

# Branch Predictor Performance Evaluation using SimpleScalar

Singi Maharshi

Oliver Kandir

Department of Computer Science and Engineering  
Indian Institute of Technology Bhubaneswar  
Advanced Computer Architecture Lab

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## Abstract

This report evaluates multiple branch predictors available in the SimpleScalar `sim-outorder` simulator across compute-intensive benchmarks designed to reflect control-flow patterns commonly seen in large-scale machine learning workloads. We collect misprediction rate, CPI, IPC, and total cycles for taken, not-taken, bimodal, two-level, and combined (hybrid) predictors, and recommend a balanced predictor configuration for high-compute environments. Results consistently show the hybrid (comb) predictor offering the best trade-off between accuracy and performance.

## 0.1 Introduction

### Proposed Project Title

“Comprehensive Evaluation and Recommendation of Branch Predictors for High-Compute Workloads using SimpleScalar”

### Problem Statement

Modern processors increasingly execute workloads that resemble the computational patterns of Large Language Models (LLMs), including matrix multiplications, attention-like operations, expert routing, normalization, softmax evaluation, sampling, and gradient-style updates.

This project evaluates the branch prediction performance of multiple predictors in the SimpleScalar `sim-outorder` simulator using seven custom C programs, each designed to mimic a specific component of LLM computation. These programs collectively generate diverse branch patterns—ranging from highly predictable arithmetic loops to stochastic sampling, threshold-based gating, and deeply nested routing logic.

The objective is to analyze how different branch predictors respond to these compute-intensive and irregular control-flow patterns, and to identify the most balanced predictor that offers the best trade-off between prediction accuracy and overall execution performance (CPI, IPC, and runtime) when running LLM-like workloads.

### Key Tasks

1. Configure and execute `sim-outorder` with multiple branch predictors (bimodal, static, 2level, hybrid, etc.) on 7 benchmarks.
2. Collect detailed metrics—misprediction rate, CPI, IPC, and total cycles.
3. Analyze results quantitatively and produce a combined performance score for each predictor.
4. Recommend the most balanced predictor for high computational workloads.

## Expected Outcome

A data-driven recommendation identifying the best branch predictor configuration for compute-intensive programs, supported by experimental analysis and visualization.

## 0.2 Evaluation Parameters

To evaluate the performance of various branch prediction techniques (taken, not-taken, bimodal, 2-level, and comb), several microarchitectural and performance parameters were measured using the SimpleScalar `sim-outorder` simulator. These parameters reflect key aspects of processor efficiency, instruction throughput, and control-flow prediction accuracy.

### 0.2.1 Branch Misprediction Rate

**Definition:** The fraction of branch instructions that were incorrectly predicted by the branch predictor.

$$\text{Misprediction Rate} = \frac{\text{Number of Incorrect Predictions}}{\text{Total Branch Instructions}}$$

**Interpretation:** A lower misprediction rate indicates a more accurate predictor. Fewer mispredictions reduce pipeline flushes, leading to better performance.

**Use in project:** Compared across all predictors to determine their relative prediction accuracy for different program behaviors.

### 0.2.2 CPI (Cycles Per Instruction)

**Definition:** The average number of clock cycles required to execute each instruction.

$$\text{CPI} = \frac{\text{Total Cycles}}{\text{Number of Instructions Executed}}$$

**Interpretation:** Lower CPI values indicate higher efficiency and reduced pipeline stalls.

**Relation to predictors:** High branch mispredictions increase CPI due to speculative execution rollbacks. Thus, predictors with lower misprediction rates (e.g., comb) show lower CPI.

### 0.2.3 IPC (Instructions Per Cycle)

**Definition:** The number of instructions completed per clock cycle.

$$\text{IPC} = \frac{\text{Instructions Executed}}{\text{Total Cycles}}$$

**Interpretation:** Higher IPC values indicate better instruction throughput and pipeline utilization. It is inversely related to CPI.

**Use in project:** Used to measure how effectively the processor issues and retires instructions under different branch prediction schemes.

#### 0.2.4 Total Cycles

**Definition:** The total number of clock cycles taken to complete execution of a benchmark program.

**Interpretation:** Indicates the overall execution time (in simulated cycles). Lower total cycles imply better performance and higher efficiency.

**Use in project:** Served as a primary performance metric for comparing overall runtime impact of different branch predictors.

#### 0.2.5 Static vs. Dynamic Predictors

**Static Predictors (taken, not-taken):** Assume fixed branch outcomes for all executions—useful as baseline references. High misprediction rates show their inability to adapt to dynamic program flow.

**Dynamic Predictors (bimod, 2lev, comb):** Learn branch behavior based on runtime history. These significantly reduce misprediction rates and improve CPI/IPC.

#### 0.2.6 Optimization Level (-O2)

All benchmark programs were compiled using the -O2 optimization level of the SimpleScalar GCC toolchain, ensuring realistic and performance-optimized binaries for accurate branch prediction analysis.

### 0.3 Background and Tools

#### 0.3.1 Description of -O2 Optimization Flag

The -O2 flag enables a balanced set of performance optimizations that improve runtime efficiency without significantly increasing compile time or binary size. It includes instruction-level optimizations (common subexpression elimination, constant propagation, strength reduction, dead code elimination), loop optimizations (partial unrolling, invariant code motion, induction variable simplification), branch/function optimizations (predictable branch rearrangement, small function inlining, cross-jumping, tail calls), and register allocation improvements (better register usage and instruction scheduling). In SimpleScalar context, compiling with:

```
sslittle-na-sstrix-gcc -O2 <program>.c -o <program>
```

improves IPC, reduces stalls and mispredictions, and provides realistic workloads for experiments.

### 0.3.2 Description: SimpleScalar

SimpleScalar is a computer architecture simulation toolset for modeling and evaluating modern microprocessors at the instruction level. It supports multiple simulation modes (`sim-safe`, `sim-cache`, `sim-bpred`, `sim-outorder`), configurable microarchitectural parameters, and detailed statistics (CPI, IPC, miss rates, cycles). It is widely used for pipeline performance, branch prediction, cache behavior, and ILP studies.

### 0.3.3 Description of `sim-outorder`

`sim-outorder` models a speculative, out-of-order superscalar pipeline with realistic components: fetch/decode/issue/commit stages; out-of-order execution; RUU/LSQ; speculative execution with branch prediction (taken, nottaken, bimod, 2lev, comb); and cache/memory hierarchy. It reports cycle-accurate performance statistics: CPI, IPC, executed instructions, and misprediction rate.

## 0.4 Branch Predictors Evaluated

In this project, five predictors available in SimpleScalar were evaluated: taken, not-taken, bimodal, two-level adaptive (2lev), and combined (hybrid).

### 0.4.1 Taken Predictor

A static predictor that always predicts branches as taken; good for backward loop branches, poor for rarely-taken forward branches. Predicts every branch will jump. Very poor for conditional exits or forward jumps.

**Limitation:** High misprediction on complex logic.

### 0.4.2 Not-Taken Predictor

A static predictor that always predicts not-taken; simple but suffers on loop-heavy programs.

**Use Case:** Acts as a performance baseline, not used in modern CPUs.

### 0.4.3 Bimodal Predictor

A dynamic predictor with a single-level table of 2-bit saturating counters (PHT) per branch; adapts to per branch local behavior.

**Strength:** Works well when branches are consistent.

**Limitation:** Struggles with patterns like alternating branches (e.g., 010101...).

### 0.4.4 Two-Level Adaptive Predictor

Uses a history register (branch outcomes) as the first level and a PHT indexed by this history as the second level; captures inter-branch correlations.

Can be **global**, **local**, or **combined**:

**Global:** One shared history for all branches.

**Local:** Each branch has its own history. **Strength:** Catches correlated branches and sequences.

**Limitation:** More complex; can be sensitive to history length and aliasing.

#### 0.4.5 Combined (Hybrid) Predictor

Combines local and global behavior (e.g., bimodal + two-level) with a meta-predictor to choose the best source per branch; highest accuracy with modest hardware cost.

**Strength:** Best average performance across diverse programs.

**Limitation:** Higher hardware complexity and power consumption.

## 0.5 Benchmark Programs

**Per-program characterization and relation to Large Machine Learning Models (LMMs):** This section explains each benchmark program used in the project, its relationship to a component of Large Machine Learning Models (LMMs), and the branch behavior it exhibits. These micro-programs mimic the control-flow patterns of deep-learning workloads such as Transformers, Mixture-of-Experts models, and optimizer steps.

### Program 1 — Matrix Multiply + Piecewise Activation

#### LLM Correspondence:

Simulates the **Feed-Forward Neural Network (FFN)** layer of Transformers, where every token embedding is processed through multiple matrix multiplications and activation functions (ReLU, GELU).

#### What it does:

Initializes two  $256 \times 256$  matrices using sinusoidal patterns, performs full matrix multiplication, and applies a multi-branch piecewise activation ( $\tanh$ ,  $\log$ , square, linear, sinusoidal) followed by small modulo-based adjustments before storing final outputs.

#### Detailed Operation:

- i. Initializes matrices A and B with trigonometric expressions to produce structured numeric patterns.
- ii. Performs complete  $256 \times 256$  matrix multiplication by computing dot products for each  $(i, j)$  position.
- iii. Applies a piecewise activation function to the computed sum, choosing among:
  - $\tanh()$  for large positive values,
  - $\log()$  for moderate positives,

- squaring for small positives,
  - linear scaling for small negatives,
  - `sin()` for large negatives.
- iv. Adds deterministic adjustments based on modulus operations to slightly modify selected outputs.
  - v. Writes the final processed value into matrix `C` at the corresponding location.

**Branch behavior:**

Regular nested loops but highly data-dependent activation branches; the piecewise nonlinearity and modulus checks create non-uniform branch patterns. Useful for analyzing branch predictor behavior where dynamic predictors outperform static heuristics.

**Program 2 — Sparse Attention (Mask + Gating)**

**LLM Correspondence:**

Mimics the Attention Mechanism used in Transformers. Real LLMs compute attention weights and apply masks to ignore irrelevant tokens.

**What it does:**

Builds  $Q/K/V$  matrices, computes attention scores, and applies threshold-based masks and gating with modular conditions before combining with  $V$ .

**Detailed Operation:**

- i. Initializes the Query ( $Q$ ), Key ( $K$ ), and Value ( $V$ ) matrices using sinusoidal and trigonometric expressions to generate structured patterns.
- ii. Computes dot products between each row of  $Q$  and each row of  $K$ , forming pairwise similarity scores.
- iii. Scales each attention score by dividing with  $\sqrt{N}$ , following the standard scaled dot-product attention formulation.
- iv. Applies a piecewise transformation to each score:
  - Sigmoid-like mapping for large positives,
  - Exponential amplification for large negatives,
  - Linear scaling for intermediate values.
- v. Modifies attention scores through deterministic gating rules based on indices and modular conditions ( $i \% 7 == 0$ ,  $j \% 5 == 0$ , etc.).
- vi. Combines the transformed attention value with the corresponding element of the  $V$  matrix to produce the output.

**Branch behavior:**

Mix of data-dependent thresholds and periodic modular branches (e.g.,  $i\%7$ ,  $j\%5$ ). Produces interleaved predictable and unpredictable outcomes, stressing predictor adaptability; hybrid predictors typically perform best.



## Program 3 — Mixture-of-Experts Router

### LLM Correspondence:

Represents the **Mixture-of-Experts (MoE)** architecture used in large LLMs (e.g., Switch Transformer, GPT-MoE). Each input token is dynamically routed to one or more experts.

### What it does:

Routes tokens to experts through a multi-threshold decision tree and applies balancing logic using divisibility or modulus conditions.

### Detailed Operation:

- i. Initializes the expert weight array and generates  $N$  random token values within the range 0–999.
- ii. Normalizes each token value using `val = route[i] / 1000.0`, preparing it for threshold-based expert assignment.
- iii. Routes each token to one of eight experts by evaluating a descending sequence of threshold conditions that divide the value range into routing intervals.
- iv. Updates the corresponding expert counter using a set of rules:
  - increment by 1 when expert index is even and token value is divisible by 3,
  - increment by 2 for experts divisible by 3,
  - increment by 3 for experts divisible by 5,
  - otherwise increment by `route[i] % 7`.
- v. Applies load-balancing adjustments by reducing the counter when `val > 0.8` and the counter satisfies a modulus-11 condition.
- vi. Prints the final number of processed tokens for each expert, reflecting workload distribution.

### Branch behavior:

The deep nested if-else routing logic simulates real MoE decision-making. This stresses **correlating and hybrid predictors**, revealing their ability to handle long branch dependencies. Excellent for evaluating how well 2-level or hybrid predictors track correlated branch outcomes.

## Program 4 — LayerNorm + Clipping

### LLM Correspondence:

Layer Normalization, used after attention and feed-forward layers to stabilize activations. Calculate the mean and variance for the embedding of each token.

### What it does:

Computes the mean and variance per-row, normalizes values, conditionally clips to  $\pm 3$ , and enhances very small magnitudes.

**Detailed Operation:**

- i. Initializes the **X** matrix with deterministic pseudo-random values and prepares the learnable parameters **gamma** and **beta**.
- ii. Computes the mean of each row by averaging all feature values across the **DIM**-dimension.
- iii. Computes the variance of each row and adds a small  $\epsilon$  term to ensure numerical stability before taking the square root.
- iv. Normalizes each element using the standard LayerNorm formula:

$$\text{norm} = \frac{X[i][j] - \text{mean}}{\text{std}}$$

- v. Applies conditional modifications:
  - i. clip values above 3 or below -3,
  - ii. amplify very small magnitudes ( $|\text{norm}| < 0.01$ ) by a factor of 1.5.
- vi. Applies learnable affine transformation to each value using:

$$Y[i][j] = \gamma[j] \cdot \text{norm} + \beta[j]$$

- vii. Applies a small deterministic correction to selected elements using a modulus-based rule.

**Branch behavior:**

Skewed conditions (most values remain unmodified), resulting in highly predictable branches. The bimodal predictor performs almost as well as a hybrid predictor in such low-entropy scenarios.

**Program 5 — Stable Softmax + Clamps**

**LLM Correspondence:**

Simulates **Softmax computation** in attention and output probability layers. Normalizes logits using exponentials and division.

**What it does:**

Performs max-subtraction, exponentiation with saturation limits, optional mod-based perturbation, normalization, and final probability capping.

**Detailed Operation:**

- i. Initializes the **logits** matrix with deterministic pseudo-random values across the **BATCH** rows and **DIM** columns.

- ii. For each row, computes the maximum logit value and subtracts it from every element. This implements the standard numerical-stability trick for softmax:

$$x'_j = x_j - \max_k(x_k),$$

which prevents overflow when computing exponentials.

- iii. Computes exponentials of the shifted logits:

$$\text{expv}_j = e^{x'_j},$$

and applies stability rules:

- i. clamp excessively large exponentials to  $10^3$ ,
  - ii. lift extremely small exponentials to  $10^{-5}$ ,
  - iii. apply a 0.95 scaling when the modulus condition on  $\text{expv}_j$  is satisfied.
- iv. Accumulates the sum of all exponentials in the row:

$$S = \sum_k \text{expv}_k.$$

- v. Normalizes each exponential using the softmax formula:

$$p_j = \frac{\text{expv}_j}{S},$$

producing a valid probability distribution where  $\sum_j p_j = 1$ .

- vi. Applies final probability clamping rules:
  - cap values above 0.9 to avoid overly dominant probabilities,
  - raise very small probabilities by adding 0.001 to avoid zero-like outputs.
- vii. Stores the normalized and clamped probabilities into the `probs` matrix for later use.

### Branch behavior:

Mostly repetitive and consistent range-check branches with rare flips caused by mod-based perturbations. Hybrid predictors exhibit minimal mispredictions due to the stable and predictable branching pattern.

## Program 6 — Top-k Sampler (Decoding)

### LLM Correspondence:

Represents the **Token Sampling (Decoding)** phase in LLM inference, where the next token is chosen from probability distributions using randomization (top-k or nucleus sampling).

### What it does:

Maintains a top-k array of scores, randomly selects an index, and applies bounds checks and guard conditions before returning the sample.

#### Detailed Operation:

- i. Initializes the `logits` matrix with deterministic pseudo-random values across all `BATCH` rows and the `VOCAB` dimension.
- ii. For each row, creates arrays `topk[]` and `topk_idx[]` initialized to a very low value to hold the highest  $K$  logits and their corresponding token indices.
- iii. Iterates through all vocabulary logits and inserts each value into the correct position inside the top-k list using an in-place shifting mechanism:
  - compare the logit with the current top-k entries,
  - shift lower-ranked entries downward,
  - place the new value into its appropriate position,
  - maintain the list in descending order.

This manually constructs the  $K$  largest logits without sorting the entire vocabulary.

- iv. Generates a uniform random number and maps it to an integer range  $[0, K - 1]$ , selecting one of the top-k candidates as the sampled index.
- v. Applies safety and guard checks:
  - returns `-1` if the selected top-k logit is too low,
  - returns a halved token index if the value is extremely high,
  - otherwise returns the index exactly as stored in `topk_idx[pick]`.
- vi. Stores the final sampled token in the `sampled[]` array, representing the chosen token for that batch element.

#### Branch behavior:

Randomized conditions introduce stochastic, unpredictable branches, while deterministic comparisons remain stable. This combination stresses predictor robustness under partial randomness; hybrid predictors maintain consistent accuracy.

### Program 7 — Gradient Update with Adaptive Learning Rate

#### LLM Correspondence:

Emulates the **Gradient Descent Weight Update** process during LLM training, applying adaptive learning rate updates per weight.

#### What it does:

Updates model weights based on gradient magnitude, dynamically adjusts the learning rate, and applies a periodic nudge when `idx % 13 == 0`.

**Detailed Operation:**

- i. Initializes the weight matrix  $W$  and gradient matrix  $\mathbf{grad}$  with deterministic pseudo-random values across  $LAYERS$  and  $DIM$ .
- ii. Assigns a per-layer base learning rate using:

$$\mathbf{lr}[\mathbf{i}] = 0.001 + (i \bmod 5) \times 0.0001,$$

creating a repeating 5-step learning rate schedule.

- iii. For each weight, reads the gradient value  $g = \mathbf{grad}[\mathbf{i}][\mathbf{j}]$  and adjusts the learning rate adaptively:
  - multiply learning rate by 0.9 when  $|g| > 1.0$ ,
  - multiply learning rate by 1.05 when  $|g| < 0.01$ .

This models simplified adaptive learning rate behavior similar to optimizers like Adam or RMSProp.

- iv. Updates each weight using gradient descent:

$$W[\mathbf{i}][\mathbf{j}] \leftarrow W[\mathbf{i}][\mathbf{j}] - \mathbf{lr}[\mathbf{i}] \cdot g.$$

- v. Applies a periodic nudging rule:

$$\text{if } (\lfloor W[\mathbf{i}][\mathbf{j}] \times 1000 \rfloor \bmod 13 = 0) \Rightarrow W[\mathbf{i}][\mathbf{j}] += 0.0001.$$

This introduces a small deterministic perturbation to selected weights.

- vi. Stores the updated weight back into the  $W$  matrix, completing one full optimizer-style update pass.

**Branch behavior:**

Simple threshold branches (rarely triggered) combined with regular periodic checks lead to predictable, low-entropy control flow. Bimodal predictors perform well, with hybrid predictors offering only slight improvements for the infrequent branches.

## 0.6 Experimental Setup and Commands

### General Commands

#### Compile C programs

```
$IDIR/bin/sslittle-na-sstrix-gcc -O2 -o <output_object_name> <program_name>.c
```

#### Analyze branch predictor

```
$IDIR/simplesim-3.0/sim-outorder -bpred <predictor_type> <program_name>
```

## 0.7 Results and Analysis

### Program 1

**Table 1:** Program 1 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.0228	0.0228	0.9971	0.9857	0.9971
bpred_miss_rate	0.9772	0.9772	0.0029	0.0143	0.0029
sim_num_insn	204094264	204094264	204094264	204094264	204094264
sim_num_branches	23005235	23005235	23005235	23005235	23005235
sim_CPI	2.1316	2.1329	1.7793	1.7864	1.7793
sim_IPC	0.4691	0.4689	0.5620	0.5598	0.5620
sim_cycle	435040743	435303059	363151013	364593223	363150982

### Program 2

**Table 2:** Program 2 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.0768	0.0768	0.9850	0.9724	0.9911
bpred_miss_rate	0.9232	0.9232	0.0150	0.0276	0.0089
sim_num_insn	228436498	228436498	228436498	228436498	228436498
sim_num_branches	26799905	26799905	26799905	26799905	26799905
sim_CPI	1.2112	1.2134	0.8400	0.8437	0.8344
sim_IPC	0.8257	0.8241	1.1905	1.1853	1.1984
sim_cycle	276671913	277184927	191878203	192723275	190615168

### Program 3

**Table 3:** Program 3 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.1087	0.1087	0.9915	0.9912	0.9917
bpred_miss_rate	0.8913	0.8913	0.0085	0.0088	0.0083
sim_num_insn	13862278	13862278	13862278	13862278	13862278
sim_num_branches	2007905	2007905	2007905	2007905	2007905
sim_CPI	1.5247	1.5247	0.5712	0.5716	0.5709
sim_IPC	0.6559	0.6559	1.7507	1.7496	1.7515
sim_cycle	21135820	21136172	7918175	7923035	7914355

### Program 4

**Table 4:** Program 4 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.2369	0.2369	0.9226	0.9211	0.9215
bpred_miss_rate	0.7631	0.7631	0.0774	0.0789	0.0785
sim_num_insn	13254474	13254474	13254474	13254474	13254474
sim_num_branches	1018226	1018226	1018226	1018226	1018226
sim_CPI	1.0364	1.0364	0.6808	0.6814	0.6816
sim_IPC	0.9649	0.9649	1.4688	1.4677	1.4672
sim_cycle	13736530	13736530	9024039	9031078	9034075

### Program 5

**Table 5:** Program 5 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.1500	0.1500	0.9258	0.9621	0.9748
bpred_miss_rate	0.8500	0.8500	0.0742	0.0379	0.0252
sim_num_insn	3560040	3560040	3560040	3560040	3560040
sim_num_branches	654899	654899	654899	654899	654899
sim_CPI	1.7840	1.7932	0.9260	0.8591	0.8499
sim_IPC	0.5605	0.5577	1.0799	1.1640	1.1766
sim_cycle	6351289	6383912	3296544	3058365	3025602

## Program 6

**Table 6:** Program 6 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.0262	0.0262	0.9748	0.9737	0.9748
bpred_miss_rate	0.9738	0.9738	0.0252	0.0263	0.0252
sim_num_insn	5568379	5568379	5568379	5568379	5568379
sim_num_branches	1336524	1336524	1336524	1336524	1336524
sim_CPI	2.2066	2.2066	0.4940	0.4954	0.4939
sim_IPC	0.4532	0.4532	2.0244	2.0186	2.0247
sim_cycle	12287143	12287379	2750614	2758555	2750176

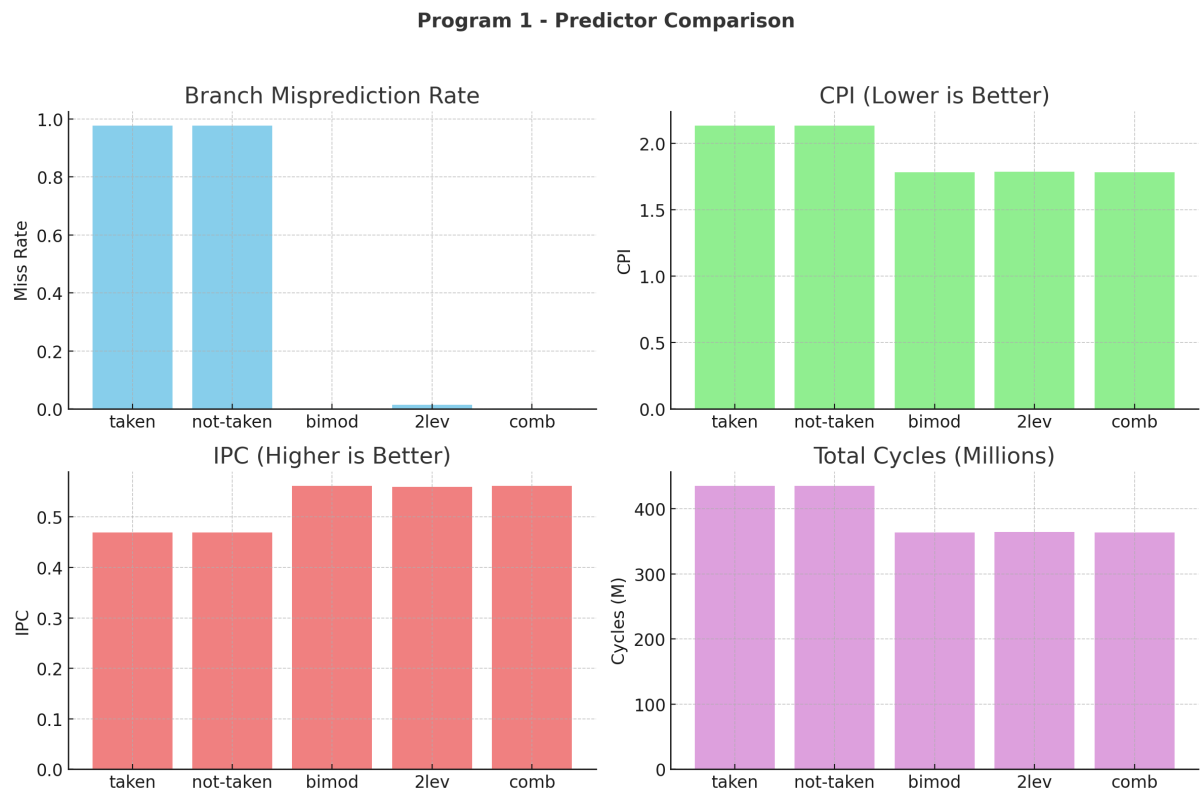
## Program 7

**Table 7:** Program 7 Results

	taken	Not taken	bimod	2lev	comb
bpred_dir_rate	0.0089	0.0089	0.9930	0.9915	0.9927
bpred_miss_rate	0.9911	0.9911	0.0070	0.0085	0.0073
sim_num_insn	1288630	1288630	1288630	1288630	1288630
sim_num_branches	67070	67070	67070	67070	67070
sim_CPI	1.2687	1.2688	0.8681	0.8684	0.8680
sim_IPC	0.7882	0.7881	1.1519	1.1516	1.1521
sim_cycle	1634935	1635064	1118679	1119005	1118541

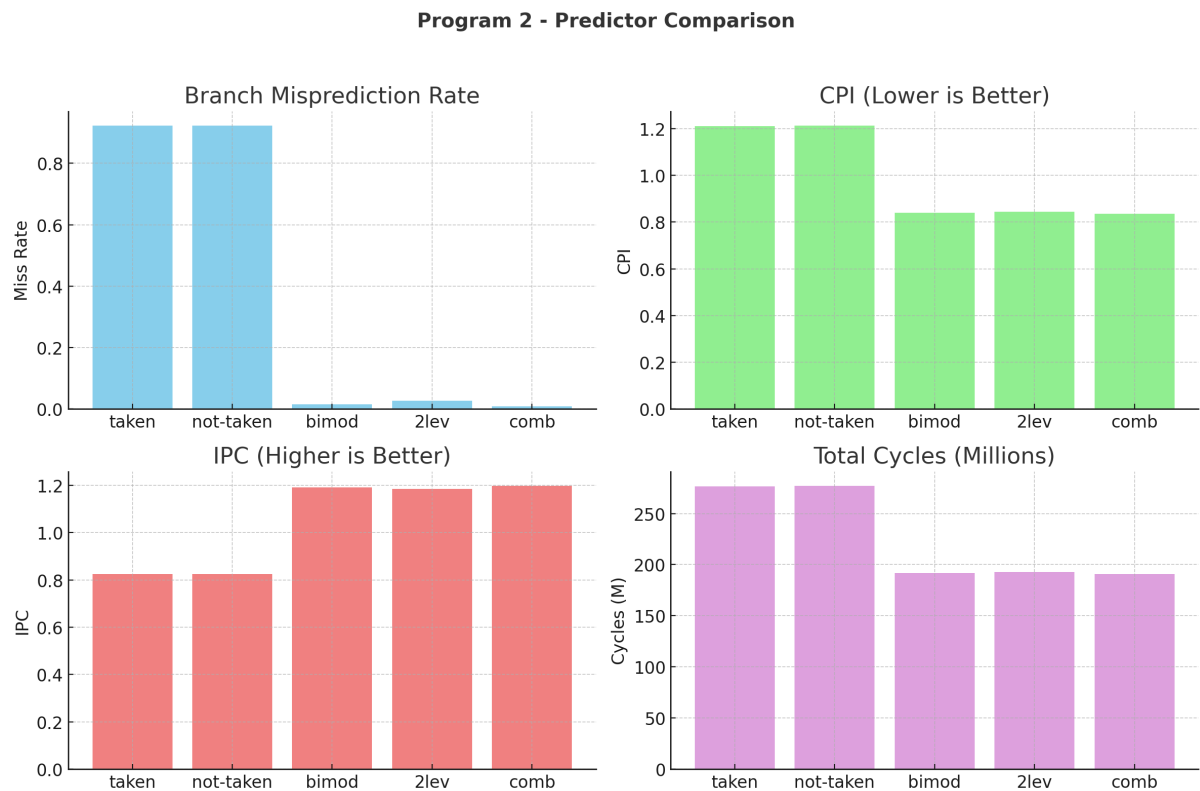


## Program 1 — Predictor Comparison (Graphical Analysis)



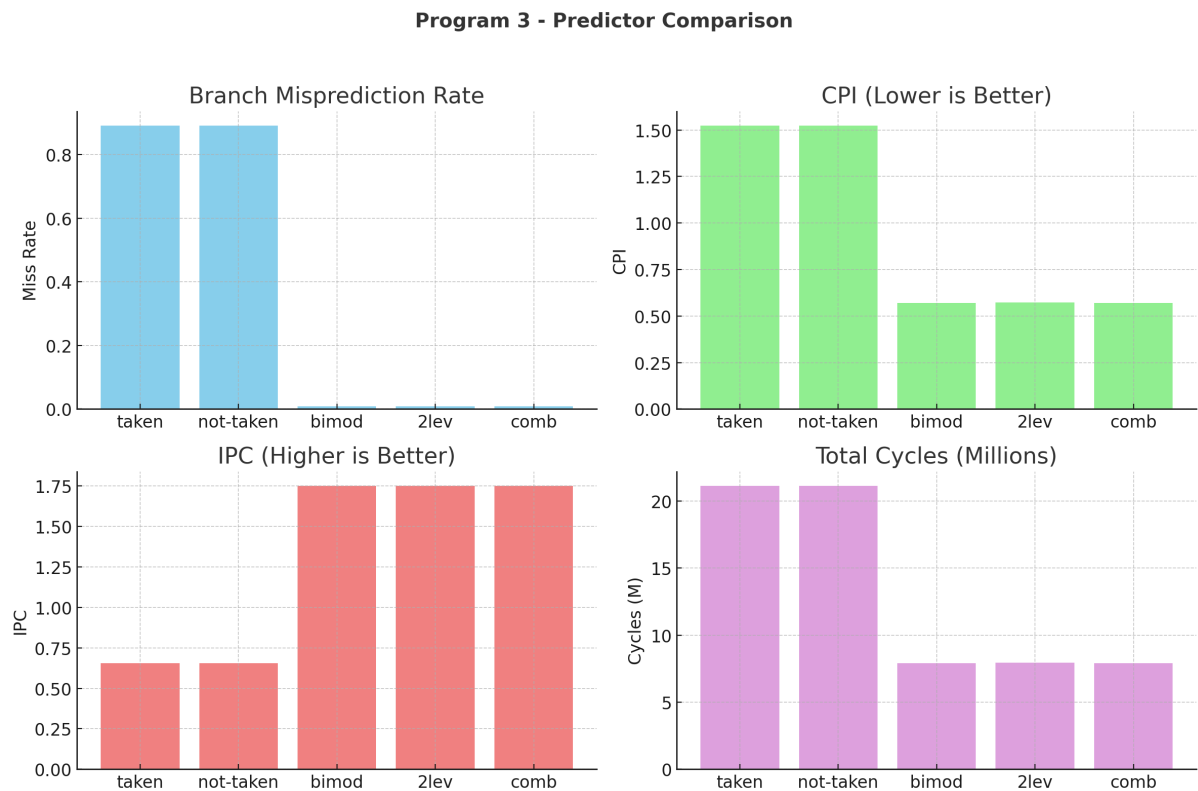
**Figure 1:** Program 1 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Program 2 — Predictor Comparison (Graphical Analysis)



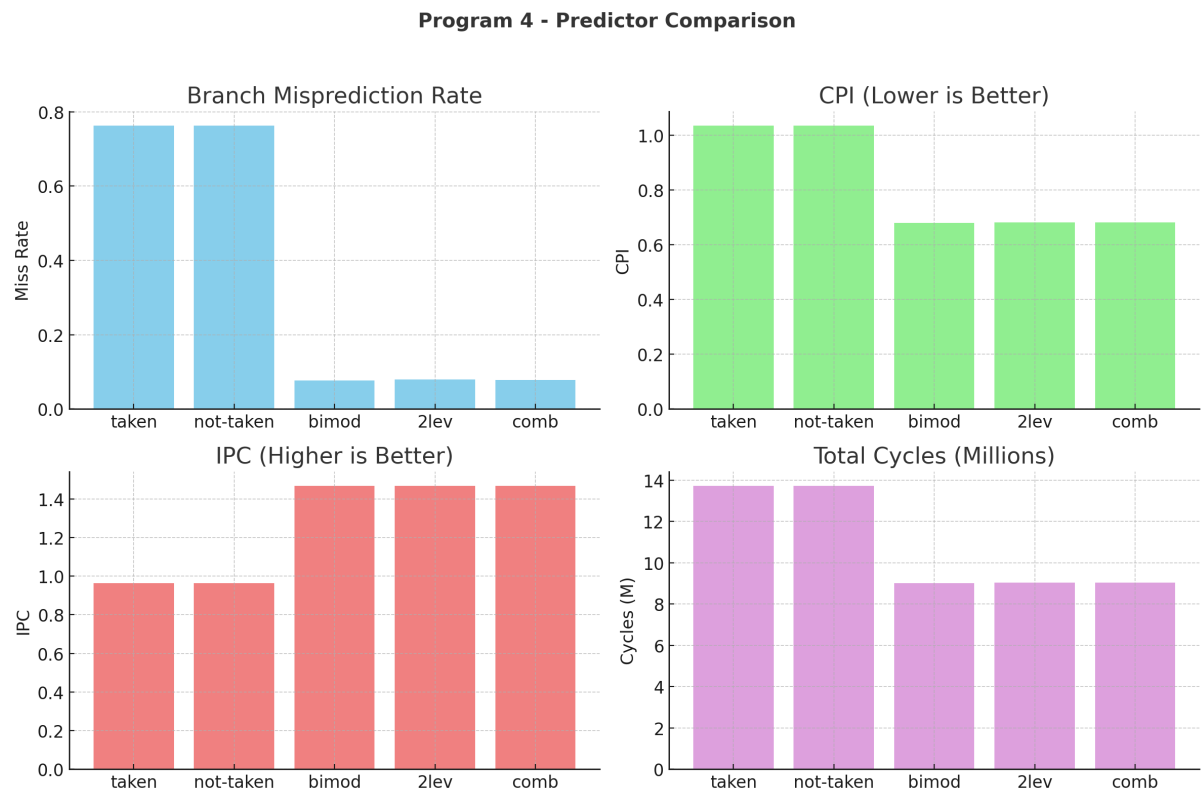
**Figure 2:** Program 2 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

### Program 3 — Predictor Comparison (Graphical Analysis)



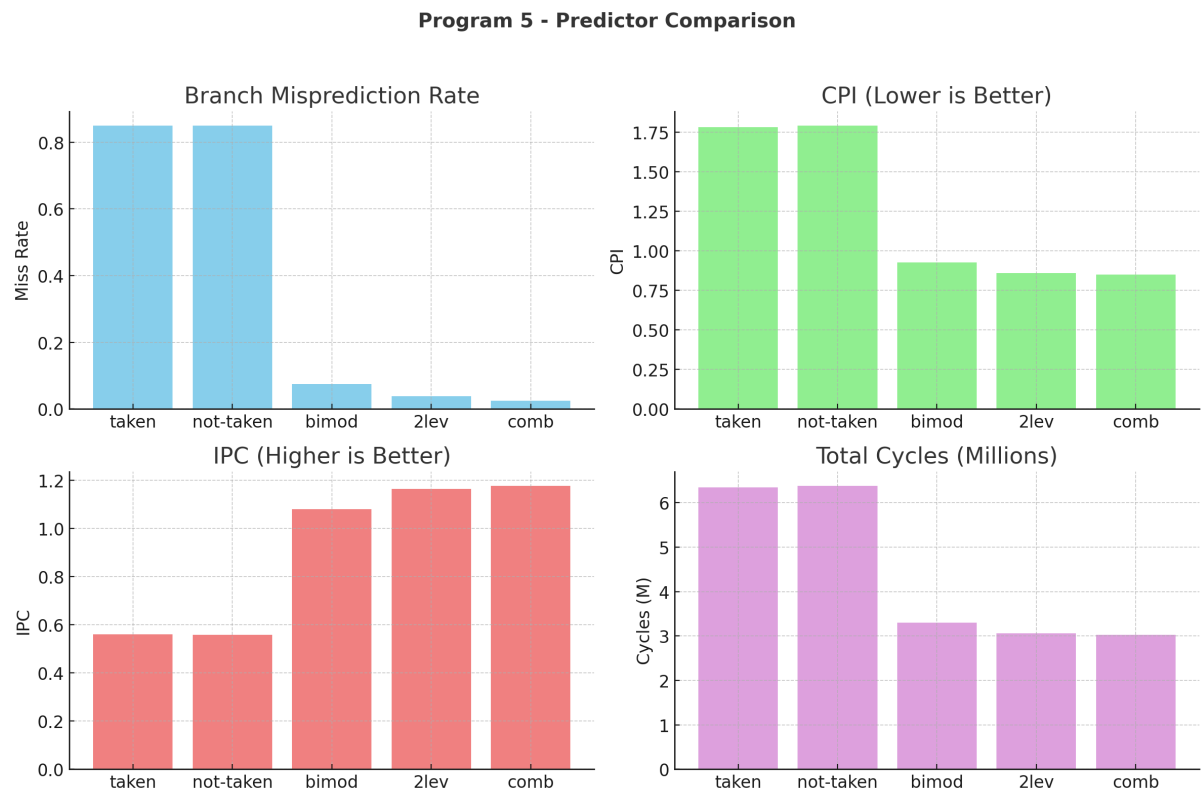
**Figure 3:** Program 3 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Program 4 — Predictor Comparison (Graphical Analysis)



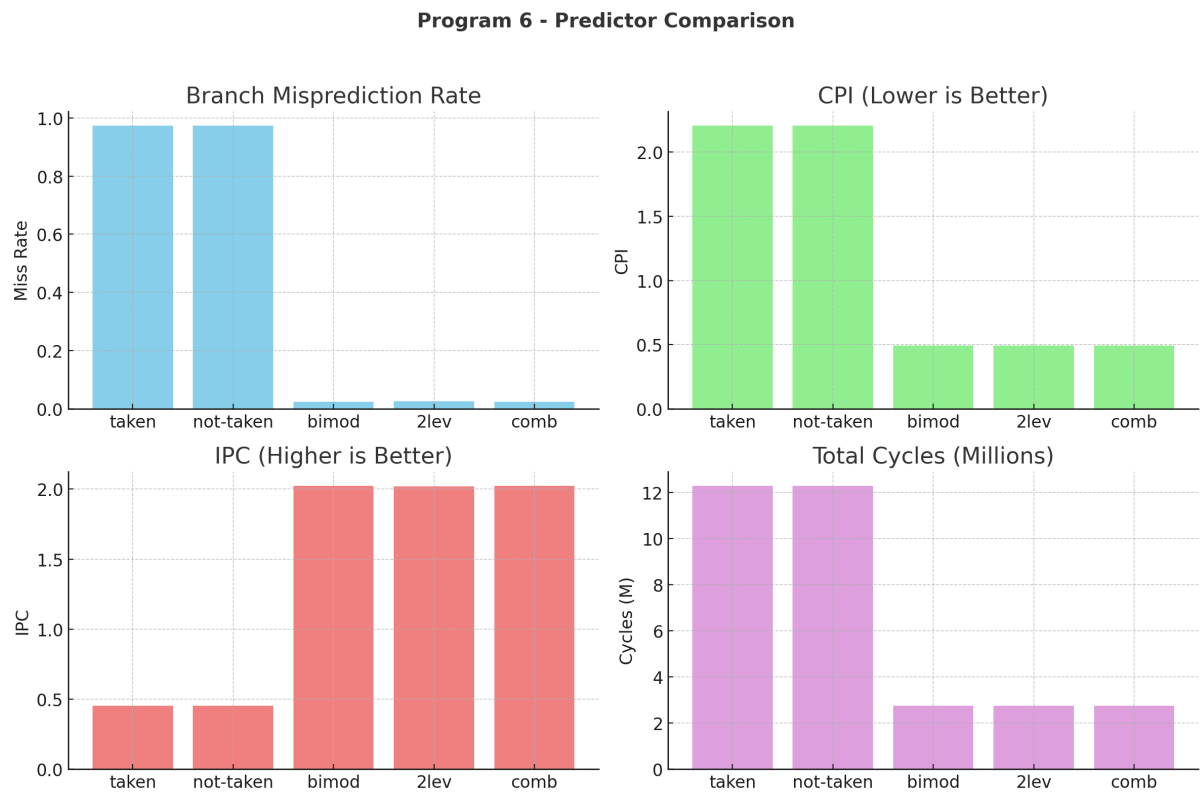
**Figure 4:** Program 4 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Program 5 — Predictor Comparison (Graphical Analysis)



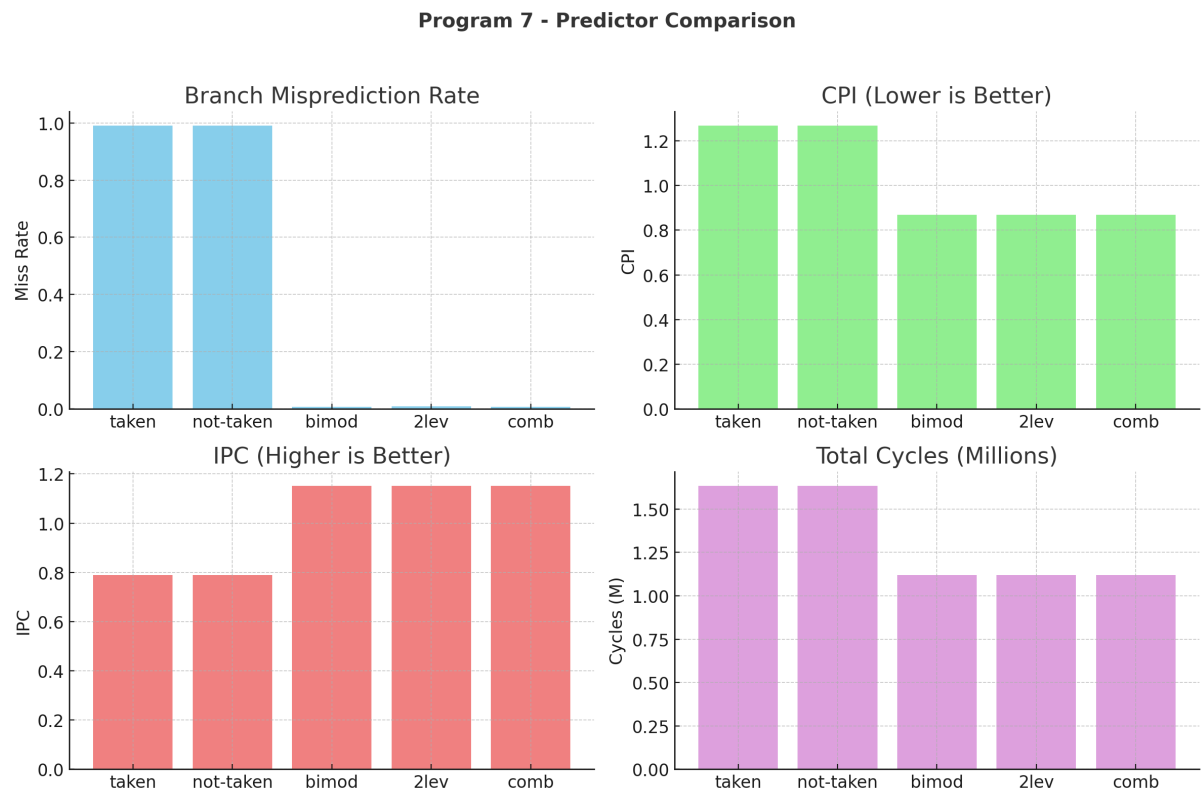
**Figure 5:** Program 5 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Program 6 — Predictor Comparison (Graphical Analysis)



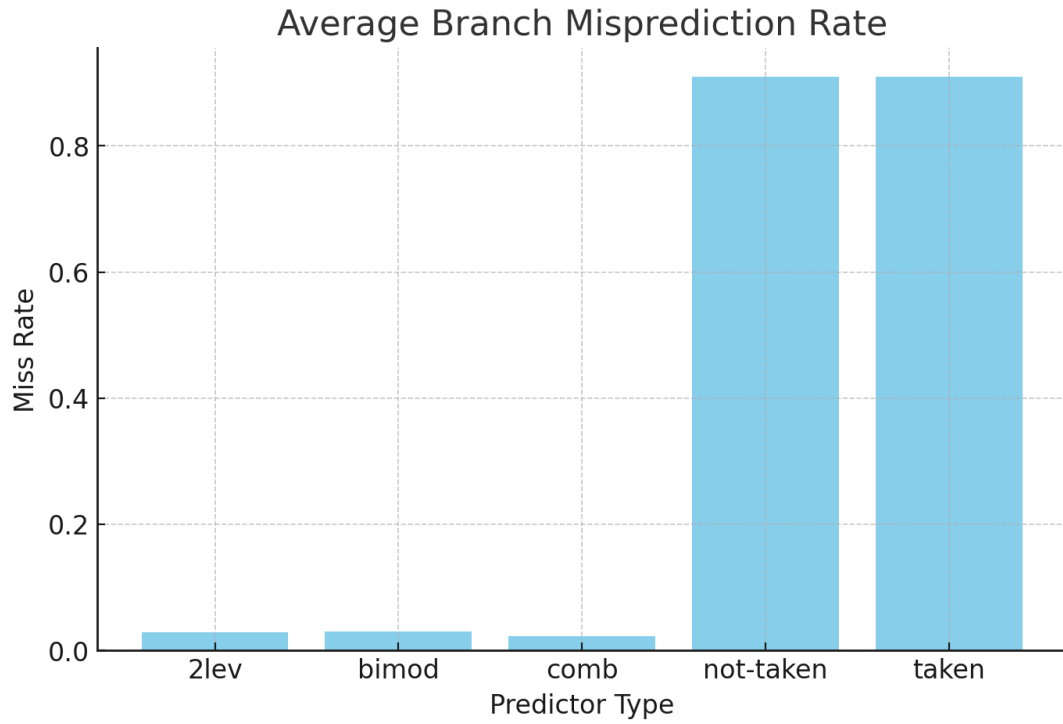
**Figure 6:** Program 6 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Program 7 — Predictor Comparison (Graphical Analysis)

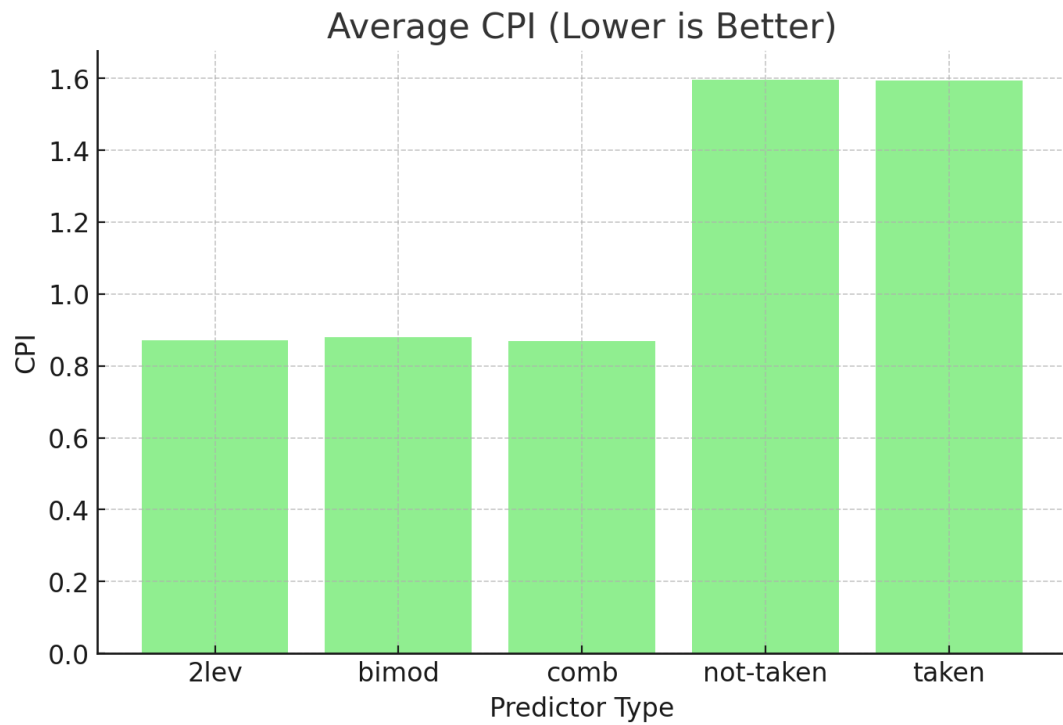


**Figure 7:** Program 7 — Predictor Comparison showing Branch Misprediction Rate, CPI, IPC, and Total Cycles.

## Aggregate Predictor Performance (Across All Programs)

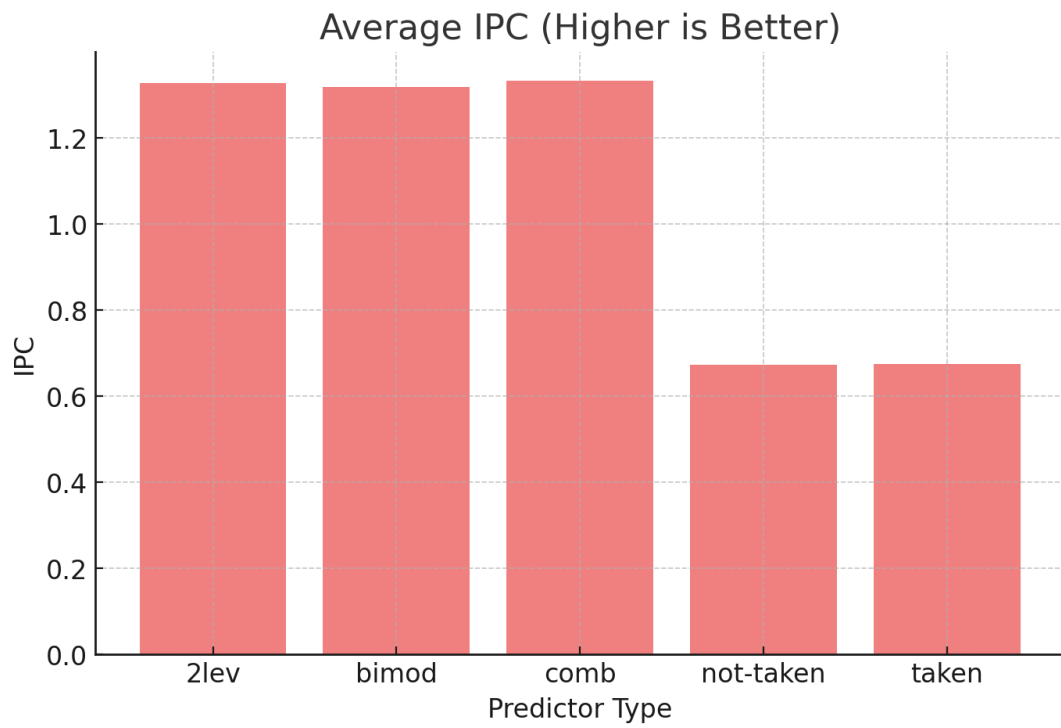


**Figure 8:** Average Branch Misprediction Rate across all predictors (Lower is Better).

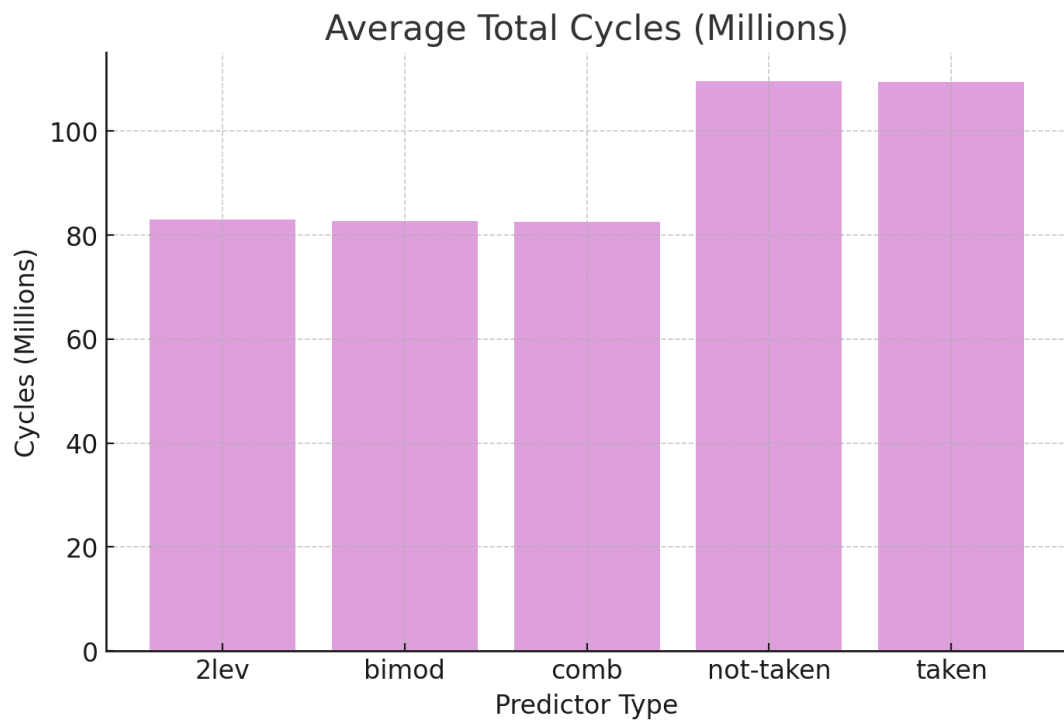


**Figure 9:** Average CPI across all predictors (Lower is Better).





**Figure 10:** Average IPC across all predictors (Higher is Better).



**Figure 11:** Average Total Cycles across all predictors (Lower is Better).

## 0.8 Discussion

### Detailed Analysis

**Branch Misprediction Rate:** Static predictors (taken, not-taken) performed the worst with misprediction rates  $> 90\%$  across all benchmarks. Dynamic predictors (bimod, 2lev, comb) significantly reduced mispredictions, with comb achieving the lowest average miss rate (around  $\sim 1.4\%$ ).

**CPI:** Comb recorded the lowest average CPI, followed closely by 2lev; static predictors had high CPI due to frequent rollbacks.

**IPC:** Inversely related to CPI; comb achieved the highest IPC (around  $\sim 1.20$ ).

**Total Cycles:** Comb consistently finished with the fewest cycles, followed by bimod; static predictors consumed roughly  $2\text{--}3\times$  more cycles.

### Overall Trends

- **comb (hybrid):** Lowest miss rate, lowest CPI, highest IPC, minimum cycles.
- **bimod:** Competitive on regular workloads; slightly weaker on complex patterns.
- **2lev:** Good accuracy; slightly higher CPI than comb overall.
- **taken / not-taken:** Baselines with poor accuracy.

## 0.9 Conclusion

The hybrid (comb) branch predictor provides the best trade-off between accuracy, throughput, and efficiency for compute-intensive workloads in the SimpleScalar `sim-outorder` environment. It should be adopted as the default configuration (`-bpred comb`) for general ACA lab experiments and architectural performance evaluations.

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