Supplementary material

for paper "Multi-Metric Algorithmic Complexity: Beyond Asymptotic Analysis", Kavun Sergii

Table 1. Comprehensive summary report

Metric	Value	Metric	Value
Analysis Timestamp	Linux-6.1.123+-x86_64-with-glibc2.35	Best Algo (Constant_O(1)_Formula) - CU	17
Architecture	x86_64	Best Algo (Constant_O(1)_Formula) - EU	0.00148
Profile - Profile	RESEARCH	Best Algo (Constant_O(1)_Formula) - CO2	0.000498
Profile - Weights	{'CU': 0.4, 'EU': 0.3, 'CO2': 0.25, '\$': 0.05}	Best Algo (Constant_O(1)_Formula) - \$	0.000169
Profile - Description	Research/Academic - focused on performance wit	Best Algo (Constant_O(1)_Formula) - CU_normalized	100
Stat - Best Algorithm	Constant_O(1)_Formula	Best Algo (Constant_O(1)_Formula) - EU_normalized	100
Stat - Worst Algorithm	Sqrt_O(sqrt_n)_PrimalityTest	Best Algo (Constant_O(1)_Formula) - CO2_normalized	100
Stat - Average Composite Score	64.85	Best Algo (Constant_O(1)_Formula) - \$_normalized	100
Stat - Median Composite Score	77.76	Best Algo (Constant_O(1)_Formula) - COMPOSITE_SCORE	100
Stat - Composite Score Std	30.05	Best Algo (Constant_O(1)_Formula) - SCORE_GRADE	A +

Metric	Value	Metric Value
Stat - Score Range	100.00	Best Algo (Constant_O(1)_Formula) - Excellent
Recommendation #1	Analysis performed using 'RESEARCH' profile: R	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - CU 129
Recommendation #2	Use 'Constant_O(1)_Formula' for optimal perfor	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - EU 0.01115
Recommendation #3	Avoid 'Sqrt_O(sqrt_n)_PrimalityTest' due to po	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - CO2 0.003637
Recommendation #4	For energy-critical applications, consider 'Sq	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - \$ 0.001285
Recommendation #5	For environmentally conscious deployment, 'Sqr	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - CU_normalized 0
Recommendation #6	Large performance variation detected - conside	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - EU_normalized 0
Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - CO2_normalized	0	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - \$_normalized 0
Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - COMPOSITE_SCORE	0	Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - EFFICIENCY_RATING Poor

Metric	Value	Metric	Value
Worst Algo (Sqrt_O(sqrt_n)_PrimalityTest) - SCORE_GRADE	F		

Baseline for comparison is 'Constant_O(1)_Formula'.

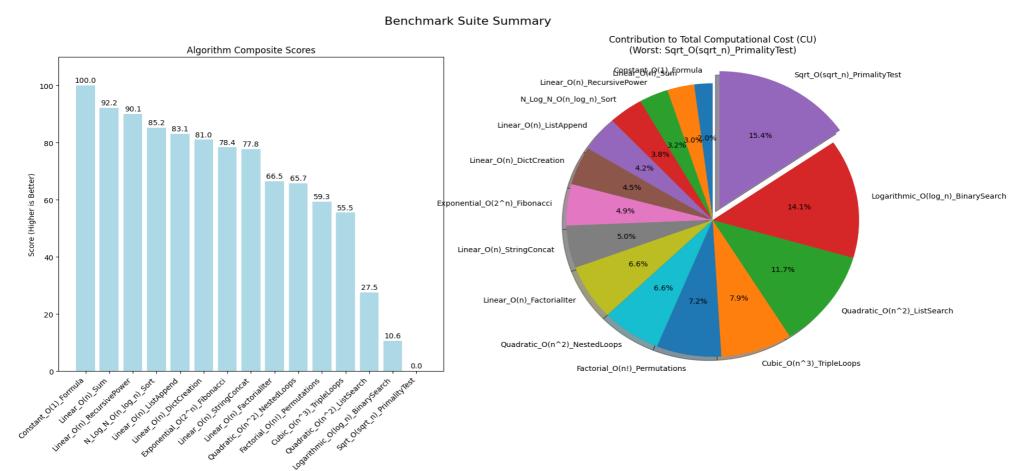


Fig. 1. Generating overall benchmark summary chart

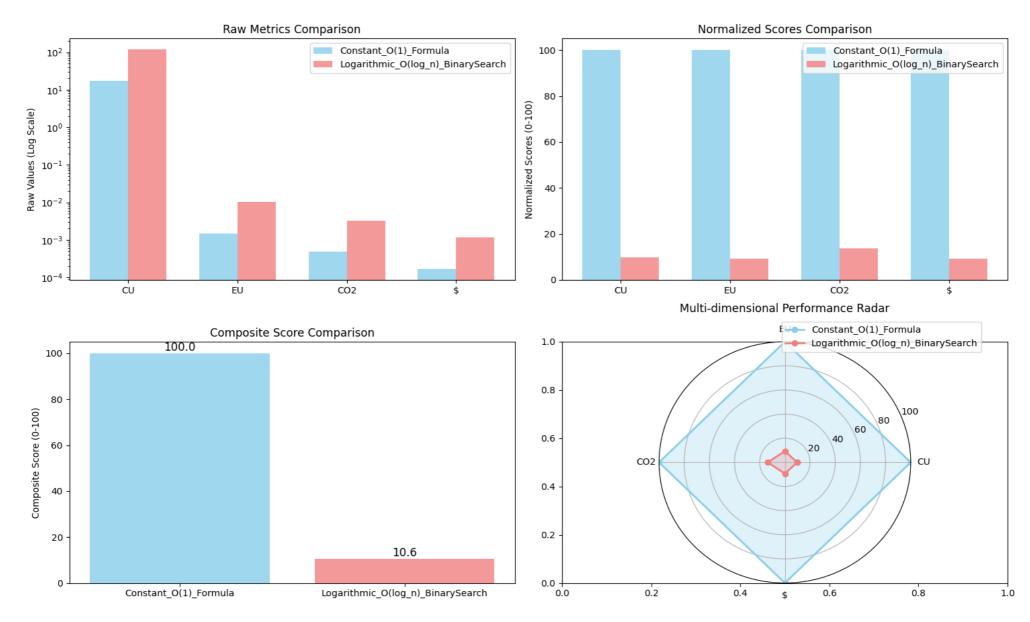


Fig. 2. Generating chart: comparison_Logarithmic_Olog_n_BinarySearch_vs_Constant_O1_Formula

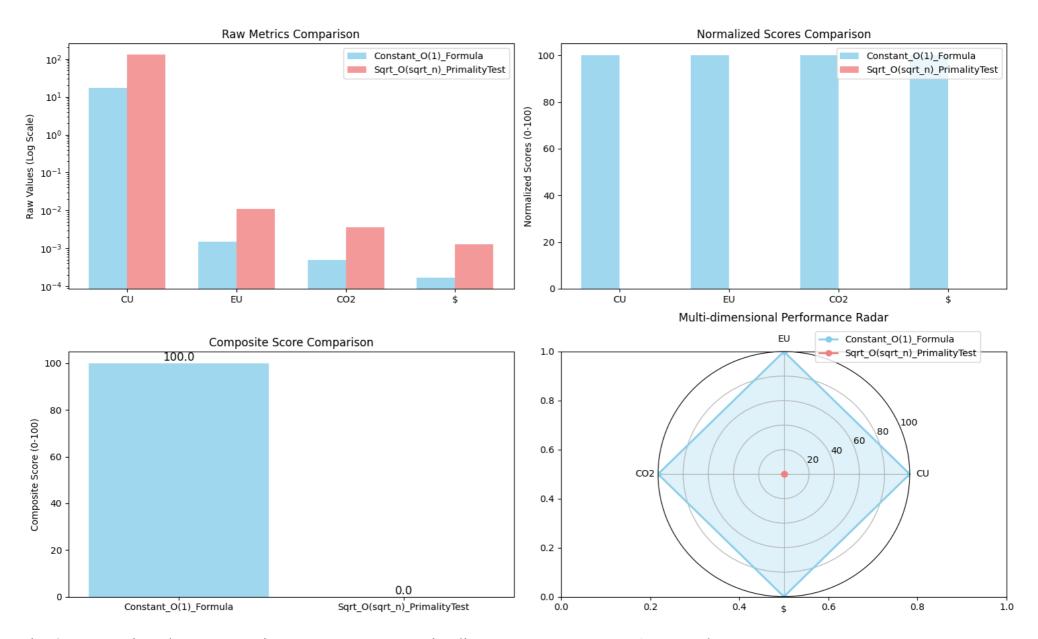


Fig. 3. Generating chart: comparison_Sqrt_Osqrt_n_PrimalityTest_vs_Constant_O1_Formula

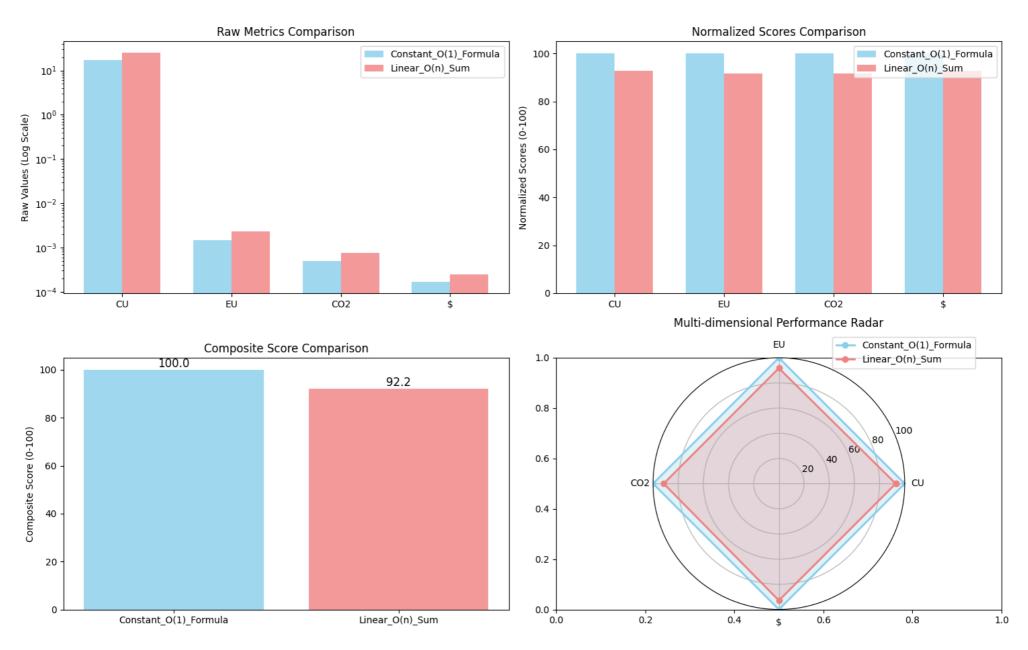


Fig. 4. Generating chart: comparison_Linear_On_Sum_vs_Constant_O1_Formula

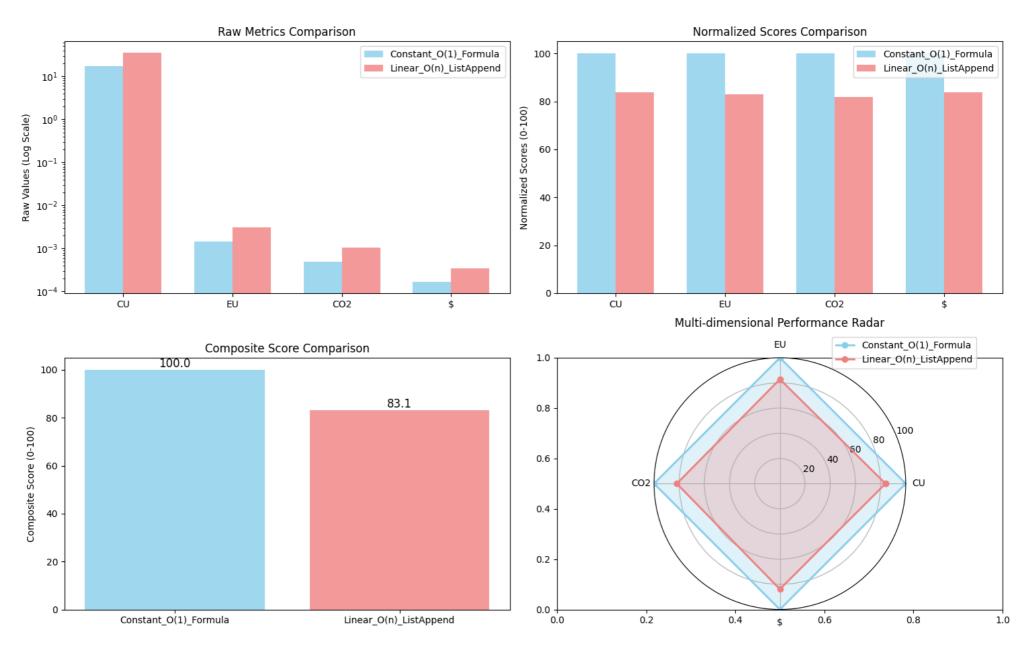


Fig. 5. Generating chart: comparison_Linear_On_ListAppend_vs_Constant_O1_Formula

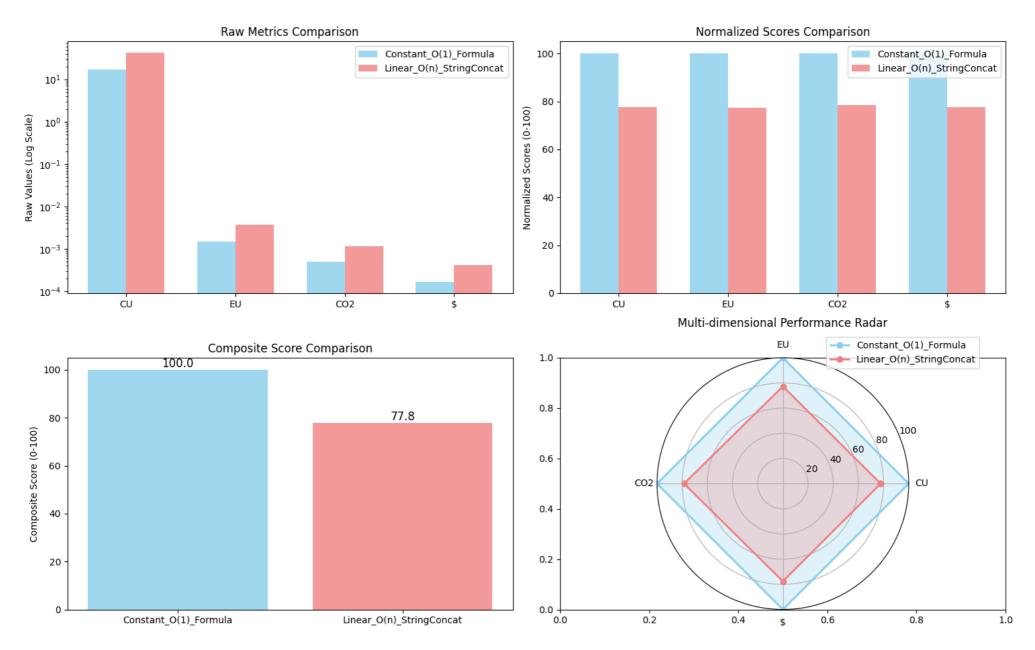


Fig. 6. Generating chart: comparison_Linear_On_StringConcat_vs_Constant_O1_Formula

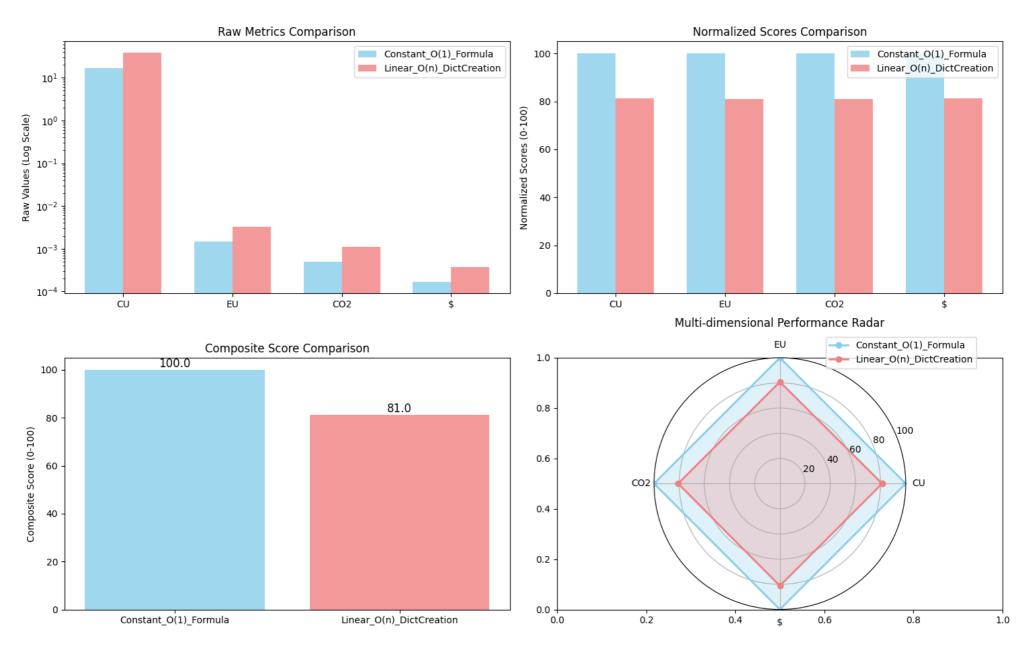


Fig. 7. Generating chart: comparison_Linear_On_DictCreation_vs_Constant_O1_Formula

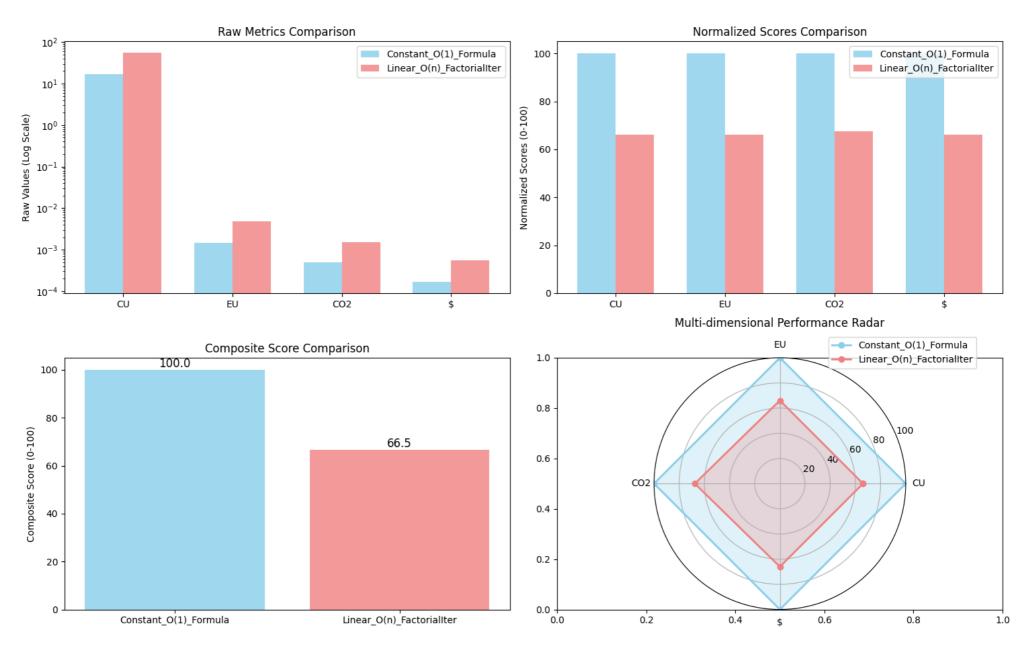


Fig. 8. Generating chart: comparison_Linear_On_FactorialIter_vs_Constant_O1_Formula

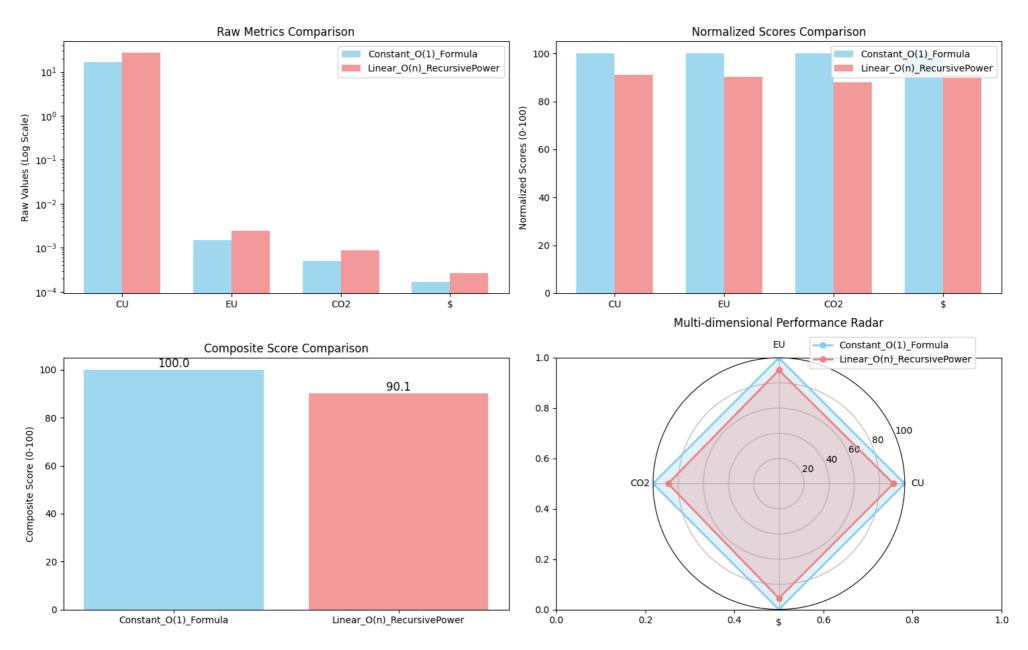


Fig. 9. Generating chart: comparison_Linear_On_RecursivePower_vs_Constant_O1_Formula

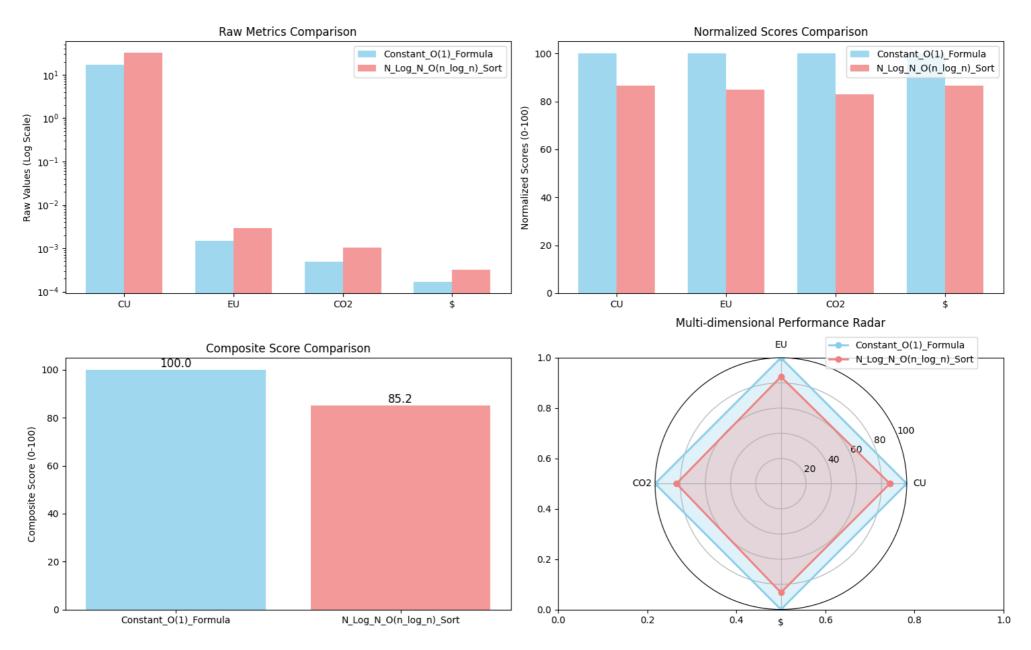


Fig. 10. Generating chart: comparison_N_Log_N_On_log_n_Sort_vs_Constant_O1_Formula

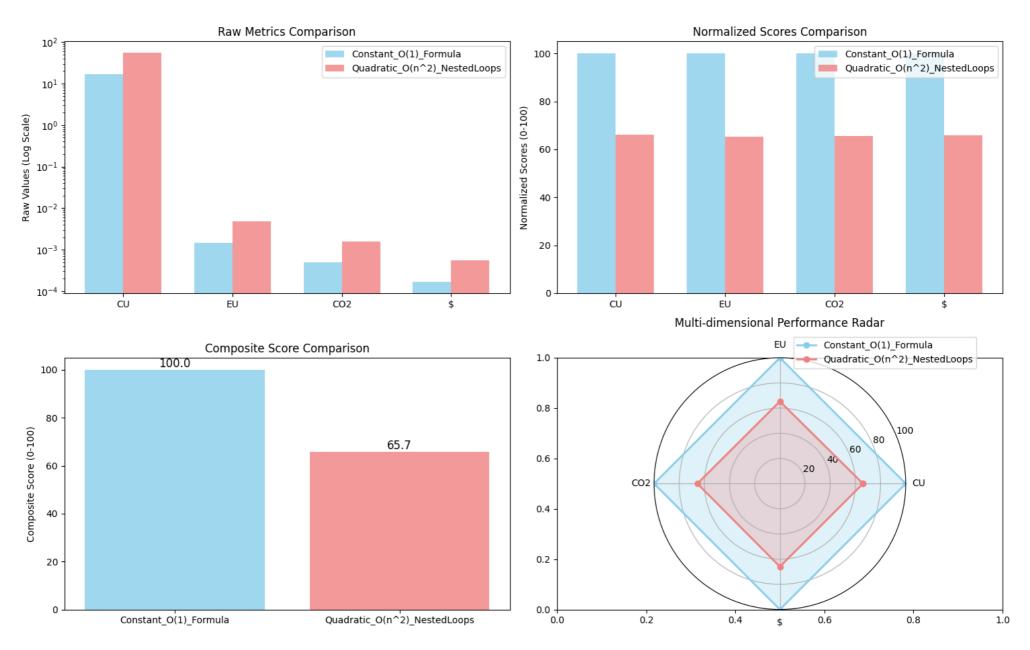


Fig. 11. Generating chart: comparison_Quadratic_On2_NestedLoops_vs_Constant_O1_Formula

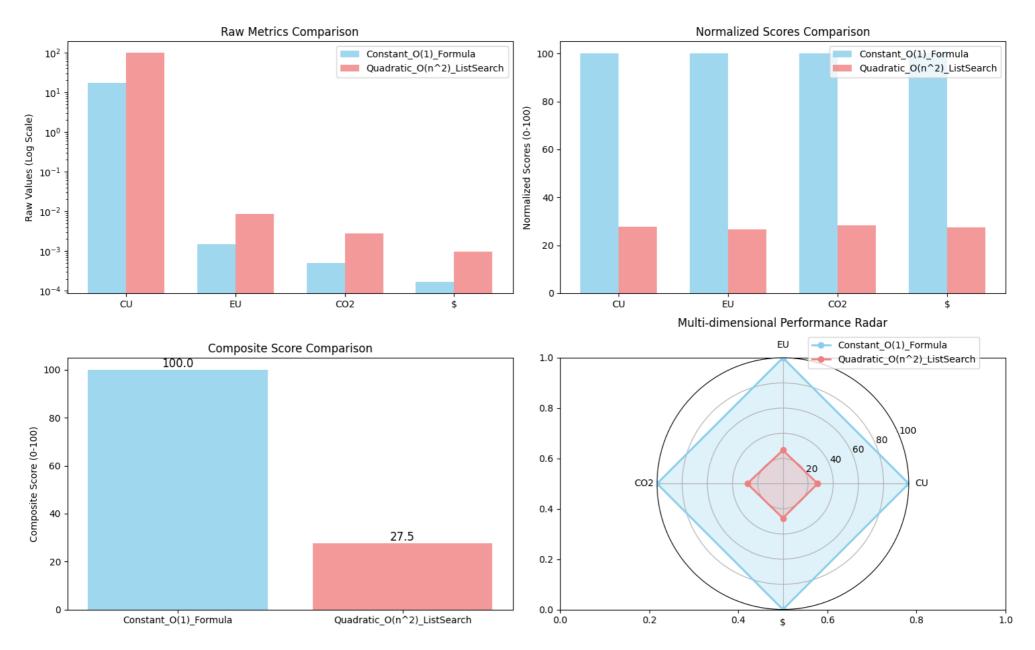


Fig. 12. Generating chart: comparison_Quadratic_On2_ListSearch_vs_Constant_O1_Formula

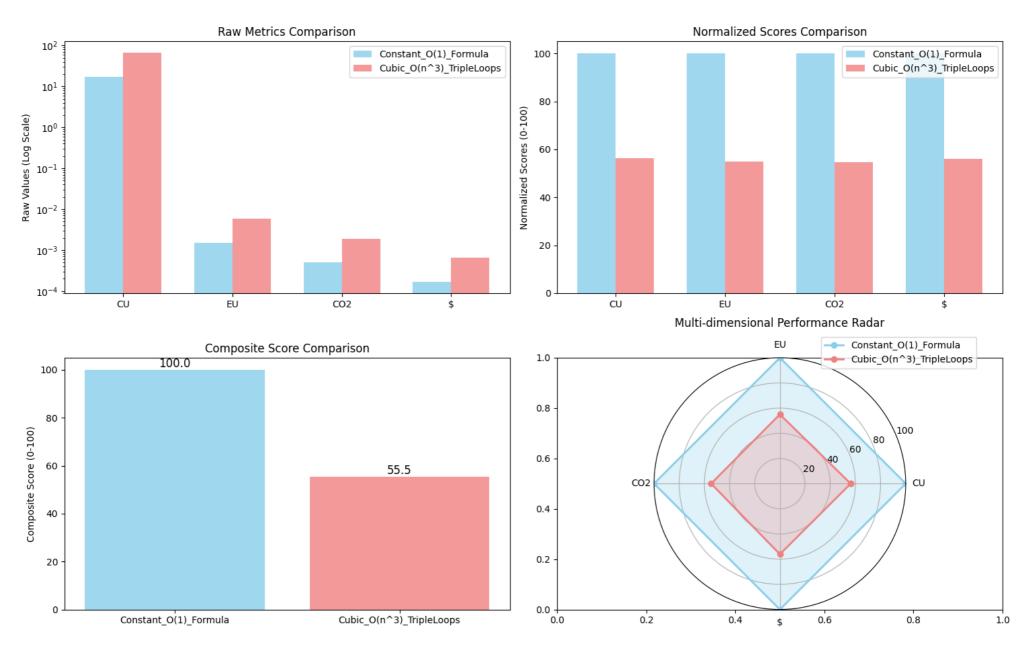


Fig. 13. Generating chart: comparison_Cubic_On3_TripleLoops_vs_Constant_O1_Formula

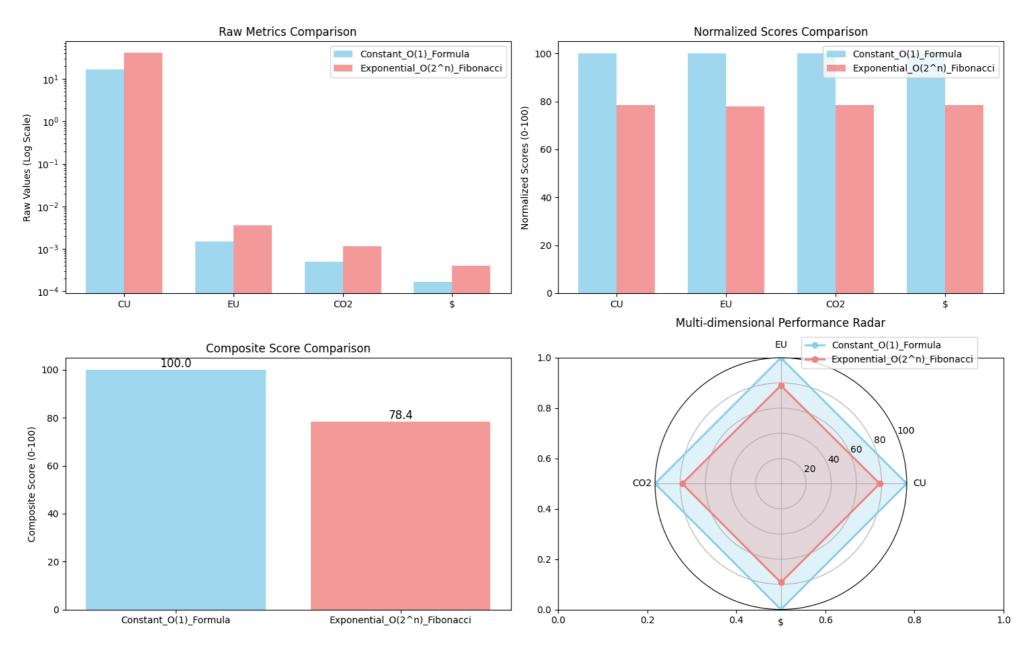


Fig. 14. Generating chart: comparison_Exponential_O2n_Fibonacci_vs_Constant_O1_Formula

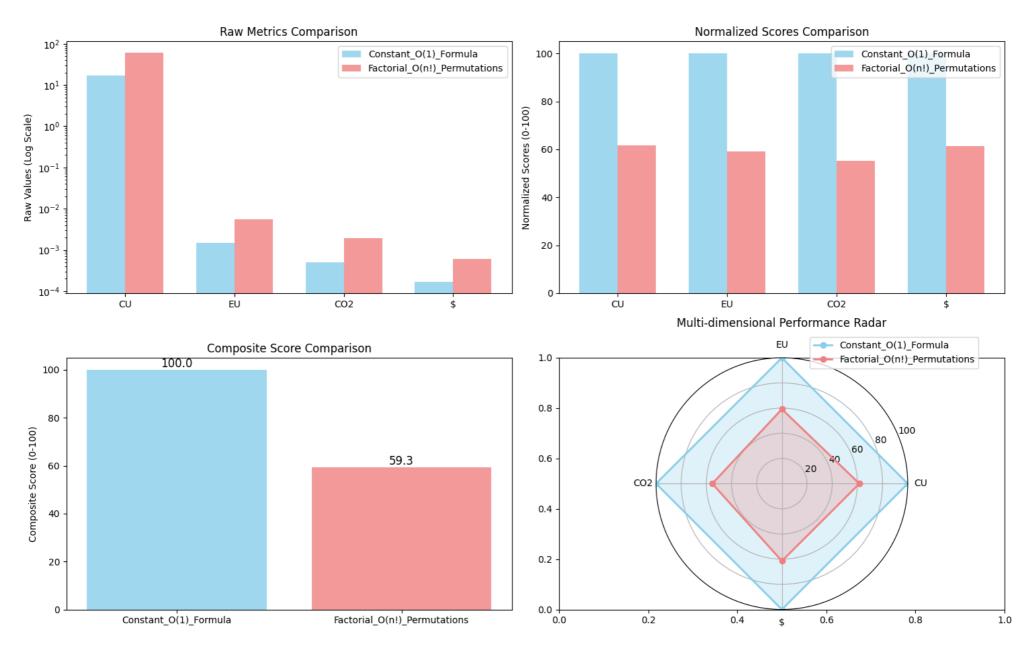


Fig. 15. Generating chart: comparison_Factorial_On_Permutations_vs_Constant_O1_Formula

Table 2. Analyzer configuration and environment

Configuration Parameter	Value
Detected Architecture	x86_64
Available Profiles	RESEARCH, COMMERCIAL, MOBILE, HPC, DEFAULT
Selected Profile	RESEARCH
Profile Description	Research/Academic - focused on performance with environmental awareness
Profile Weights	{'CU': 0.4, 'EU': 0.3, 'CO2': 0.25, '\$': 0.05}

Table 3. Enhanced algorithm analysis: full suite summary

Algorithm	CU	EU	CO ₂	\$	CU_nor m	EU_norm	CO2_nor m	\$_nor m	SCORE GRADE	EFFICIE NCY RATING	COMPOSI TE SCORE
Constant_O(1)_ Formula	17	0.001 48	0.0004 98	0.0001 69	100	100	100	100	A+	Excellen t	100
Linear_O(n)_ Sum	25	0.002 28	0.0007 63	0.0002 49	92.857 1	91.727	91.5578	92.83 15	A+	Excellen t	92.192
Linear_O(n)_ RecursivePower	27	0.002 43	0.0008 72	0.0002 69	91.071 4	90.1758	88.0854	91.03 94	A+	Excellen t	90.0546
N_Log_N_O(n_ log_n)_Sort	32	0.002 93	0.0010	0.0003 19	86.607 1	85.0052	82.9882	86.55 91	A	Excellen t	85.2194

Algorithm	CU	EU	CO ₂	\$	CU_nor m	EU_norm	CO2_nor m	\$_nor m	SCORE GRADE	EFFICIE NCY RATING	COMPOSI TE SCORE
Linear_O(n)_Li stAppend	35	0.003	0.0010 65	0.0003 49	83.928 6	82.9369	81.9369	83.87	A-	Good	83.1303
Linear_O(n)_Di ctCreation	38	0.003	0.0010 98	0.0003 79	81.25	80.8687	80.8856	81.18 28	A-	Good	81.0411
Exponential_O(2^n)_ Fibonacci	41	0.003 61	0.0011 75	0.0004 08	78.571 4	77.9731	78.4326	78.58 42	B+	Good	78.3579
Linear_O(n)_Str ingConcat	42	0.003 68	0.0011 72	0.0004 19	77.678 6	77.2492	78.5282	77.59 86	B+	Good	77.7582
Linear_O(n)_Fa ctorialIter	55	0.004 76	0.0015 15	0.0005 48	66.071 4	66.0807	67.6011	66.03 94	В-	Average	66.455
Quadratic_O(n^ 2)_NestedLoops	55	0.004 83	0.0015 79	0.0005 49	66.071 4	65.3568	65.5623	65.94 98	В-	Average	65.7237
Factorial_O(n!) _ Permutations	60	0.005 43	0.0019	0.0005 99	61.607	59.152	55.3042	61.46 95	С	Average	59.288
Cubic_O(n^3)_ TripleLoops	66	0.005 83	0.0019	0.0006 59	56.25	55.0155	54.6352	56.09 32	С	Average	55.4681
Quadratic_O(n^ 2)_ ListSearch	98	0.008 58	0.0027 48	0.0009 79	27.678 6	26.577	28.3211	27.41 94	F	Poor	27.4958
Logarithmic_O(log_n)_ BinarySearch	118	0.010 25	0.0032 09	0.0011 81	9.8214	9.30714	13.6349	9.319	F	Poor	10.5954

Algorithm	CU	EU	CO ₂	\$	CU_nor m	EU_norm	CO2_nor m	\$_nor m	SCORE GRADE	EFFICIE NCY RATING	COMPOSI TE SCORE
Sqrt_O(sqrt_n)_ PrimalityTest	129	0.011 15	0.0036 37	0.0012 85	0	0	0	0	F	Poor	0

	COMPOSITE_SCORE	Scor	e_vs_Best	CU_%_vs_Best	EU_%_vs_Best	CO2_%_vs_Best	\$_%_vs_Best
Algorithm							
Constant_O(1)_Formula	100.00		+0.00	+0.00%	+0.00%	+0.00%	+0.00%
Linear_O(n)_Sum	92.19		-7.81	+47.06%	+54.05%	+53.21%	+47.34%
Linear_O(n)_RecursivePower	90.05		-9.95	+58.82%	+64.19%	+75.10%	+59.17%
N_Log_N_O(n_log_n)_Sort	85.22		-14.78	+88.24%	+97.97%	+107.23%	+88.76%
Linear_O(n)_ListAppend	83.13		-16.87	+105.88%	+111.49%	+113.86%	+106.51%
Linear_O(n)_DictCreation	81.04		-18.96	+123.53%	+125.00%	+120.48%	+124.26%
Exponential_O(2^n)_Fibonacci	78.36		-21.64	+141.18%	+143.92%	+135.94%	+141.42%
Linear_O(n)_StringConcat	77.76		-22.24	+147.06%	+148.65%	+135.34%	+147.93%
Linear_O(n)_FactorialIter	66.46		-33.54	+223.53%	+221.62%	+204.22%	+224.26%
Quadratic_O(n^2)_NestedLoops	65.72		-34.28	+223.53%	+226.35%	+217.07%	+224.85%
Factorial_O(n!)_Permutations	59.29		-40.71	+252.94%	+266.89%	+281.73%	+254.44%
Cubic_O(n^3)_TripleLoops	55.47		-44.53	+288.24%	+293.92%	+285.94%	+289.94%
Quadratic_O(n^2)_ListSearch	27.50		-72.50	+476.47%	+479.73%	+451.81%	+479.29%
Logarithmic_O(log_n)_BinarySearch	10.60		-89.40	+594.12%	+592.57%	+544.38%	+598.82%
Sqrt_O(sqrt_n)_PrimalityTest	0.00		-100.00	+658.82%	+653.38%	+630.32%	+660.36%

Fig. 16. Detailed comparison against the best performing algorithm (Baseline algorithm (highest score): 'Constant_O(1)_Formula')

Let the following lists for "Function Names":

List_1 (complexity_cost_profiler.py) = [CostAnalyzer.__init__, CostAnalyzer.analyze_function, CostAnalyzer.analyze_llvm_ir,

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InstructionCostModel. load weights, InstructionCostModel.get cost]
List 2 (custom imputer.py) = [KZImputer. getstate , KZImputer. init , KZImputer. repr , KZImputer. setstate ,
KZImputer. sklearn clone , KZImputer. sklearn tags , KZImputer. check feature names, KZImputer. check n features,
KZImputer. find nan blocks, KZImputer. get doc link, KZImputer. get metadata request, KZImputer. get tags,
KZImputer. impute 1 gap, KZImputer. impute 2 gap, KZImputer. impute 3 gap, KZImputer. impute 4 gap,
KZImputer. impute 5 gap, KZImputer. impute series, KZImputer. more tags, KZImputer. repr html inner,
KZImputer. repr mimebundle, KZImputer. validate data, KZImputer. validate params, KZImputer.evaluate metrics,
KZImputer.fit, KZImputer.fit transform, KZImputer.generate synthetic gaps, KZImputer.get metadata routing,
KZImputer.get params, KZImputer.impute gap, KZImputer.impute gap old, KZImputer.set output, KZImputer.set params,
KZImputer.transform]
List 3 (complexity cost profiler en.py) = [CompositeScoreCalculator. init , CompositeScoreCalculator. get efficiency rating,
CompositeScoreCalculator. get profile description, CompositeScoreCalculator. get score grade,
CompositeScoreCalculator. z to percentile, CompositeScoreCalculator.calculate composite score,
CompositeScoreCalculator.get profile info, CompositeScoreCalculator.normalize metric,
CompositeScoreCalculator.update reference values, EnhancedCostAnalyzer. init ,
EnhancedCostAnalyzer. calculate benchmark stats, EnhancedCostAnalyzer.analyze function,
EnhancedCostAnalyzer.analyze llvm ir, EnhancedCostAnalyzer.analyze ptx, EnhancedCostAnalyzer.benchmark suite,
EnhancedCostAnalyzer.compare functions, EnhancedCostAnalyzer.fetch carbon intensity, InstructionCostModel. init ,
InstructionCostModel. get bytecode mapping, InstructionCostModel. get default cost model,
InstructionCostModel. load weights, InstructionCostModel.get cost, create benchmark summary chart,
create enhanced comparison chart, generate recommendations, main, save enhanced csv
List 4 (ds tool.py) = [CorrelationConfig. copy , CorrelationConfig. deepcopy , CorrelationConfig. delattr ,
CorrelationConfig. eq , CorrelationConfig. getattr , CorrelationConfig. getstate , CorrelationConfig. init ,
CorrelationConfig. iter , CorrelationConfig. pretty , CorrelationConfig. replace , CorrelationConfig. repr ,
CorrelationConfig. repr args , CorrelationConfig. repr name , CorrelationConfig. repr recursion ,
CorrelationConfig. repr str , CorrelationConfig. rich repr , CorrelationConfig. setattr , CorrelationConfig. setstate ,
CorrelationConfig. str , CorrelationConfig. calculate keys, CorrelationConfig. copy and set values, CorrelationConfig. iter,
```

CostAnalyzer.analyze ptx, CostAnalyzer.compare functions, CostAnalyzer.fetch carbon intensity, InstructionCostModel. init,

```
CorrelationConfig. setattr handler, CorrelationConfig.copy, CorrelationConfig.dict, CorrelationConfig.json,
CorrelationConfig.model copy, CorrelationConfig.model dump, CorrelationConfig.model dump json,
CorrelationConfig.model post init, DSTools. init, DSTools.add missing value features, DSTools.calculate entropy,
DSTools.calculate kl divergence, DSTools.category stats, DSTools.chatterjee correlation, DSTools.check NINF,
DSTools.compute metrics, DSTools.corr matrix, DSTools.describe categorical, DSTools.describe numeric, DSTools.df stats,
DSTools.evaluate classification, DSTools.function list, DSTools.generate alphanum codes, DSTools.generate distribution,
DSTools.generate distribution from metrics, DSTools.grubbs test, DSTools.labeling, DSTools.min max scale,
DSTools.plot confusion matrix, DSTools.read dataframes from zip, DSTools.remove outliers iqr,
DSTools.save dataframes to zip, DSTools.sparse calc, DSTools.stat normal testing, DSTools.test stationarity,
DSTools.trials res df, DSTools.validate moments, DistributionConfig. copy , DistributionConfig. deepcopy ,
DistributionConfig. delattr , DistributionConfig. eq , DistributionConfig. getattr , DistributionConfig. getstate ,
DistributionConfig. init , DistributionConfig. iter , DistributionConfig. pretty , DistributionConfig. replace ,
DistributionConfig. repr , DistributionConfig. repr args , DistributionConfig. repr name ,
DistributionConfig. repr recursion , DistributionConfig. repr_str_, DistributionConfig. rich_repr_,
DistributionConfig. setattr , DistributionConfig. setstate , DistributionConfig. str , DistributionConfig. calculate keys,
DistributionConfig. copy and set values, DistributionConfig. iter, DistributionConfig. setattr handler, DistributionConfig.copy,
DistributionConfig.dict, DistributionConfig.json, DistributionConfig.model copy, DistributionConfig.model dump,
DistributionConfig.model dump json, DistributionConfig.model post init, DistributionConfig.validate max greater than min,
GrubbsTestResult. copy , GrubbsTestResult. deepcopy , GrubbsTestResult. delattr , GrubbsTestResult. eq ,
GrubbsTestResult. getattr , GrubbsTestResult. init , GrubbsTestResult. iter ,
GrubbsTestResult. pretty , GrubbsTestResult. repr args , GrubbsTestResult. repr args ,
GrubbsTestResult. repr name , GrubbsTestResult. repr recursion , GrubbsTestResult. repr str ,
GrubbsTestResult. rich repr , GrubbsTestResult. setattr , GrubbsTestResult. setstate , GrubbsTestResult. str ,
GrubbsTestResult. calculate keys, GrubbsTestResult. copy and set values, GrubbsTestResult. iter,
GrubbsTestResult. setattr handler, GrubbsTestResult.copy, GrubbsTestResult.dict, GrubbsTestResult.json,
GrubbsTestResult.model copy, GrubbsTestResult.model dump, GrubbsTestResult.model dump json,
GrubbsTestResult.model post init, MetricsConfig. copy , MetricsConfig. deepcopy , MetricsConfig. delattr ,
MetricsConfig. eq , MetricsConfig. getattr , MetricsConfig. getstate , MetricsConfig. init , MetricsConfig. iter ,
MetricsConfig. pretty , MetricsConfig. replace , MetricsConfig. repr , MetricsConfig. repr args ,
MetricsConfig. repr name , MetricsConfig. repr recursion , MetricsConfig. repr str , MetricsConfig. rich repr ,
```

MetricsConfig.__setattr__, MetricsConfig.__setstate__, MetricsConfig.__str__, MetricsConfig._calculate_keys,
MetricsConfig._copy_and_set_values, MetricsConfig._iter, MetricsConfig._setattr_handler, MetricsConfig.copy, MetricsConfig.dict,
MetricsConfig.json, MetricsConfig.model_copy, MetricsConfig.model_dump, MetricsConfig.model_dump_json,
MetricsConfig.model_post_init, OutlierConfig.__copy__, OutlierConfig.__deepcopy__, OutlierConfig.__delattr__,
OutlierConfig.__eq__, OutlierConfig.__getattr__, OutlierConfig.__getstate__, OutlierConfig.__init__, OutlierConfig.__iter__,
OutlierConfig.__pretty__, OutlierConfig.__replace__, OutlierConfig.__repr__, OutlierConfig.__repr_args__,
OutlierConfig.__repr_name__, OutlierConfig.__repr_recursion__, OutlierConfig.__repr_str__, OutlierConfig.__rich_repr__,
OutlierConfig.__setattr__, OutlierConfig.__setstate__, OutlierConfig.__str__, OutlierConfig._calculate_keys,
OutlierConfig._copy_and_set_values, OutlierConfig._iter, OutlierConfig._setattr_handler, OutlierConfig.copy, OutlierConfig.dict,
OutlierConfig.json, OutlierConfig.model_copy, OutlierConfig.model_dump_json,
OutlierConfig.model_post_init]

List_5 (s3_act_function.py) = [_compute_activation, _compute_derivative, smooth_s3_activation]

Table 4. Analysis of external source files (LLVM, PTX, PY)

File Name	File Type	Function Name	COMPOSITE SCORE	SCORE GRADE	CU	EU	CO2	\$
test.ptx	PTX GPU	-	99.4093	A+	15	0.0015	0.00075	0.00015
file_io.ll	LLVM IR	-	98.2849	A+	42	0.004	0.001641	0.00042
fibonacci.ll	LLVM IR	-	96.172	A+	93	0.0083	0.002939	0.00093
str_cat.ll	LLVM IR	-	92.1819	A+	189	0.01705	0.005821	0.00189
s4_act_function.py	Python	s4	89.8761	A	245	0.02121	0.006749	0.002448

File Name	File Type	Function Name	COMPOSITE SCORE	SCORE GRADE	CU	EU	CO2	\$
generate_instr_models.py	Python	enrich, generate_models	87.9534	A	291	0.02563	0.008528	0.00291
s3_act_function.py	Python	List_5	87.6258	A	299	0.02627	0.008592	0.002986
matrixMul_kernel_32.ptx	PTX GPU	-	74.2815	В	612	0.0612	0.0306	0.00612
complexity_cost_profiler.py	Python	List_1	62.6856	C+	898	0.08056	0.028342	0.008977
custom_imputer.py	Python	List_2	50.0176	C-	6611	0.58633	0.196669	0.066143
complexity_cost_profiler_en.py	Python	List_3	49.524	D	6941	0.61612	0.206337	0.069394
ds_tool.py	Python	List_4	29.7495	F	24725	2.20735	0.745148	0.247147

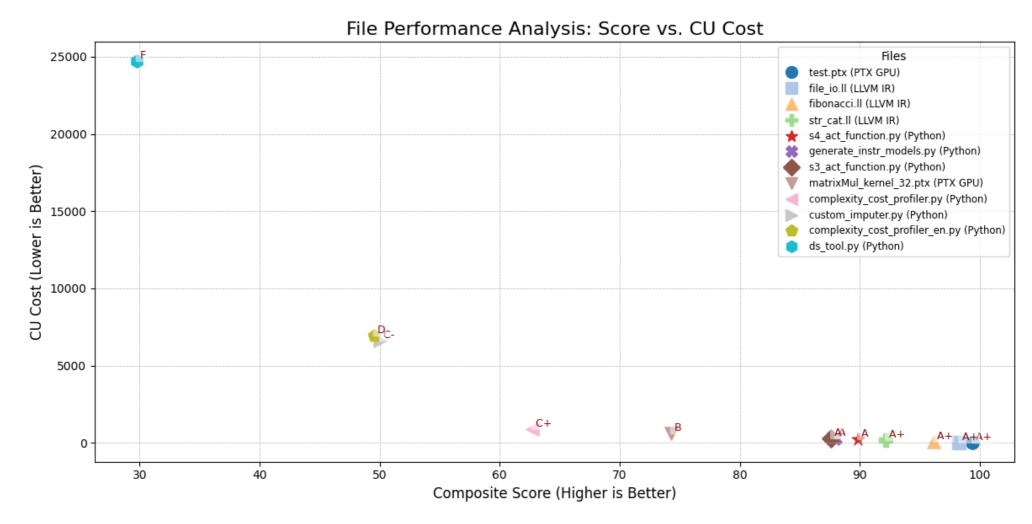


Fig. 17. Displaying top 12 files sorted by COMPOSITE_SCORE (for CU-metric, based on Table 4)

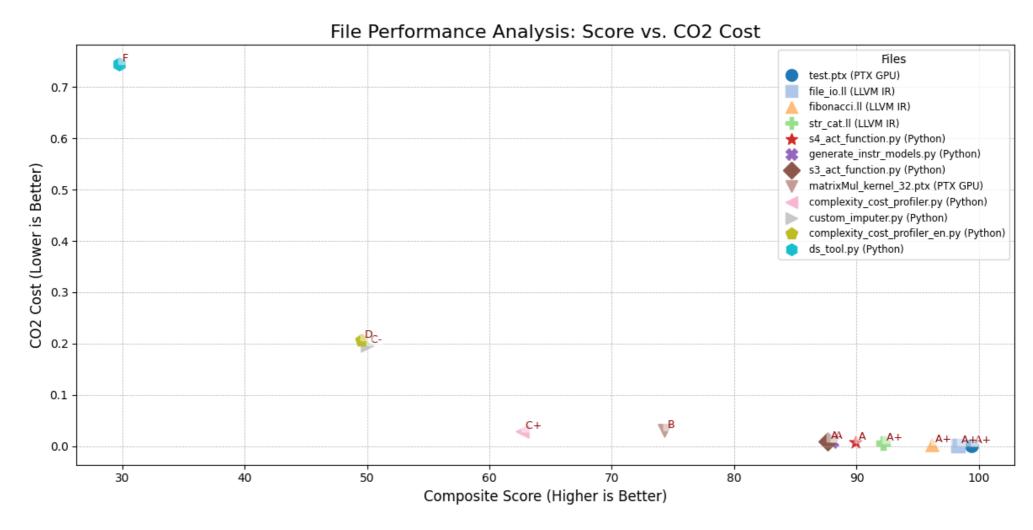


Fig. 18. Displaying top 12 files sorted by COMPOSITE_SCORE (for CO₂-metric, based on Table 4)

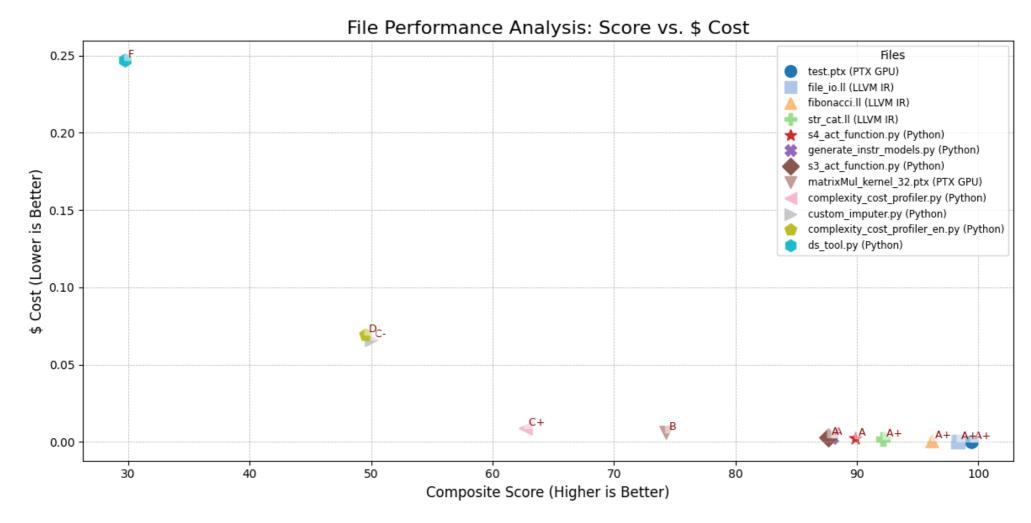


Fig. 19. Displaying top 12 files sorted by COMPOSITE_SCORE (for \$-metric, based on Table 4)

Table 5. Analysis of external repository (LLVM, PTX, PY): aggregated assessment for repository: 'kz_data_imputation' [1]

PROFILE NAME	File Type	Function Name	COMPOSITE_SCORE	SCORE_GRADE	CU	EU	CO2	\$
RESEARCH	Python (12)	89	42.23	D	12,607	1.1194	0.3763	0.1261
COMMERCIAL	Python (12)	89	30.24	F	12,607	1.1194	0.3763	0.1261
MOBILE	Python (12)	89	53.76	C-	12,607	1.1194	0.3763	0.1261
НРС	Python (12)	89	36.00	F	12,607	1.1194	0.3763	0.1261
DEFAULT	Python (12)	89	37.79	F	12,607	1.1194	0.3763	0.1261
TOTAL	All Files (12)	89	40.00	D	12,607	1.1194	0.3763	0.1261

Table 6. Analysis of external repository (LLVM, PTX, PY): aggregated assessment for repository: 'ds_tools' [1]

PROFILE NAME	File Type	Function Name	COMPOSITE_SCORE	SCORE_GRADE	CU	EU	CO2	\$
RESEARCH	Python (30)	272	22.58	F	31,540	2.8188	0.9585	0.3152
COMMERCIAL	Python (30)	272	15.19	F	31,540	2.8188	0.9585	0.3152
MOBILE	Python (30)	272	36.53	F	31,540	2.8188	0.9585	0.3152
НРС	Python (30)	272	22.17	F	31,540	2.8188	0.9585	0.3152
DEFAULT	Python (30)	272	18.99	F	31,540	2.8188	0.9585	0.3152
TOTAL	All Files (30)	272	23.09	F	31,540	2.8188	0.9585	0.3152

File Performance Analysis: Score vs. CU Cost Files MOBILE (Python (12)) 13200 RESEARCH (Python (12)) TOTAL (All Files (12)) DEFAULT (Python (12)) HPC (Python (12)) 13000 COMMERCIAL (Python (12)) CU Cost (Lower is Better) 12800 **√**F D D 12600 12400 12200 12000

Composite Score (Higher is Better)

50

Fig. 20. Displaying repo performance analysis result (for CU-metric, based on Table 5) for all profiles

35

30



Fig. 21. Displaying repo performance analysis result (for CU-metric, based on Table 6) for all profiles

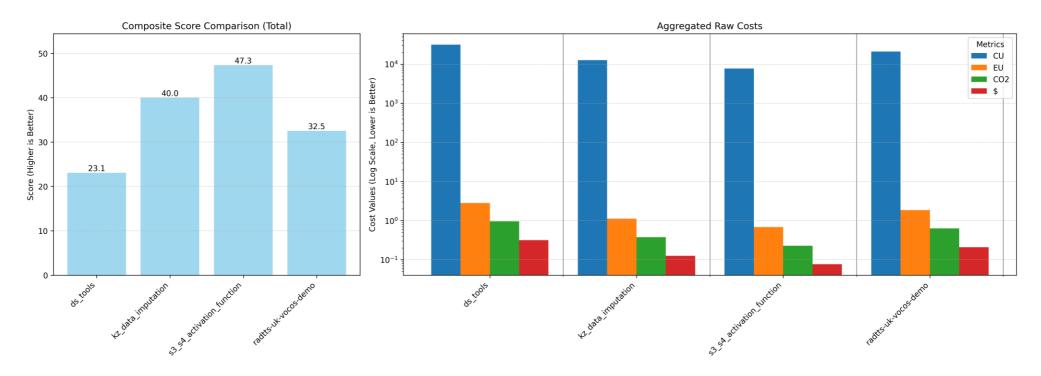


Fig. 22. Displaying repo performance analysis result (for 4 repositories) for all profiles

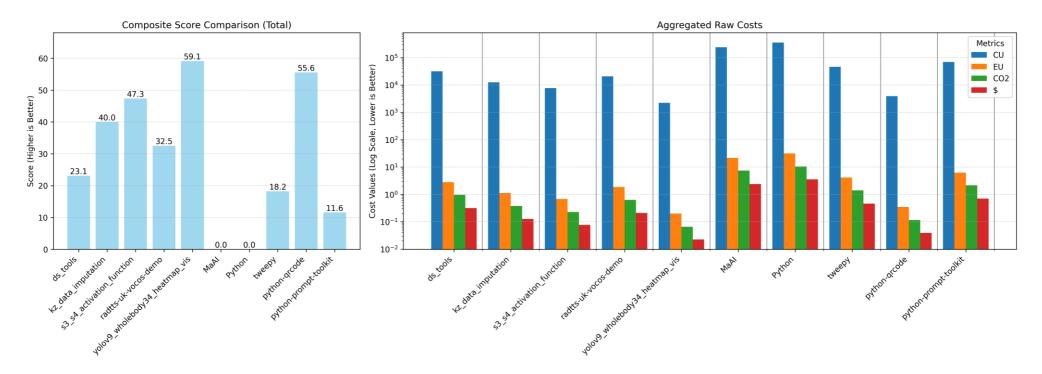


Fig. 23. Displaying repo performance analysis result (for 10 repositories) for all profiles

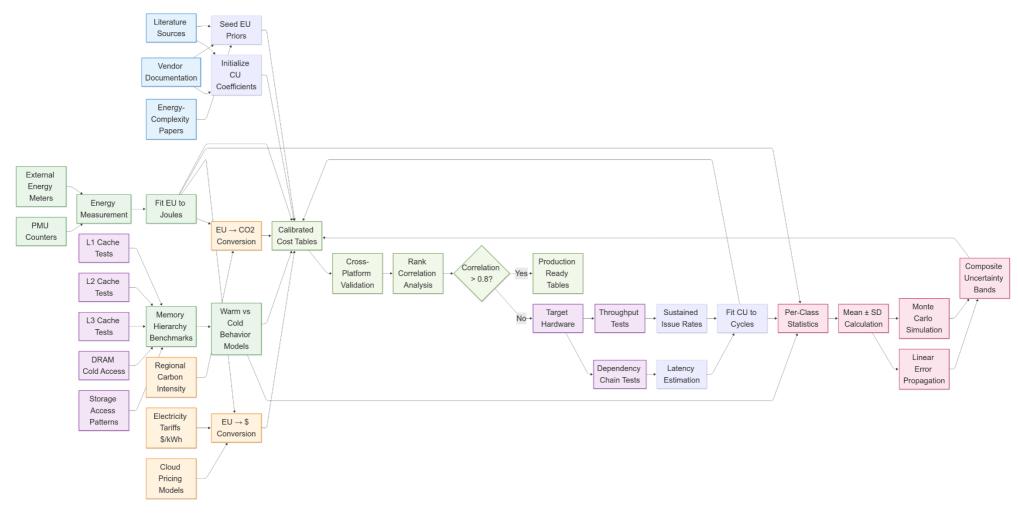


Fig. 24. Multi-architecture calibration protocol architecture

The diagram shows:

1. Five Main Phases: literature priors (blue) - initial coefficient seeding from academic sources; microbenchmarking (purple) - hardware-specific latency and throughput testing; memory hierarchy (green) - cache behavior characterization across levels; dimension mapping (orange) - converting energy to CO₂ and monetary costs; uncertainty quantification (pink) - statistical analysis and error propagation.

- 2. Key Features: validation loop with correlation thresholds for quality assurance; multiple measurement sources (PMU, external meters, various cache levels); regional/temporal factors (carbon intensity, electricity pricing); statistical rigor (mean±SD, error propagation, Monte Carlo); production readiness gate based on validation results.
- 3. Color-coded components make it easy to follow different aspects: literature sources and documentation; hardware testing and measurement; energy/performance data collection; cost dimension conversions; statistical analysis steps; final output and validation.

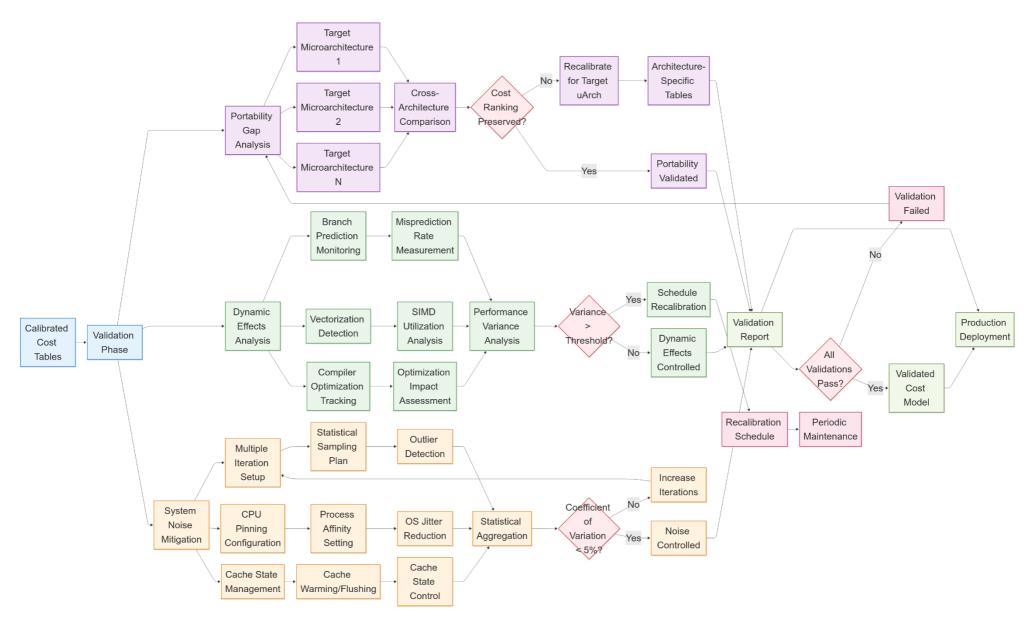


Fig. 25. Comprehensive validation phase diagram

The diagram shows:

- 1. Three parallel validation streams: portability gap analysis (purple); cross-architecture comparison testing; ranking preservation validation; architecture-specific recalibration when needed.
- 2. Dynamic effects monitoring (green): branch prediction, vectorization, and compiler tracking; performance variance analysis with thresholds; scheduled recalibration for significant changes.
- 3. System noise control (orange): multiple iterations and statistical sampling; cpu pinning and process affinity management; cache state control and outlier detection.
- 4. Key validation features: quality gates with specific thresholds (cv < 5%, ranking preservation); feedback loops for iterative improvement; decision points that trigger recalibration or additional testing; production readiness assessment combining all validation streams.
- 5. Practical implementation: statistical rigor with coefficient of variation checks; automated monitoring of dynamic effects; systematic approach to noise reduction; clear pass/fail criteria for each validation aspect.
- 6. Output pathways: validated cost models ready for production; recalibration schedules for maintenance; architecture-specific tables when portability fails.

Validation methodology (Model Validation Charts)

The charts presented below provide a visual assessment of the predictive accuracy of our static cost model compared to simulated "measured" hardware performance. Each chart plots the **Predicted Values** from a model (on the Y-axis) against the **Measured Values** (on the X-axis) for a diverse set of algorithmic workloads.

How to Interpret the Charts:

- Data Points (Blue Circles): Each point represents a single algorithm from our benchmark suite. Its position shows the relationship between what the model *predicted* and what was *measured*.
- Ideal y = x Line (Black, Solid): This is the line of perfect prediction. If a data point falls directly on this line, it means the model's prediction was 100% accurate. The goal is for all data points to cluster as tightly as possible around this line.
- Linear Fit (Red, Dashed): This line shows the actual linear trend of the predictions. A fit line that is steep and closely aligned with the "Ideal Line" indicates a strong, positive correlation, meaning the model correctly captures the performance trend (i.e., if one algorithm is twice as expensive as another, the model predicts this ratio correctly).

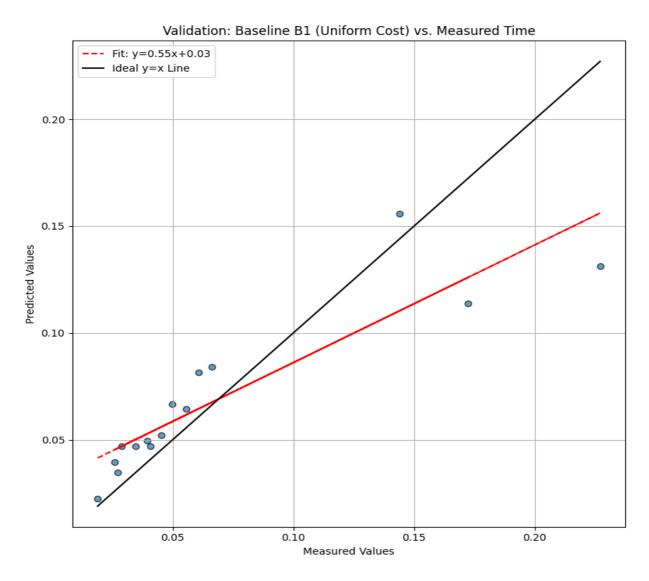


Fig. 26. Validation: Baseline B1 (Uniform Cost) vs. Measured Time: this chart evaluates a naive model where all instructions are assumed to have the same cost. A wide scatter of points, especially for memory-bound tasks, demonstrates the limitations of ignoring instruction-specific weights.

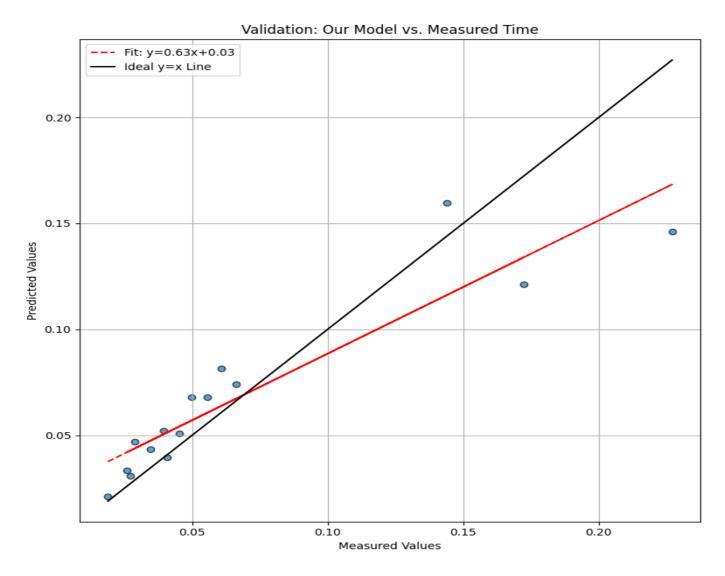


Fig. 26. Validation: Our Model vs. Measured Time: this chart shows the performance of our primary, architecture-aware static model. A tight clustering of points around the ideal line signifies high accuracy and a strong ability to rank algorithms correctly across different workload types (compute-bound, memory-bound, etc.).

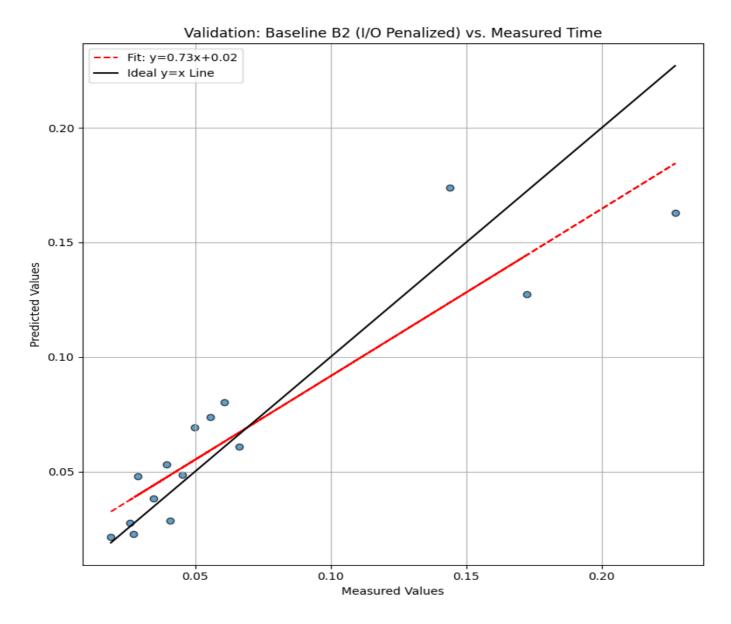


Fig. 27. Validation: Baseline B2 (I/O Penalized) vs. Measured Time: this chart tests a slightly more advanced baseline that heavily penalizes memory operations. While often more accurate than the naive model, it may still fail to capture the nuances that our more detailed model does.

	algorithm	type	predicted_cu	predicted_eu	measured_time_s	measured_energy_j	b1_predicted_cu	b2_predicted_cu
0	Constant_O(1)_Formula	Compute-bound	17.0	0.00148	0.017176	0.000150	9.0	125.0
1	Logarithmic_O(log_n)_BinarySearch	Memory-bound	118.0	0.01025	0.259299	0.001802	53.0	955.0
2	Sqrt_O(sqrt_n)_PrimalityTest	Mixed	129.0	0.01115	0.143448	0.001240	63.0	1020.0
3	Linear_O(n)_Sum	Mixed	25.0	0.00228	0.026473	0.000241	14.0	133.0
4	Linear_O(n)_ListAppend	Mixed	35.0	0.00313	0.033694	0.000301	19.0	224.0
5	Linear_O(n)_StringConcat	Mixed	42.0	0.00368	0.040955	0.000359	20.0	312.0
6	Linear_O(n)_DictCreation	Mixed	38.0	0.00333	0.040561	0.000355	19.0	281.0
7	Linear_O(n)_FactorialIter	Compute-bound	55.0	0.00476	0.057227	0.000495	26.0	433.0
8	Linear_O(n)_RecursivePower	Mixed	27.0	0.00243	0.028887	0.000260	16.0	162.0
9	N_Log_N_O(n_log_n)_Sort	Memory-bound	32.0	0.00293	0.060846	0.000446	19.0	167.0
10	Quadratic_O(n^2)_NestedLoops	Compute-bound	55.0	0.00483	0.048212	0.000423	27.0	406.0
11	Quadratic_O(n^2)_ListSearch	Memory-bound	98.0	0.00858	0.109534	0.000767	46.0	746.0
12	Cubic_O(n^3)_TripleLoops	Compute-bound	66.0	0.00583	0.064948	0.000574	33.0	471.0
13	Exponential_O(2^n)_Fibonacci	Mixed	41.0	0.00361	0.042119	0.000371	21.0	284.0
14	Factorial_O(n!)_Permutations	Compute-bound	60.0	0.00543	0.062943	0.000570	34.0	357.0

Fig. 28. Generated Validation Data (with all model predictions)



Fig. 29. Sensitivity of composite scores to profile weights and of \$ cost to EU/price uncertainties.

References:

1. Sergii Kavun. (2025). s-kav/complexity_cost_profiler: version 1.0 (v.1.0). Zenodo. https://doi.org/10.5281/zenodo.16761183
2.