled to ensure correct execution. WAW and WAR hazards do not occur in simple in-order pipelines but must be addressed in more complex architectures such as out-of-order model, which will will be discussed in more details in the subsequent sections.

2.3.2 Control Hazards

Control hazards, also known as branch hazards, occur when the pipeline cannot determine the address of the next instruction to fetch due to the presence of a branch instruction. The outcome of the branch is typically resolved in the execute stage, leaving the pipeline uncertain about which instruction to fetch next.

To address this uncertainty, the pipeline introduces bubbles – cycles in which no useful work is performed – until the branch outcome is known. Figure 2.1 illustrates a pipeline stall caused by a control hazard following a branch instruction.

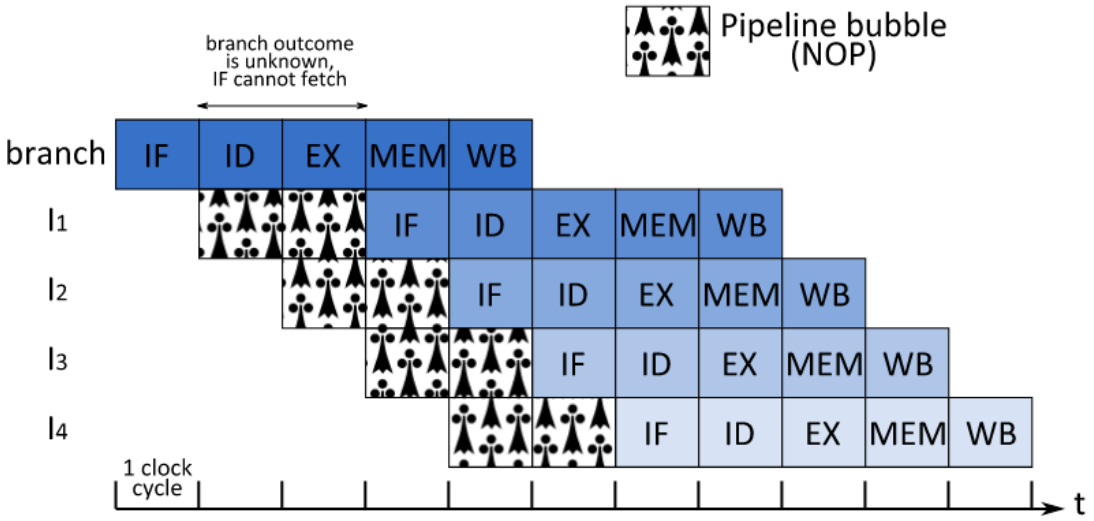


Figure 2.1: Example of control hazard: the pipeline is stalled until branch finished the execution (from [13])

2.4 Pipeline optimizations against data hazards

2.4.1 Bypass network

In a conventional pipeline, operands for an instruction are read from the register file during the ID stage. Consequently, if instruction *B* depends on the result of instruction *A*, *B* must wait until *A* completes its WB stage before it can proceed, introducing pipeline stalls. A bypass (or forwarding) network mitigates this delay by routing the result directly from the output of the EX or MEM stage to the input of the dependent instruction in the ID or EX stage, thereby reducing or eliminating the stall cycles caused by RAW dependencies. Figure 2.2 illustrates the effect of a bypass network on pipeline execution by comparing the 2 executions: without and with bypass network. As it can be observed, waiting for WB causes IF and ID stages to stall (noted with as *if* and *id* in lowercase).

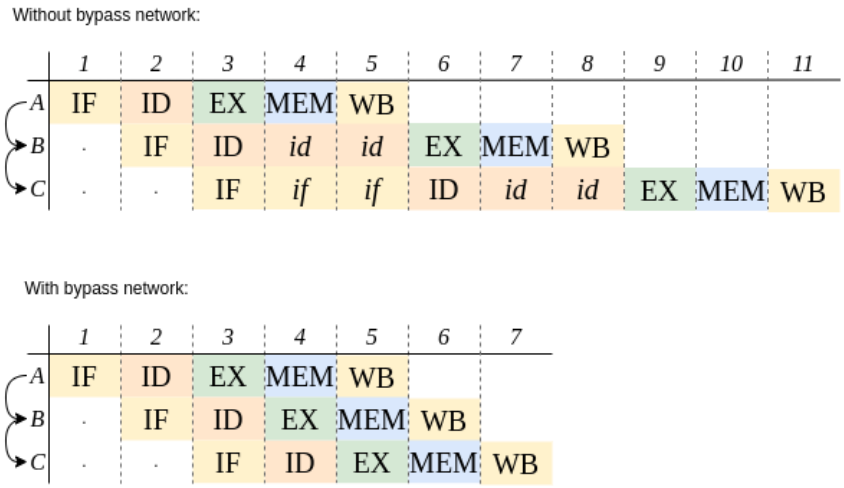


Figure 2.2: Execution of the same 3 instructions with RAW dependencies (noted with arrow). Comparison of pipeline without and with bypass network.

2.4.2 Superscalar Execution

Superscalar execution allows the processor to fetch and execute multiple instructions at the same time. This means that some pipeline stages, such as instruction fetch (IF), decode (ID), and commit (COM), are duplicated to handle several instructions in parallel. For example, in Figure 2.3, six instructions are fetched as three pairs, which saves one clock cycle for each pair compared to a non-superscalar pipeline. If the instructions are independent, this can greatly improve performance. However, duplicating every pipeline stage is expensive. While it is relatively easy to duplicate IF, ID, and COM stages, it is much harder to duplicate the execution and memory access stages, so creating high superscalar-degree pipelines comes with a great hardware cost.

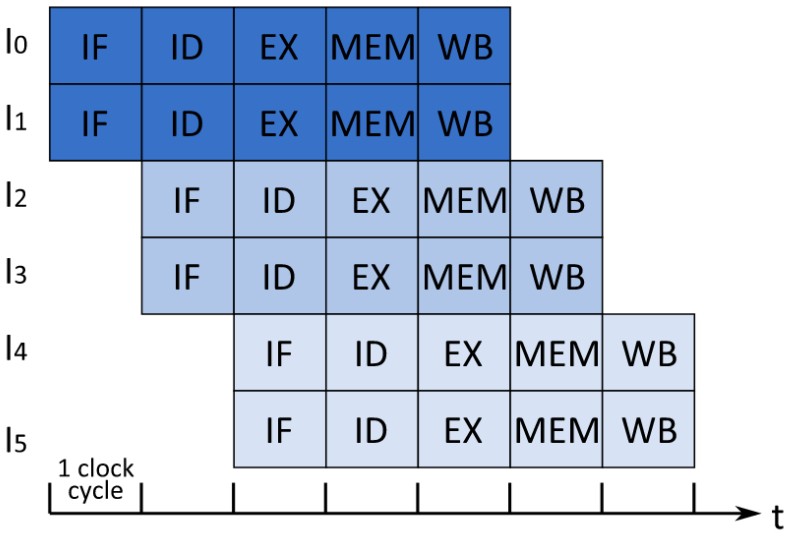


Figure 2.3: Degree 2 superscalar pipeline: each pipeline stage can process up to two instructions per cycle, provided the instructions are independent.

2.4.3 Out-of-Order (OoO) Pipeline

Out-of-Order (OoO) execution enables instructions to be processed based on data dependencies rather than strictly adhering to program order. While the architectural state (as defined by the ISA) must be updated in program order to preserve correctness, many instructions are independent and can be executed as soon as their operands are available. This parallelism improves resource utilization and overall throughput.

To support OoO execution while maintaining a consistent ISA-visible state, the processor pipeline is logically divided into in-order and out-of-order regions. The in-order region typically includes the instruction fetch (IF), decode (ID), and commit (COM) stages, while the out-of-order region encompasses execution and memory access stages. Instructions are fetched and decoded in program order, but may be executed and completed out of order, provided their dependencies are satisfied. Final commitment to the architectural state occurs in order, ensuring correctness.

Key hardware structures enable OoO execution:

Reservation Stations (RS): Each functional unit (FU) is associated with a reservation station, which buffers instructions waiting for execution. Once an instruction is decoded, it is dispatched to the appropriate RS based on its type. If the FU is busy or operands are not yet available, the instruction waits in the RS. The FU selects ready instructions from its RS for execution according to a scheduling policy.

Reorder Buffer (ROB): The ROB is a FIFO structure that tracks all instructions in flight between decode and commit. When an instruction enters the out-of-order region, it is allocated an entry in the ROB. Upon completion of execution, the instruction is marked as complete in the ROB. The commit stage retires instructions from the ROB in program order, updating the architectural state only when instructions at the head of the ROB have finished execution. This mechanism ensures that the ISA state is updated in the correct order, even though execution may have occurred out of order.

Figure 2.4 shows the diagram of stage interconnections in processor. It represents the two optimizations discussed: superscalar and OoO execution.

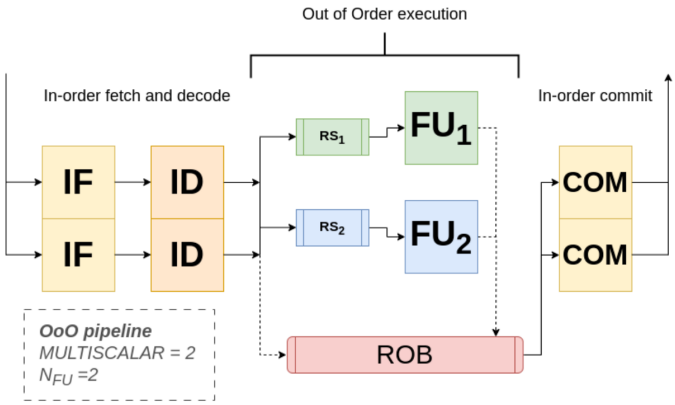


Figure 2.4: Out-of-Order superscalar pipeline diagram

2.5 Branch Prediction

Thus far, we have discussed optimizations that address issues arising from data dependencies. Another critical aspect is the control flow of the program. When encountering a control divergence, such as a conditional branch, the processor cannot determine which instruction to fetch next until the branch condition is resolved.

In the processor pipeline, the Instruction Fetch (IF) stage is responsible for retrieving the next instruction. However, when a conditional jump instruction is encountered, the address of the subsequent instruction remains undefined until the branch outcome is computed. As a result, the pipeline must stall until the branch instruction completes execution.

To improve efficiency, modern processors employ branch prediction mechanisms to guess the likely outcome of a branch and speculatively fetch the corresponding instruction. These speculatively executed instructions are not committed to the architectural state until the branch decision is confirmed. If the prediction is incorrect, the speculative instructions are flushed from the pipeline (this is also called squashing), and execution resumes from the correct path.

Branch prediction by far is one of the most efficient optimizations in modern processors. By accurately predicting the outcome of branches, processors can keep their pipelines filled and minimize the number of stalls caused by control hazards. This leads to significant improvements in instruction throughput and overall performance, especially in workloads with frequent branching. The effectiveness of branch prediction is a key factor in the performance of superscalar and deeply pipelined architectures.

2.5.1 Static Branch Predictors

Static branch prediction utilizes information available at compile time to determine the likely outcome of each branch. Several strategies are commonly employed:

Always Not Taken: This strategy assumes that branches are never taken, and the processor continues fetching instructions sequentially. It generally yields lower prediction accuracy, particularly in programs with frequent branching.

Always Taken: Here, the predictor assumes that every branch will be taken. This approach often achieves higher accuracy than the "always not taken" strategy, especially in code with loops, where branches are typically taken except at loop exit.

Backward Taken, Forward Not Taken (BTFNT): This method predicts that backward branches (those targeting a lower address) are taken, while forward branches are not taken. BTFNT is particularly effective for loop constructs, as loop-closing branches are usually backward and taken, whereas forward branches often correspond to loop exits or conditional statements.

2.5.2 Dynamic Branch Predictors

Dynamic Branch Predictors rely on information retrieved from execution and are usually based on previous branch outcomes. The usage of dynamic branch predictors requires additional hardware components which are discussed below.

Pattern History Table (PHT) is used to store information about each branch. It can be a bit denoting whether the branch was taken last time, or a more complex data. PHT is usually indexed by the lower bits of branch instruction address.

Branch Target Buffer (BTB) stores the destinations of previously computed branch. When starting speculative execution, values from BTB are used.

Return Stack Buffer (RSB) is used to predict the outcome of *ret* instructions.

One-Bit Predictor

The one-bit predictor is the simplest type of dynamic branch predictor. It uses PHT indexed by lower bits of address where one-bit value encodes the last branch outcome. Such a simple predictor is efficient when branch decision is not often changed throughout execution. For example, loop conditions are mispredicted only twice by this type of predictor: on the first and the last iterations of the loop.

However, more complex patterns diminish the efficiency of one-bit predictor. For instance, if branch outcome changes each time, the predictor accuracy is zero.

Two-Bit Predictor

The two-bit predictor uses the same idea of PHT-indexing, but instead of storing just the outcome of previous branch, it has 4-state automaton encoded by 2 bits. The states are STRONG-TAKEN, WEAK-TAKEN, WEAK-NTAKEN and STRONG-NTAKEN. Figure 2.5 shows the transitions between the states.

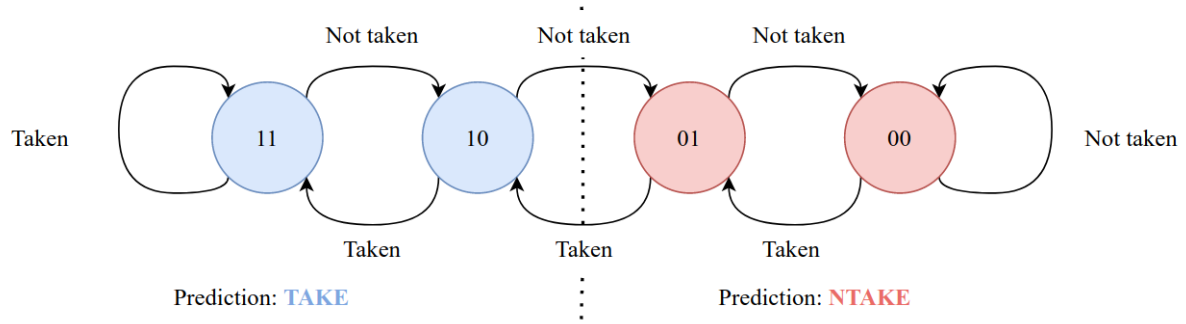


Figure 2.5: Two-bit predictor state machine (from [12])

The two-bit predictor outperforms the one-bit predictor because it requires two consecutive mispredictions before changing its prediction direction. This makes it more resilient to occasional anomalies, where a one-bit predictor would immediately flip its prediction after a single misprediction. As a result, the two-bit predictor achieves higher accuracy, especially in scenarios with repetitive branch behavior.

— 3 —
Timing Analysis and Anomalies

3.1 Evolution of TA-definitions

A timing anomaly (TA) is a situation where a local favorable condition leads to a globally worse state (for example, a cache hit leading to slowdown of the program). The notion of timing anomalies dates back to 1999 when they were first introduced by Lundqvist and Stenström [11] in context of timing analysis. Basically, TA is a feature of an architecture which makes it hard to analyze timing behavior properly. Such anomalies may have a tremendous impact on execution time which is not captured by the WET analysis. Especially dangerous is so-called domino effect, also discovered by Lundqvist and Stenström. It leads to an unbounded slowdown effect of the TA.

Despite the fact that timing anomalies have been known for a long time, the exact TA definition is a subject to debates. Since 1999 several attempts were made to formalize the notion of TA, some of them being more focused on the exact microarchitecture (like [5]) and some being more abstract and general (like [1], [6]). In this section we are giving an overview of existing definitions comparing their strengths and weaknesses.

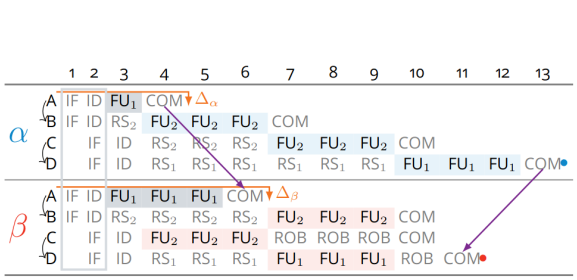
3.1.1 Step Heights

Gebhard [4] gives a timing-anomaly definition based on local execution time of instructions in comparison to global execution time defined as sum of local ones. A TA exists when local execution time of earlier instruction is lower and the global execution time of some later instruction is higher (compared to other trace).

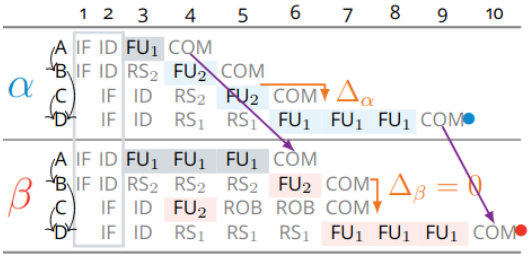
Figure 3.1a shows this definition applied to example 1. Orange arrow illustrates the local execution time of instruction A. The global time for instruction D is different between traces α and β (13 and 11 respectively).

In his thesis [1], Binder provides a counterexample (figure 3.1b), where it is clear that there is no TA (trace β has both unfavorable variation and longer execution time). However, Gebhard's definition signals an anomaly because of shorter local execution time of instruction C in trace β.

This poses a question whether it is reasonable to capture a local execution time as difference between instruction completion times.



(a) Interpretation of example 1 using Gebhard's definition



(b) Counterexample to the definition

Figure 3.1: Gebhard's definition applied to execution traces (from [1])

3.1.2 Step-functions Intersections

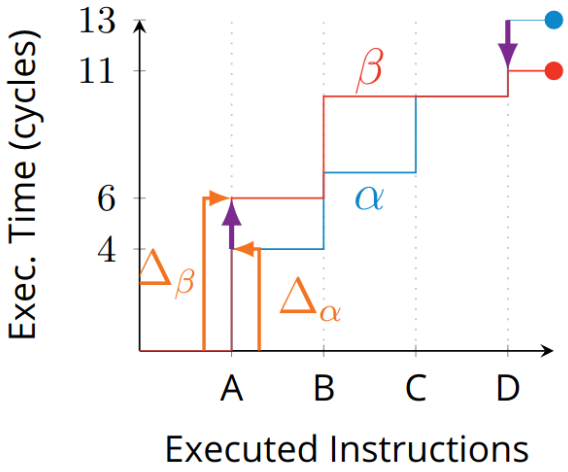


Figure 3.2: Execution time as step functions (from [1])

Similar definition is proposed by Cassez et al. [2]. The difference is that only global execution time is taken into account. Thus, TA arises when step-functions (that map instructions to their absolute completion time) of two traces intersect. For example, Figure 3.2 shows execution times as step functions from example 1. The two functions intersect between C and D thus signalling an anomaly.

This definition also leads to misleading effect with scenario found by Binder [1]. Figure 3.3 illustrates this by comparing two traces. Step-functions of traces α and β intersect, however there is no counter-intuitive TA happening as α is both longer and has a longer latency for IF stage of instructions C and D.

3.1.3 Component Occupation

An alternative approach is proposed by Kirner et al. [9]. In their work the idea is to partition hardware into components and for each define the occupation by instruction (for how many

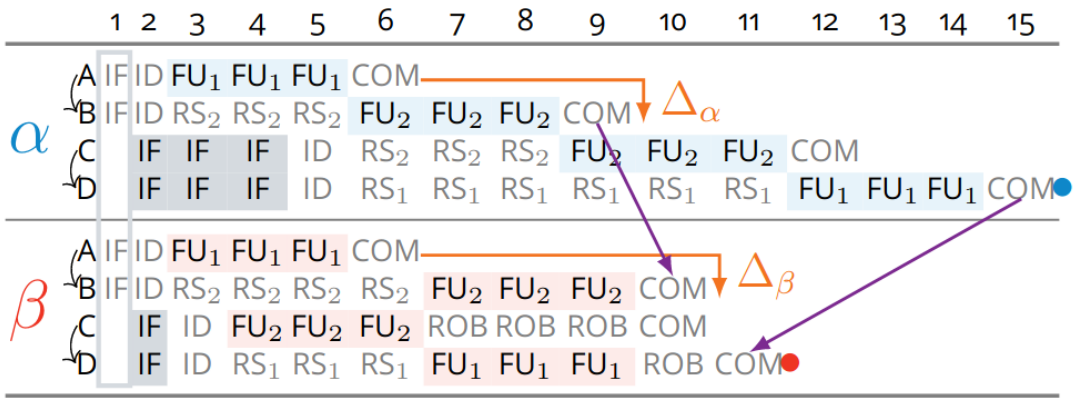


Figure 3.3: Contradicting result of Cassez's definition (from [1])

cycles it processes the instruction). TA arises when a shorter component occupation coincides with a longer execution time in a chosen trace. For example, take Figure 3.1a and consider FU_1 and FU_2 as hardware components. In total, FU_1 is occupied for 4 cycles in trace α and 6 cycles in trace β. In the same time the execution time of α is longer, so a TA is identified.

A main challenge with this definition is choosing the right components. The authors do not give a formal way to define what a component is or what properties it should have. For example, in the previous case, it is not clear if the chosen partitioning is valid, since functional units like FU_1 and FU_2 are controlled by the processor's instruction scheduling and thus are not fully independent. Another problem is that the occupation time of a component can change because of instructions that are not directly related to the timing anomaly. For instance, an earlier or later instruction, which does not affect the total execution time, might still reduce the occupation time of a component and cause a false positive. Similarly, false negatives can also occur. Additionally, if a resource switch happens (for example, an instruction is executed on a different functional unit in another trace), it can make the comparison of occupation times unreliable and further complicate the detection of timing anomalies.

Hahn and Reineke [6] introduce the notion of progress, ... [5]

3.1.4 Event Time Dependency Graph

Binder et al. [1] define TAs using the notion of causality between events in execution trace. In this work, superscalar OoO pipeline is considered. The processor state is described as a composition of states of each of the resource: *IF, ID, set of RS, set of FU, ROB, COM*. Each component holds the information about instruction it is currently processing, including required registers and remaining clock cycles.

Notion of event is introduced based on qualitative changes in the pipeline associated to instruction progressing through stages. Event from execution trace (denoted as $e \in Events(\alpha)$) is a triple (i,r,t), where i is the instruction to which event is related, r is the associated resource and the action (acquisition or release) and t is a timestamp corresponding to the clock cycle when event occurs.

In the proposed framework events are related to *IF, ID, FU* and *COM* stages. For each instruction there are 7 types of events: $\uparrow$ IF, $\downarrow$ IF, $\uparrow$ ID, $\downarrow$ ID, $\uparrow$ FU, $\downarrow$ FU and *COM*. $\uparrow$ signs the

acquisition of a resource and $\downarrow$ its release. *COM* denotes the acquisition of the commit stage; hence its release always happens one clock cycle after and no subsequent stages exist, it is not included into framework.

Latency is defined as the time difference between the acquisition and release of a resource. Each instruction passes through the same pipeline stages and is associated with corresponding events. Therefore, for each pair of traces corresponding to the same program, the sets of events differ only in their timestamps or, potentially, in the functional unit (FU) used (although resource switching is not modeled within this framework). Consequently, for each event in one trace, there exists a corresponding event in the other. Formally, this correspondence is defined by the function $CospEvent : Events(\alpha) \rightarrow Events(\beta)$.

A **variation** signs that the latency in one trace differs from latency of corresponding events in the other trace. On the pair of traces α and β. The variation is considered favorable for α if the latency in α is smaller than in β.

Variations are chosen as a source of timing anomalies. They may represent different memory behavior (cache hit or miss) for fetch and memory accesses in FU. Other sources of TA such as memory bus contention or branching are not considered by the framework.

Event Time Dependency Graph (ETDG) of trace τ denoted as $G(\tau) = (\mathscr{N}, \mathscr{A})$ is composed of a set of nodes $\mathscr{N} = Events(\tau)$ and a set of arcs $\mathscr{A} \subseteq \mathscr{N} \times \mathscr{N} \times \mathbb{N}$.

Arc is a triple (e_1, e_2, w) written as $e_1 \xrightarrow{w} e_2$ where e_1 is the source event node, e_2 – destination node and w is a lower bound of the delay between the two events. The arc means that at least w clock cycles must pass between e_1 and e_2.

Arcs are derived from a set of rules:

1. **Order of pipeline stages**

   Every instruction goes through the pipeline stages in a fixed order: first it is fetched, then decoded, then executed and only then committed. This creates a following dependencies for a given instruction I:

   - $(I, \downarrow \text{IF}, t_1) \xrightarrow{0} (I, \uparrow \text{ID}, t_2)$
   - $(I, \downarrow \text{ID}, t_3) \xrightarrow{0} (I, \uparrow \text{FU}, t_4)$
   - $(I, \downarrow \text{FU}, t_5) \xrightarrow{0} (I, COM, t_6)$

2. **Resource use**

   An instruction takes one or several clock cycles to go through each stage and cannot pass them faster.

   - $(I, \uparrow \text{IF}, t_0) \xrightarrow{lat_{IF}} (I, \downarrow \text{IF}, t_1)$
   - $(I, \uparrow \text{ID}, t_2) \xrightarrow{1} (I, \downarrow \text{ID}, t_3)$
   - $(I, \uparrow \text{FU}, t_4) \xrightarrow{lat_{FU}} (I, \downarrow \text{FU}, t_5)$

   lat_{IF} and lat_{FU} are the latencies of IF and FU stages respectively.

   $lat_{IF} = t_1 - t_0$, $lat_{FU} = t_5 - t_4$

3. **Instruction order**

   In-order part of the pipeline is constrained by instruction order. Thus, for successive instructions I_1 and I_2:

   $(I_1, RES\uparrow, t) \xrightarrow{0} (I_2, RES\uparrow, t'), RES \in \{IF, ID, COM\}$

4. **Data dependencies**

   RAW dependency between I_1 and I_2 restricts the execution order of the instructions: $(I_1, \downarrow \mathrm{FU}, t) \xrightarrow{0} (I_2, \uparrow \mathrm{FU}, t')$.

5. **Resource contention**

   Also some instruction can be delayed because of limited resources. For instance, FU contention happens when I_1 and I_2 use the same FU, and it is busy by I_1 at the moment when I_2 is ready. This creates $(I_1, \downarrow \mathrm{FU}, t) \xrightarrow{0} (I_2, \uparrow \mathrm{FU}, t')$.

   Resource contention can also be caused by reaching the capacity limit of ROB or RS.

Causality graph is achieved from ETDG by removing unnecessary edges. For each event we keep only the most relevant constraint. Only arcs of the form $e_1 \xrightarrow{e_2.time - e_1.time} e_2$ are left. Also arcs related to variations are excluded.

Timing anomaly according to Binder consists of three observations: variation, causality and slowdown. If a trace exhibits a favorable variation and in a causal region there is an event which is delayed, then TA is signalled.

Formally, TA is observed on pair of traces α and β if there exists a favorable variation in α relative to β. Let $\downarrow e_\alpha$ and $\downarrow e_\beta$ be the events corresponding to the end of the variation in both traces. If there exist events e'_α and e'_β, where $e'_\beta = CospEvent(e'_\alpha)$ and there is a path in causality graph of α between $\downarrow e_\alpha$ and e'_α, s.t. $\Delta(\downarrow e_\beta, e'_\beta) < \Delta(\downarrow e_\alpha, e'_\alpha)$.

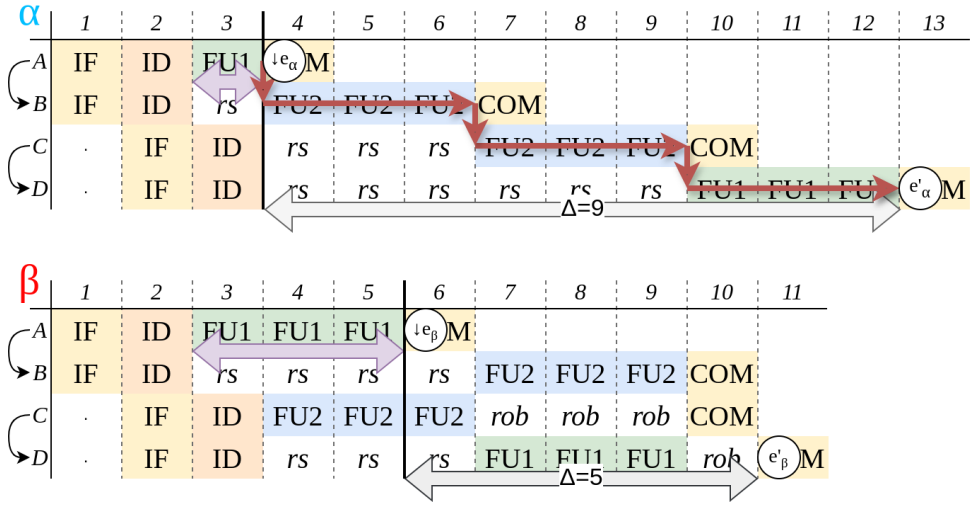


Figure 3.4: Causality-based TA detection applied to Example 1. $e_\alpha \downarrow = (A, \downarrow \mathrm{FU}, 4), e_\beta \downarrow = (A, \downarrow \mathrm{FU}, 6), e_\alpha = (A, COM, 13), e_\beta = (A, COM, 11)$. Purple arrow denotes latency which has a variation between two traces. Gray arrow shows delay between events which is greater in favorable trace. Causality in path α is marked by red arrows.

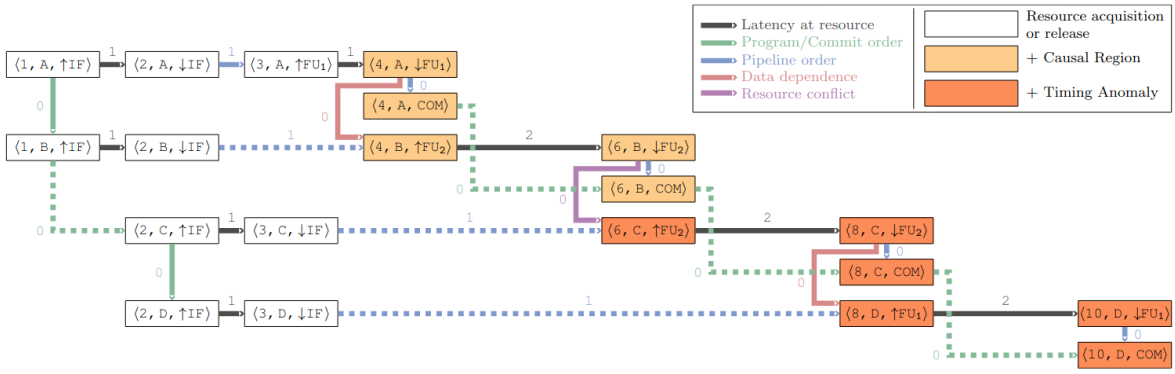


Figure 3.5: Complete ETDG for trace α from Figure 3.4, trace α.

Figure 3.4 shows how the framework captures TA for example 1. Figure 3.5 presents the complete ETDG for trace α with different dependency rules highlighted with different colors. The arcs reflecting causality are depicted in solid lines.

In contrast to other definition, this one measures relative time from the acquisition of the resource instead of global time. This approach allows the separation of different variations and isolates the part of the trace that experiences TA-effect.

3.2 TA-classifications

— 4 —
Contribution

The definition by Binder et al. [1] provides a solid foundation for analyzing timing anomalies. However, it does not address branch prediction and related effects. Our goal is to extend this definition to cover such cases. We begin by reviewing Binder's framework and then introduce our own, which supports speculative execution. We describe a new input format that can represent speculative execution, present examples generated by our tool, and discuss how the existing definition can be adapted to these new scenarios.

4.1 Methodology

To systematically investigate timing anomalies induced by branch predictors, it is essential to efficiently generate and analyze relevant examples. Manual construction of such examples is both time-consuming and error-prone, motivating the need for a tool that can automatically or semi-automatically produce and validate them. With such a tool, we can iteratively generate candidate scenarios, analyze their behavior, and assess the applicability of Binder et al.'s definition to these new cases. This process enables us to refine and adapt the definition as necessary, guided by empirical evidence from the generated examples.

Our initial efforts focused on studying and extending the TLA$^+$ [10] framework developed by Binder et al. to support branch behavior. However, we encountered significant performance limitations and found the input format insufficiently flexible for rapid prototyping and adjustment of examples.

Consequently, we reimplemented the framework in C++, drawing on insights from the TLA$^+$ model. We also use TLA$^+$ as a reference to check the correctness. The new implementation offers substantial performance improvements and introduces randomized search capabilities, enabling efficient exploration of the space of possible instruction traces and facilitating the discovery of timing anomalies related to branch prediction.

4.2 Framework

4.2.1 Existing Framework Overview

Exploration by Model Checking

The implementation provided by Binder is written in TLA$^+$ [10]. The pipeline state is specified in set-theory notation. The model checker step corresponds to a one clock cycle and derives a new HW state from the previous one. This allows to simulate the non-deterministic timing behavior: each time when a variation can happen, multiple next state are generated. TLA$^+$ covers all reachable states ensuring that all possible behaviors are covered.

The pair of trace constitutes a whole model state. TA is expressed as an invariant for the pair of traces, so its is verified in each model checking step.

As well as a construction of traces, the framework provides visualization methods for the traces and ETDG.

Input Trace Format

The input of the framework is a pair of:

1. Pipeline parameters: superscalar degree, FU latencies and memory access latencies depending on the cache events (hit or miss). sequence of instructions;

2. Instruction sequence: for each instruction its type and registers are specified as well as set of cache behaviors to be explored by the model checker. The type is used to know which FU will be used by the instruction and based on registers data dependencies are retrieved.

Figure 4.1 illustrates the instruction sequence that causes TA in Example 1. We can simplify this view by directly expressing the resource, dependencies and possible latencies of instruction. Figure 4.2 shows the input for instruction trace from example 1. First column is instruction label, second is the resource used, thirds is the set of data dependencies and the last one captures possible execution latencies. In the same fashion we could specify variations of latencies for IF stage, but we skip them for simplicity. This table is sufficient to express a pair of execution traces derived from instruction trace.

```
missLat == 3
mayDMiss == {1}
program == <<
[ ind |-> 1, type |-> "MemRead",  r0 |-> "ra", r1 |-> "",   r2 |-> "", addr |-> "0x1" ],
[ ind |-> 2, type |-> "IntAlu",   r0 |-> "",   r1 |-> "ra", r2 |-> "", addr |-> "0x2" ],
[ ind |-> 3, type |-> "IntAlu",   r0 |-> "rb", r1 |-> "",   r2 |-> "", addr |-> "0x3" ],
[ ind |-> 4, type |-> "MemWrite", r0 |-> "",   r1 |-> "rb", r2 |-> "", addr |-> "0x4" ]
>>
```

Figure 4.1: TLA$^+$ input format for Binder's framework. Some lines are excluded for brevity

	Resource	Dependencies	Latencies
A:	FU1		1|3
B:	FU2	$\{A\}$	3
C:	FU2		3
D:	FU1	$\{C\}$	3

Figure 4.2: Simplified input format of example from figure 1.3a

4.2.2 Limitations

Despite using a model checker, the existing framework is capable to explore only the traces that fit the instruction template. This limits the explored space to what is manually defined by the user. Considering that branches are to be added, this limitation is becoming even more restricting.

Nevertheless, the framework may be used to manually specify the instruction trace using a template and generate a resulting pair execution traces. This allows to quickly sketch the examples and analyze them. Unfortunately this feature comes up with some issues.

The significant flaw we noticed was the performance. Firstly, the TLA$^+$ itself takes a few seconds to generate initial states of the model. Secondly, the graph is analyzed using java embedding which calls a script in python which in its turn deserializes a graph from text output of the model checker tool.

Moreover, the input is specified in lengthy TLA+ notation, which prevents fast sketching the examples. Thus it was decided not to write an extension of the existing framework, but to design a new one from scratch.

4.2.3 Our Novel Framework

We introduce a novel framework inspired by Binder et al., designed to address the limitations of the original implementation. Our framework features a lightweight input format that natively supports branch behavior and speculative execution, enabling concise and intuitive specification of instruction traces. To overcome the performance bottlenecks of TLA$^+$, we implement our solution in C++, providing significant speedup and enabling real-time feedback for rapid prototyping. Also, the performance enhancement allows to explore the larger state spaces effectively. Our framework facilitates efficient analysis of timing anomalies and supports both manual and automated exploration modes.

Misprediction Region

The format of the input traces was adapted to handle speculative execution. We decided to use a simplified format as in figure 4.2 as a baseline. In Binder's framework instruction trace format is straightforward: it specifies all instructions that are fetched, executed and finally committed. In case of speculative execution, some instructions enter the pipeline, but are never committed, being squashed by the resolution of the branch. To tackle this problem we introduce the notion of *misprediction region of branch instruction*.

As an input trace we specify all instructions that can enter the processor pipeline. As we focus only on timing behavior of the program, abstracting from memory and registers state, we also assume that the control flow is known for a given instruction trace. Thus for each branch

we may specify the instructions in only one branch in case of correct prediction. However, in case of misprediction, the instructions from the incorrect branch are fetched until the branch is resolved. We call such instructions *mispredicted* and the set of such instructions after the branch a *misprediction region*.

In our input format, each line describes a single instruction, beginning with the functional unit to be used (`FU1`, `FU2`, etc.). This may be followed by an optional label, prefixed with `#`. Data dependencies can be specified by listing the labels of dependent instructions, each prefixed with `@`. Next, the possible execution latencies are provided as a list. For branch instructions, an optional $*$ denotes variation in branch prediction behavior. Misprediction regions are indicated by indentation: an indented instruction belongs to the misprediction region of the most recent less-indented branch instruction.

Figures 4.3a and 4.3b present an example of the input format. Figure 4.3a displays the raw input as understood by the framework, while Figure 4.3b provides a more readable, tabular representation that will be used throughout the remainder of this article. In this example, instructions *C* and *D* reside within the misprediction region of instruction *B*. Figure 4.4 illustrates the two possible execution traces derived from this instruction trace: trace α corresponds to correct branch prediction, where *C* and *D* are skipped and never enter the pipeline; trace β demonstrates the misprediction scenario, in which *C* and *D* are fetched but subsequently squashed from the pipeline at clock cycle 5.

```
1 FU1   #1 [4]
2 FU2   @1 [1] *
3     FU2 [4]
4     FU2 [4]
5 FU2     [4]
```

(a) Input format understandable for framework

		Res	Dep.	Lat.
A:		FU1		4
**B:*		FU2	$\{A\}$	1
	C:	FU2		4
	D:	FU2		4
E:		FU2		4

(b) Input format used further in the text

Figure 4.3: Two equivalent representations of input format supporting speculative execution

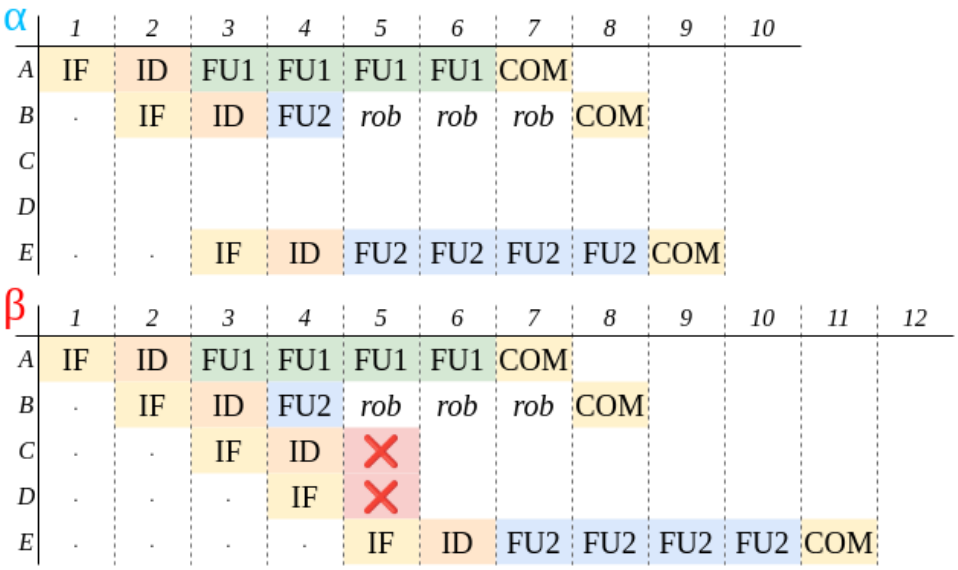


Figure 4.4: Pair of traces with correct and incorrect predictions. The squashing event is denoted with a red cross.

Framework Implementation

We decided to take C++ [15] as an implementation language as it is fast and includes a number of useful data structures in a standard library.

We define a single instruction as follows. It consists of type of FU to be scheduled at (we do not consider resource switch), latency in this FU, set of RAW dependencies. If instruction is a branch, `mispred_region` is set to a positive value n denoting the next n instructions are in misprediction region of current instruction. If we want to model only the correct prediction, then `mispred_region` is set to 0; this way branch behaves as an ordinary instruction. `br_pred` flag specifies if the prediction is correct, which is needed when generating a pair of traces with variation in branch behavior.

```
struct Instr {
    int              fu_type = 0;
    int              lat_fu = 1;
    std::set<int>    data_deps;
    int              mispred_region = 0;
    bool             br_pred = false;
};
```

At the core of our framework is the `PipelineState` structure, which models the state of all pipeline stages. The `executed` set tracks instructions that have completed execution in the functional units, enabling dependency resolution. The `branch_stack` maintains the context for misprediction regions: each time a branch is fetched, it is pushed onto the stack and remains there until resolved. Together with the `squashed` set, this mechanism ensures correct handling of mispredicted regions. For simplicity, we do not impose capacity limits on the reservation stations (RS) or reorder buffer (ROB). The `next()` function advances the pipeline state by one clock cycle and returns whether execution has completed. It operates on the instruction sequence, which is accessed via the program counter (`pc`).

To obtain an execution trace from a given instruction sequence, we initialize an empty pipeline state (with no instructions present) and repeatedly call `next()` until the final state is reached. This process yields a sequence of pipeline states, which together form an execution trace.

```
struct StageEntry {
    int idx = -1;
    int cycles_left = 0;
};

struct PipelineState {
    int clock_cycle = 0;
    int pc = 0;
    vector<StageEntry>  stage_IF =  vector<StageEntry>(SUPERSCALAR);
    vector<int>         stage_ID =  vector<int>(SUPERSCALAR);
    vector<set<int>>    stage_RS =  vector<set<int>>(FU_NUM);
    vector<StageEntry>  stage_FU =  vector<StageEntry>(FU_NUM);
    vector<int>         stage_COM = vector<int>(SUPERSCALAR);
    deque<int>          ROB =       deque<int>();
    set<int>    executed;
    set<int>    squashed;
    vector<int> branch_stack;

    bool next(const vector<Instr>& prog);
};
```

To enable efficient exploration of trace pairs that demonstrate timing anomalies (TA) and to support analysis over larger state spaces, not limited to a fixed instruction trace template, the framework provides three operating modes:

1. **Manual mode**: The user provides an instruction trace in the format given above. The framework then generates the corresponding pair of execution traces. This mode enables rapid construction and analysis of custom scenarios.

2. **Random search**: The framework generates random instruction traces within user-defined constraints and checks the resulting execution traces against a specified property. For example, it can explore all traces of length 5 containing one branch instruction and at most two RAW dependencies. While this method cannot guarantee exhaustive coverage of the state space, it is effective for quickly finding counterexamples in large spaces.

3. **State exploration**: The trace template is specified as a generator function, similar to random search mode. The framework then exhaustively verifies the property on every possible input, ensuring complete state space coverage. This mode is useful for proving properties about the model, but may be inefficient for finding counterexamples in large spaces due to the potential for excessive exploration of uninteresting subspaces.

In summary, we created a tool capable of studying traces both in automated and guided way. Our time-efficient implementation enables exploration of significantly larger state spaces that are infeasible to analyze using Binder's original framework. While TLA$^+$ offers greater expressive power for formalizing properties such as leveraging temporal logic, in the context of Binder et al., the verified property was ultimately specified as a state predicate embedded in Python code. Therefore, we believe that our choice of implementation does not result in a substantial loss of expressiveness or rigor for the intended analyzes.

4.3 Generating TA Examples

We begin by generating representative examples of branch-induced timing anomalies (TAs). Our working hypothesis is that correct branch prediction can, in certain scenarios, result in longer execution times compared to cases with misprediction. To obtain minimal and illustrative examples, we perform an exhaustive search over the space of programs characterized by the following constraints:

1. 4 committed instructions with;
2. At most 2 dependencies;
3. 1 branch instruction.

The latency of the branch instruction was set to 1, reflecting the fact that conditional jumps typically involve simple, single-cycle operations (e.g., equality, greater-than-or-equal, less-than-or-equal comparisons). The latencies of all other instructions in this setting were fixed at 4. We considered a single-issue pipeline equipped with two functional units. Our framework explored 4608 input traces in approximately 150 ms, identifying two timing anomalies, as detailed in Examples 2 and 3.

Example 2:

Figure 4.5a presents an instruction trace identified through random example generation. Here, C is a branch instruction with a misprediction region comprising $\{D, E\}$. The only data dependency is $A \rightarrow B$. The corresponding pair of execution traces is depicted in Figure 4.6a. In trace α, instructions D and E are skipped due to correct branch prediction, allowing F to be fetched immediately. This results in F executing earlier and occupying $FU2$ at clock cycle 7, which in turn delays the execution of instruction B and leads to an overall slowdown.

Example 3:

The second timing anomaly, illustrated in Figures 4.5b and 4.6b, differs from Example 2 only in the functional unit assigned to instruction C; all other instructions remain unchanged. Additionally, the misprediction region is extended due to the increased delay between branch prediction and branch resolution.

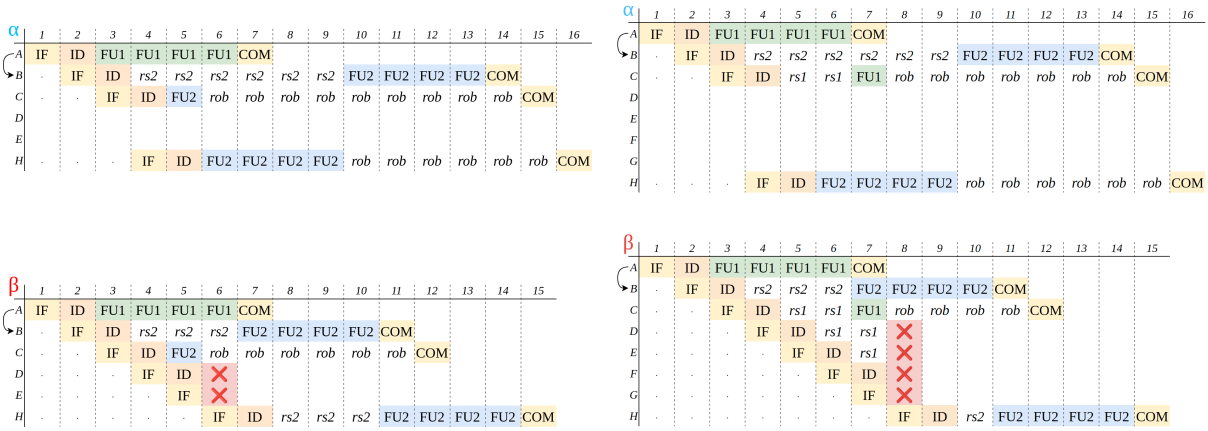
	Res.	Dep.	Lat.
A:	FU1		4
B:	FU2	$\{A\}$	4
**C:*	**FU2**		1
D:	FU1		4
E:	FU1		4
H:	FU2		4

(a) Input from Example 2

	Res.	Dep.	Lat.
A:	FU1		4
B:	FU2	$\{A\}$	4
**C:*	**FU1**		1
D:	FU1		4
E:	FU1		4
F:	FU1		4
G:	FU1		4
H:	FU2		4

(b) Input from Example 3

Figure 4.5: Two anomalous inputs found from the setting



(a) Trace from Example 2

(b) Trace from Example 3

Figure 4.6: Two TA traces found by the framework

The only essential difference between Examples 2 and 3 is the length of the misprediction region. The scheduling of instructions A, B, and H remains identical in both examples. This suggests that certain anomalies may share underlying mechanisms, potentially enabling a classification of timing anomalies (TAs) based on their structural similarities.

Another notable observation is that, in these cases, the anomalous effect can be attributed solely to the delayed fetch of instruction H. Remarkably, an equivalent effect can be reproduced by introducing a cache miss during the fetch of H, as illustrated in Figure 4.7. In this scenario, both α and β traces feature correct branch prediction; however, a cache hit occurs in α, while a cache miss occurs in β. This equivalence may help us to adapt the existing definition.

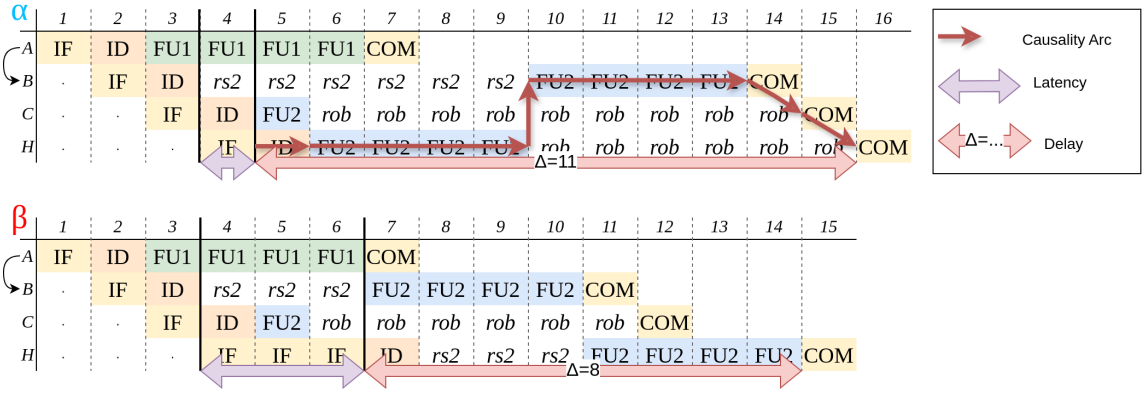


Figure 4.7: Cache miss on fetch of *H* causing the same effect as branch misprediction

4.4 Formalizing Definition

Given that an equivalent behavior exists (as shown in Figure 4.7) for Examples 2 and 3, it should be feasible to adapt Binder's definition to these cases. Consider Example 2: in Binder's framework, the source of a timing anomaly is a variation, which must be clearly identified. In the trace illustrating the equivalent behavior (Figure 4.7), the variation occurs in the IF latency, i.e., the delay between ↑ IF and ↓ IF. However, in Example 2, both ↑ IF and ↓ IF differ between traces α and β, so the same variation cannot be directly applied. To address this, we observe that for a given instruction, ↑ IF coincides with the ↓ IF of the preceding instruction. Therefore, the latency can be measured between the ↓ IF of the branch instruction and the ↓ IF of the first instruction following the misprediction region.

However, it is important to account for other variations that may occur concurrently, as variations in the IF stage of the post-branch instruction can overlap with branch-related variations, potentially confounding their respective latencies. To address this, we propose marking two distinct events to capture the variation:

1. **Branch Prediction (BP)** – moment when prediction happens and speculative executions starts;

2. **Correct Branch Taken (BT)** – the instruction from correct branch enters the pipeline.

Note that *BP* corresponds to ↓ IF of branch instruction and *BT* is ↑ IF of a first instruction after misprediction region of the branch. In case of a single variation that is in branch prediction, the TA pattern is detected in the same way as shown in Figure 4.7, but with latency being shorter by 1 clock cycle and the delay being longer by the same value.

Figure 4.8 shows this idea applied to Example 2. Both latencies corresponding to variation are 1 clock cycle shorter compared to example shown in Figure 4.7. The causality region also starts 1 clock cycle earlier, however is still going through the same events. Note here that we do not need any additional rules to build causality arcs.

A major assumption that allowed us to adapt the definition is that the branch behavior is just postponing the fetch of instruction following misprediction region. In this case the behavior can be compared to the effect of cache miss in IF stage – this is also not completely true, as the

penalty for cache miss is fixed while the size of misprediction region depends on the time between the prediction and the resolution of the branch. Therefore, in the rest of the article we focus more on examples that do not fit the assumption.

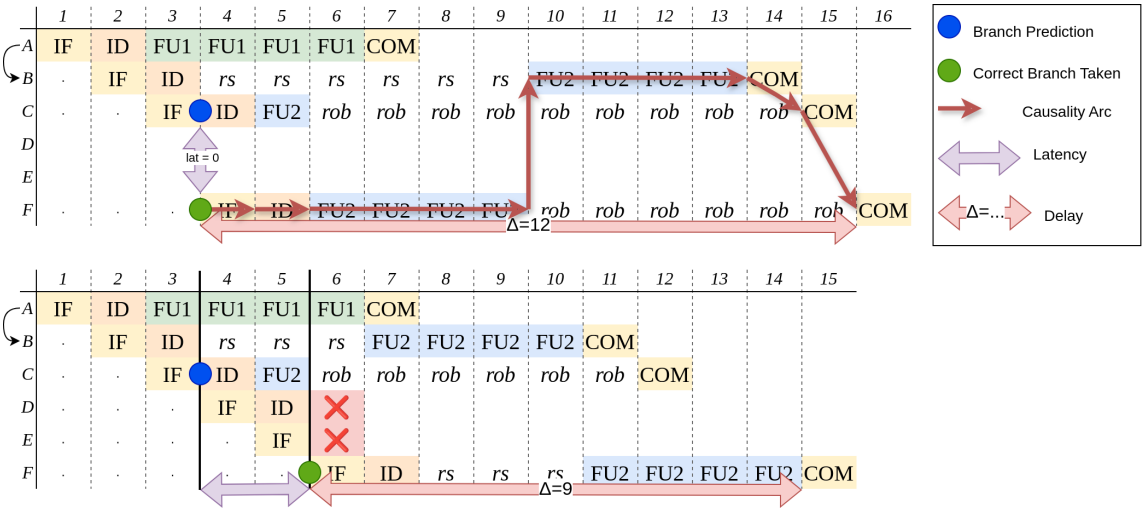


Figure 4.8:

4.5 Limitations of the Definition

So far we have demonstrated the potential of using Binder's definition in detecting branch prediction-related TAs. Now we discuss the limitations of the method by providing the relevant examples. We start from describing the problem that we found that appears within the existing framework and is not even related to branch prediction. Then we give more complex examples of branch prediction-caused TAs and try to reason whether they exhibit the same type of flaw or some new issues.

4.5.1 Gap Problem

While testing an existing definition using framework made by Binder et al. we encountered a situation when TA clearly exists but is not captured by the framework. Such an issue we called the *gap problem*. Figure 4.9 shows an example of such a problem: pair of traces α/β shows and example of TA similar one seen in Example 1, Binder's definition works fine for this pair. In a pair of traces α'/β' we change a latency for fetch of instruction B. This creates a so-called *gap* between $\downarrow$ FU of A and $\uparrow$ FU of B: a situation where a ETDG arc does not become a causality arc. Here it happens because a more strong causality link $(\downarrow \mathrm{IF}_B) \rightarrow (\uparrow \mathrm{FU}_B)$ is established using the rule of the most relevant constraint. Therefore, there is no causality path between end of the variation $\uparrow \mathrm{FU}_A$ and COM_D, so the timing anomaly is not signalled.

However, one can argue, that TA exists in α'/β' as we observe a slowdown in the trace α' with a favorable variation. Moreover, the two pairs of traces share the same suffixes and the scheduling pattern that leads to TA is the same. The only thing that prevents the TA from being detected is the absence of causality path between $\downarrow$ FU of A and $\uparrow$ FU of B in trace α'.

The understanding of the flaws of a base definition allows us to reason about further results in terms of gap problem: following we describe some examples of branch prediction TA ex-

amples that do not fit into causality-based approach and identify whether it is the same type of problem or not.

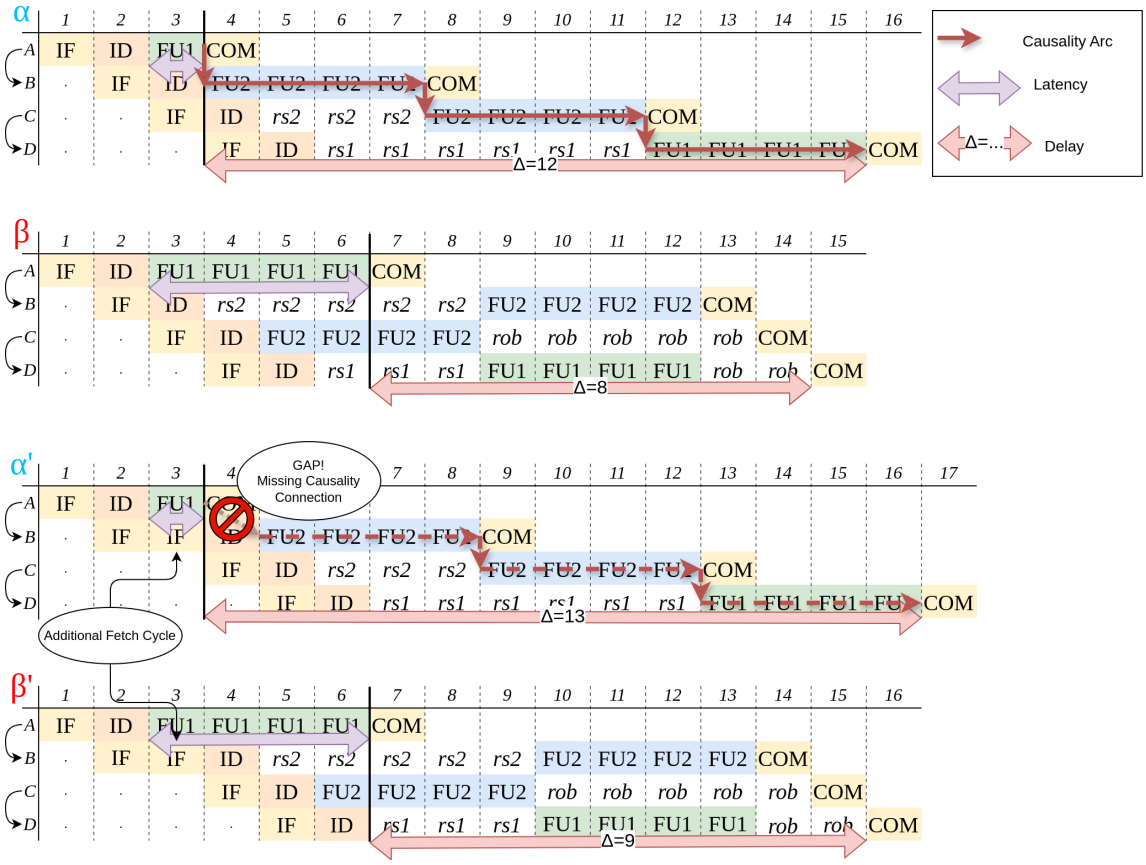


Figure 4.9: Gap problem

4.5.2 Early FU release

Up to this point, we have considered branch predictor-related timing anomalies (TAs) arising from the postponement of the fetch of the first non-mispredicted instruction. This occurs when no instructions within the misprediction region are in the execution phase, and thus the region does not affect functional unit (FU) scheduling. In the following examples, we analyze the impact of the misprediction region on instructions that were fetched prior to the branch.

Example 4:

Nested Misprediction Region

We consider the instruction trace shown in Figure 4.11, which features two nested misprediction regions corresponding to instructions C and D. We analyze the effect of varying the prediction outcome for D: in trace α (Figure 4.11), the prediction is correct, resulting in a longer overall execution time compared to trace β, where the prediction is incorrect.

	Res.	Dep.	Lat.
A:	FU1		5
B:	FU2	$\{A\}$	4
C:	FU1		1
**D:*	FU2		1
E:	FU2		4
F:	FU2		4
G:	FU2		4

Figure 4.10: Instruction trace from example 4

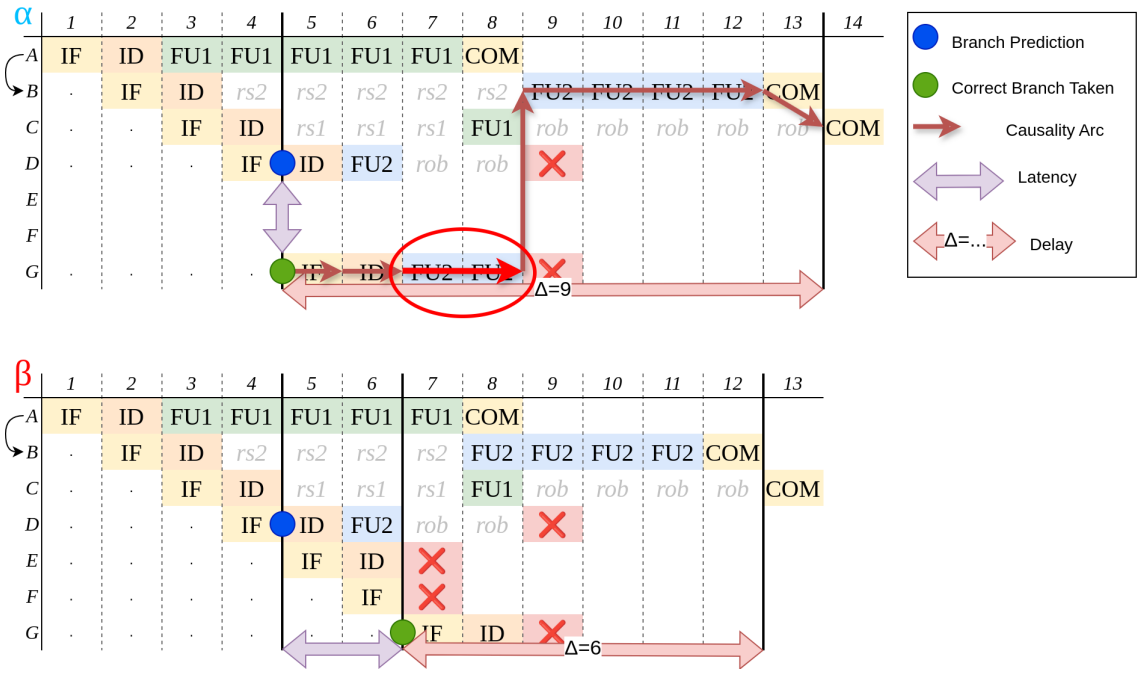


Figure 4.11: Execution trace of Example 4

In Figure 4.11 we try to construct a causality graph for trace α. On the picture we show the causal path form variation to the commit of *C*. However, one causal arc on the path (encircled in red) does not fit in the definition: Remember that in Binder's definition we have the *rule 4* which creates a ETDG-arc $(\uparrow \text{FU} \xrightarrow{lat_{FU}} \downarrow \text{FU})$. In Example 4 the FU-latency of *G* is 4, however in trace α the delay between $\uparrow \text{FU}_G$ and $\downarrow \text{FU}_G$ is only 2 clock cycles because of the earlier release of FU2 as the result of squashing. So according to the Binder's definition the arc cannot be established and not TA exists.

Likely, we are just missing a rule that suffices to describe anomaly here. Intuitively, $\downarrow \text{FU}_G$ is caused by the squashing by the branch resolution. Therefore, $(\uparrow \text{FU}_C \xrightarrow{0} \downarrow \text{FU}_G)$ arc would make sense (Assumption 1). However, it does not allow to construct a causality path in Example 4 that can explain the TA happening.

Assumption 1:

If FU is released as the result of squashing, the FU release of corresponding branch is causal to FU release of the squashed instruction.

Indeed, what we see in this example is that the earlier fetch of G allows it to start executing, which prevents B from starting the execution earlier. In fact, it is a reordering problem similar to Example 2. For that reason we take an Assumption 2 that effectively fills the gap in the causality path.

Assumption 2:

The FU acquisition is always causal to the respective FU release.

However, the following example shows that Assumption 2 is not always correct.

Example 5:

Latency Impact Through Misprediction Region We consider an instruction trace from Figure 4.12 the pair of execution traces with TA is shown at Figure 4.13. Here the variation is in latency of B, but the effect propagates through misprediction region of F which consists of one instruction G.

	Res.	Dep.	Lat.
A:	FU3		9
B:	FU1		6|7
C:	FU2	$\{A,B\}$	4
D:	FU1	$\{C\}$	4
E:	FU2	$\{B\}$	4
F:	FU1		1
G:	FU2		4

Figure 4.12: Instruction trace of Example 5

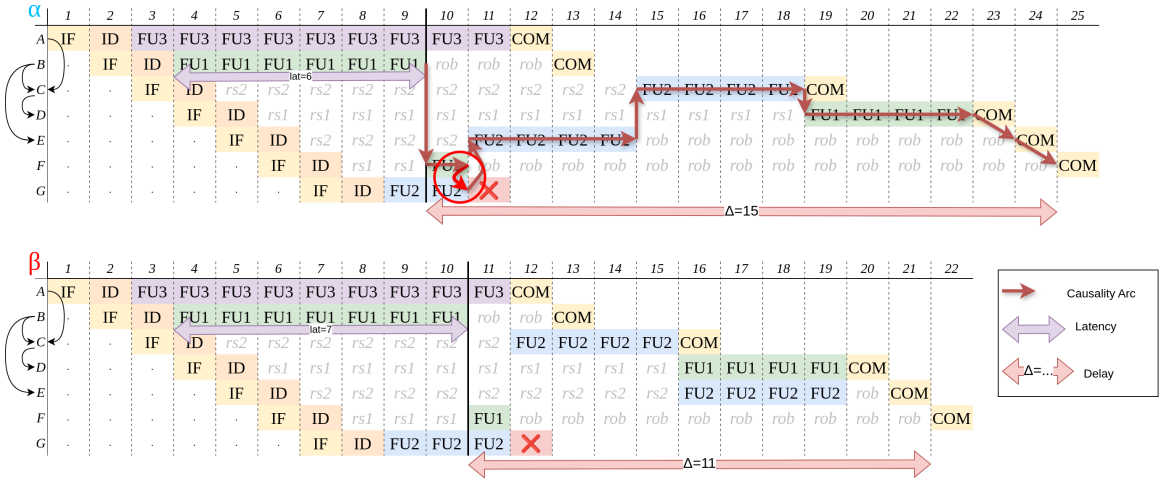


Figure 4.13: Execution trace of Example 5

Example 5 illustrates the problem with Assumption 2: here if we try to draw a causality arc ($\uparrow \mathrm{FU}_G \xrightarrow{2} \downarrow \mathrm{FU}_G$) in trace α, the causality path can not build between FUr_B and COM_E. Instead, the Assumption 1 works here allowing us to draw an arc ($\downarrow \mathrm{FU}_F \xrightarrow{0} \downarrow \mathrm{FU}_G$).

Example 6:

Branch Prediction + Gap problem
We modify Example 4 by increasing latencies of instructions A and C by 2 (input trace in Figure 4.14). This also requires us to define a larger misprediction region. The resulting pair of traces (Figure 4.15) exhibit a similar TA: instruction J is fetched in trace α and postpones B.

	Res.	Dep.	Lat.
A:	FU1		7
B:	FU2	$\{A\}$	4
C:	FU1		1
**D:*	FU2		3
E:	FU2		4
F:	FU2		4
G:	FU2		4
H:	FU2		4
I:	FU1		4
J:	FU2		4

Figure 4.14: Instruction trace from Example 6

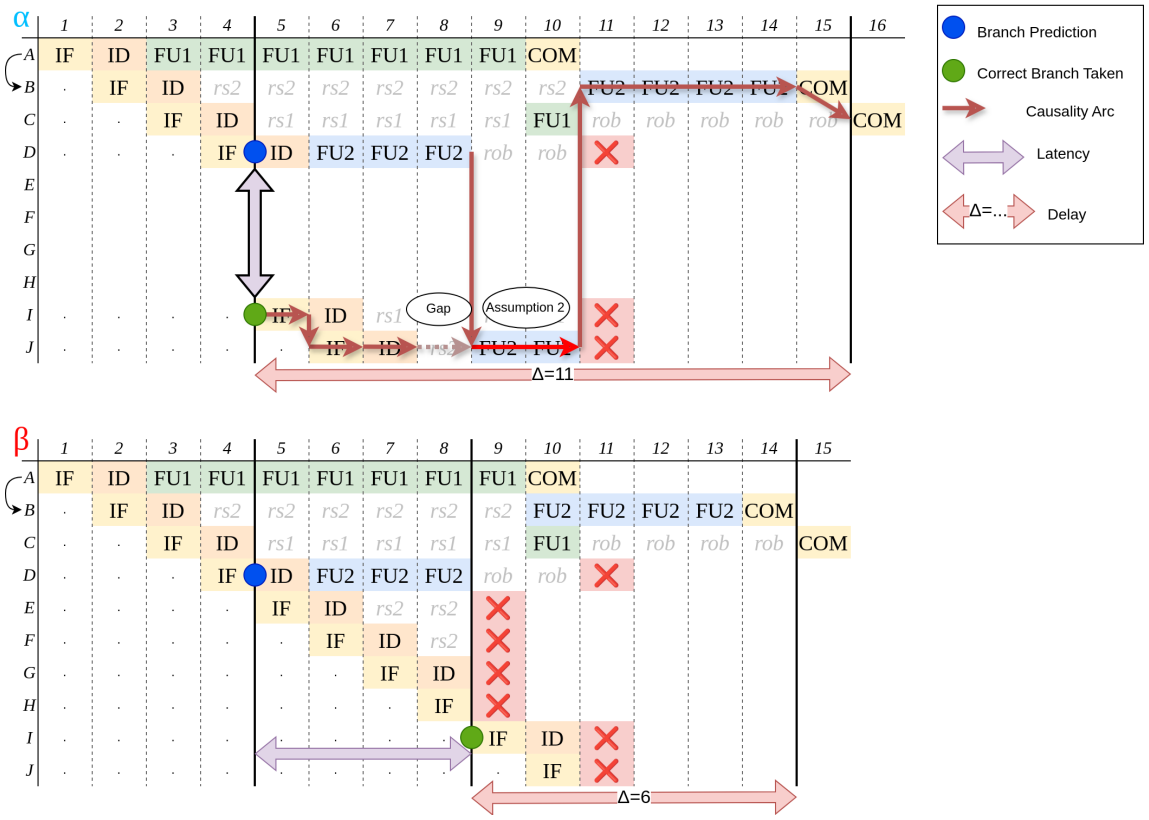


Figure 4.15: Execution trace from Example 6

Example 6 shows that the gap problem can also arise in misprediction region. $\downarrow \mathrm{FU}_J$ in trace α is not detected as a part of causal region of the end of the variation $\uparrow \mathrm{IF}_I$ because of the resource contention rule which creates a stronger arc $(\downarrow \mathrm{FU}_D \xrightarrow{0} \uparrow \mathrm{FU}_J)$.

In summary, our analysis demonstrates that while the definition of Binder et al. shows promise for application to branch prediction scenarios, its adaptation requires the introduction of additional assumptions. However, the two assumptions we considered are mutually contradictory, precluding the formulation of a consistent and comprehensive definition. Furthermore, the original definition is susceptible to the gap problem, which also manifests in the context of branch prediction-induced timing anomalies.

We contend that these issues stem from fundamental limitations in the underlying notion of causality employed by the framework. Both the gap problem and the contradictions between the proposed assumptions appear to arise from the same conceptual shortcomings. Therefore, we believe that a serious adjustments to the notion of causality shall be introduced.

— 5 —
Conclusion

In this study, we developed a framework to investigate branch prediction-induced timing anomalies (TAs). This framework enables the construction of representative examples, allowing us to systematically explore the phenomenon. Utilizing this tool, we demonstrated that the definition proposed by Binder et al., which we identified as the most prominent among existing definitions, can be adapted to scenarios involving branch prediction. Nevertheless, our analysis revealed controversial cases that challenge whether Binder's notion of causality truly captures the intuitive understanding of causality in this context. Consequently, we conclude that further investigation into this aspect is necessary.

There are several features that we did not implement in the current framework, such as a shared memory bus model and limitations on the reservation station (RS) and reorder buffer (ROB). These extensions could be incorporated with minimal changes to the framework. Additionally, we did not address the effects of multiple TAs or how effectively their impacts can be separated using the current definition. However, given the lack of a consistent definition, it is premature to pursue this direction.

Another important aspect not addressed by our model is the state of the branch predictor. In our approach, prediction and misprediction are treated as black-box events, similar to how we abstract cache-induced latencies as non-deterministic. While this abstraction simplifies the model, it overlooks the potential to explicitly represent the branch predictor state. As discussed in Chapter **??**, different implementations of branch predictors, such as Pattern History Tables (PHT) and Branch Target Buffers (BTB), could be modeled as part of the pipeline state, allowing us to consider related events in greater detail. This extension could provide deeper insights into how branch decisions propagate through the system and enable us to study not only individual prediction or misprediction events, but also sequences of such events, potentially revealing new types of timing anomalies.

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Appendix

Appendix goes here...