

Evaluating the Energy-Efficiency of the Code Generated by LLMs

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Abstract

As the quality of code generated by Large Language Models (LLMs) improves, their adoption in the software industry for automated code generation continues to grow. Researchers primarily focus on enhancing the functional correctness of the generated code while commonly overlooking its energy efficiency and environmental impact. This paper investigates the energy efficiency of the code generated by 20 popular LLMs for 878 programming problems of varying difficulty levels and diverse algorithmic categories selected from the LeetCode platform by comparing them against canonical human-written solutions. Although LLMs can produce functionally correct results in most cases, our findings show that the performance and energy efficiency of LLM-produced solutions are often far below those of human-written solutions. Among the studied LLMs, DeepSeek-v3 and GPT-4o generate the most energy-efficient code, whereas Grok-2 and Gemini-1.5-Pro are among the least energy-efficient models. On average, human-generated canonical solutions are approximately **1.17** times more energy efficient than DeepSeek-v3, **1.21** times more energy efficient than GPT-4o, and over **2** times more energy efficient than Grok-2 and Gemini-1.5-Pro. For specific algorithmic groups such as dynamic programming, backtracking, and bit manipulation, LLM-generated code can consume up to **450** times more energy than human-generated canonical solutions.

1 Introduction

In software development, AI-assisted code generators have become vital to increase productivity, maintain consistency, enforce standards, and refine existing codebases. Industry leaders are increasingly adopting LLMs to automate the process of code generation, testing, and project document writing. Similarly, LLMs help developers create code structures based on specifications, enhance development efficiency, and decrease the likelihood of errors.

Traditionally, evaluations of code generators have centered around runtime efficiency and code quality, while they commonly ignore the energy consumption and environmental impact of generated code. However, evolutions in Generative AI and the increasing demand for Information Technology (IT) software systems have caused emerging sustainability issues, particularly due to generative models [1]. The IT industry contributes about 10% of global energy use today [2] and is responsible for approximately 3% of global carbon emissions[3], exceeding the emissions of the aviation industry [4]. Training a large neural network can cause over 626,000 pounds of CO₂ emissions, nearly five times the lifetime emissions of an average car [5]. The demand for computing power, mainly due to technologies like Generative AI, is expected to cause data centers to consume 20% of global electricity by 2030 [6]. On the other hand, improving these power-hungry models regarding energy efficiency

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can reduce the high power demand. Li et al. [7] show that transformations in code execution can enable savings in cloud computing costs of around 42 percent without losing any functionality.

This paper fills an important gap in this area by investigating the energy efficiency of code generated by LLMs and comparing it to canonical human-written solutions. We systematically evaluate the energy efficiency of code snippets generated by 20 popular LLMs for 878 programming problems with different difficulty levels selected from EffiBench [8]. We compare generated code with human-generated canonical solutions to find patterns by measuring and evaluating the energy consumption. This study allows us to gain insights into the environmental impact and economic cost of using LLM-generated code. We highlight the importance of sustainable models in code generation. By raising awareness of the energy costs associated with AI-assisted code generation, we aim to encourage the development of AI tools that produce environmentally sustainable code.

Among the studied LLMs, DeepSeek-v3, GPT-4o, and Claude-3.5-Sonnet generate the most energy-efficient code in general, whereas Llama-3.3-70B, Grok-2, and Gemini-1.5-Pro are among the least energy-efficient models. On average, human-generated canonical solutions were approximately **1.17** times more energy efficient than DeepSeek-v3, **1.2** times more energy efficient than GPT-4o and Claude-3.5-Sonnet, **1.93** times more energy efficient than Llama-3.3-70B, and over **2** times more energy efficient than Grok-2 and Gemini-1.5-Pro. For specific algorithmic groups such as dynamic programming, backtracking, and bit manipulation, the LLM-generated code can consume significantly more energy compared to human-generated canonical solutions. For these problem categories, GPT-4o generates solutions consuming up to **46** times more energy than the canonical solution. Similarly, LLaMA-3.3-70B generates solutions with energy consumptions up to **149** times that of the canonical solution, and Gemini-1.5-Pro generates solutions that consume energy up to **449** times that of the canonical solution. These results suggest that energy efficiency optimization should become an important consideration in the development of next-generation AI-assisted code generation systems.

In summary, the paper makes the following contributions:

- (1) We conduct an extensive evaluation of 20 LLMs, and compare the energy efficiency of the code generated by them.
- (2) We ensure fair prompt inputs during code generation and fair comparison of LLMs against each other and canonical solutions by considering problems correctly generated by all models.
- (3) We propose a comprehensive evaluation framework that jointly measures energy consumption, runtime performance, memory usage, the number of input and output tokens used for code generation, and the monetary cost of generating the code, providing a holistic understanding of the environmental and economic costs associated with LLM-generated code.
- (4) Our findings reveal that while advanced LLMs like DeepSeek-v3, GPT-4o, and Claude-3.5-Sonnet can produce more efficient code than other models, they still are considerably less efficient than human-written solutions in terms of energy consumption.
- (5) Our analysis identifies clear patterns in energy inefficiency, showing that LLMs particularly struggle with Dynamic Programming, Backtracking, Bit Manipulation, and Greedy algorithms; while performing relatively better on problems involving Binary Search and Divide and Conquer.

2 Related Works

Green Software Practices: The idea of green software practices relates to energy consumption and sustainability in the end-to-end software development lifecycle [9, 10]. Green software examples include energy-aware coding and sustainable development methodologies [11, 12]. Sustainability requires consideration from the start of all aspects of development, rather than an after-thought [10]. Clean code methodology can help to execute with better efficiencies [13], and it can focus on reducing instructions, removing duplicate code, and optimizing an algorithm [14]. Additional suggestions to reduce energy use include parallelization, caching, and compression [15]. Henderson et al. [16] offer standardized energy reporting to allow others' projects to replicate it. The ESC framework provides a consistent sustainability computing paradigm to take a holistic approach [17]. Addressing the carbon footprint of computation, the study on "Green Algorithms" [18] introduces a quantitative model for assessing the environmental impact of computational processes.

Efficiency of LLM-generated Code: When examining efficiency for LLM-generated code, models should consider correctness, memory, runtime, and energy [19]. Chen et al. [20] propose developing multi-faceted assessments. EffiBench [8] constructs an LLM code efficiency benchmark with 1000 coding problems representing different algorithmic complexities. Cruz et al. [21] state that efficiency can only be evaluated after correctness is established, whereas Niu et al. [22] argue that efficiency depends neither on correctness nor model size, but efficiency does scale up through prompting piecewise. LLMs have a well-documented issue with selecting unoptimized algorithms and iterations and data structures [23]; perhaps the most obvious comparison is QuickSort vs InsertionSort regarding time complexity [23]. Energy-aware prompting could make a 30 percent reduction [24], and subsequent feedback loops using evaluator LLMs could identify further means for optimizing the code generated [25]. In green code, the system produces emission reductions of 23 to 50 percent for generation tasks, through reinforcement learning, rewarding the reduction of emissions [26]. Wang et al. [27] study the effect of providing energy rewards. There is also emerging research interest in the utility of prompt engineering for reduced energy use, though with less clearly predictable results so far [28]. Vartziotis et al. [1] define "green capacity" to capture sustainability in AI-generated code.

3 Benchmarking Approach and Experiments

To construct our benchmark for comparing different LLMs in terms of their energy efficiency, we use an approach similar to EffiBench [8], which is inspired by the common practice of evaluating developers' coding ability using problems from the competitive coding platform – LeetCode [29]. EffiBench includes 1000 Leetcode problems that are asked in interviews frequently (>40%). These problems are paired with the most efficient solutions from the LeetCode discussion forum, labeled as the canonical human-written solutions. 100 test cases for each problem are included in EffiBench which are generated using a test case generator based on GPT-3.5-turbo.

3.1 Problem Dataset Selection

Before using the EffiBench dataset for our study, we thoroughly analyzed and tested the dataset. The following are the findings from our analysis: (i) 12 problems in the dataset do not have comprehensive test cases; (ii) 110 problems throw errors when we run canonical solutions against comprehensive test cases. This is due to one or all of the following reasons: syntax errors in canonical solutions, syntax errors in comprehensive test cases, and improper definition of test cases for TreeNode, GraphNode, and LinkedList problems. We excluded these 122 problems from our dataset and considered 878 problems for our comprehensive study.

Table 1: Algorithm categories and difficulty-wise problem distribution in the selected dataset.

Algorithm	Greedy	DP	Backtrack	Divide & Conquer	DFS	BFS	Binary Search	Two Pointers	Sliding Window	Bit Manip.	Sorting	TOTAL
Easy	32	7	1	4	3	0	23	31	8	25	62	145
Medium	161	140	31	6	37	36	68	52	40	54	128	510
Hard	38	111	8	9	13	22	48	5	14	18	40	223
TOTAL	231	258	40	19	53	58	139	88	62	97	230	878

Table 1 shows the detailed breakdown of the 878 problems we use to compare the energy efficiency of the LLMs in our study. There are 145 easy, 510 medium, and 223 hard problems in the dataset. Leetcode defines easy, medium, and hard problems based on the complexity of the algorithms or data structures required to solve the problems. The algorithmic methods include Greedy, Dynamic Programming (DP), Backtracking, Divide and Conquer, Depth-First Search (DFS), Breadth-First Search (BFS), Binary Search, Two Pointers, Sliding Window, Bit Manipulation, and Sorting. The diverse set of algorithmic methods in the problem set provides a fair comparison of the studied LLMs across multiple problem subcategories with different computational complexities. In the table, one problem may be tagged to more than one algorithmic category and hence the sum of the number of problems across different algorithmic categories for a given difficulty level may be greater than the reported total.

3.2 LLMs Under Study

We analyze 20 popular LLMs that are widely used by developers for code generation tasks. In our study, we choose 7 open-source models (from DeepSeek, Meta, and Mistral), and 13 closed-source

models (from Amazon, Antropic, Google, OpenAI, and xAI). The selected models are listed in Table 2. The table also shows the access type and cost of using each model – based on the cost per 1 Million input tokens used and the cost per 1 Million output tokens generated. Some closed-source models such as GPT-4 Turbo and Claude 3.5 Sonnet incur significantly higher token processing costs, with input/output costs reaching up to \$5/\$15 per Million tokens. In contrast, open-source models such as Llama are less expensive to access with input/output costs as low as \$0.05/\$0.08 per Million tokens. Among all LLMs studied, the least expensive one is Nova-micro, with input/output costs of \$0.02/\$0.07 per Million tokens. The input/output token cost information is used in our study to compare the average cost of using each model to generate the correct code for the set of given problems. The cost of open-source LLMs was determined based on their publicly available API pricing, without accounting for any additional hardware or infrastructure costs. Specifically, the models were accessed via third-party platforms such as Fireworks.ai and Groq Cloud, where the API usage charges directly reflect the input and output token processing costs. Since these experiments did not run the models on private hardware or owned cloud servers, no supplementary hardware-related expenses were included in the cost calculations.

Table 2: List of LLMs included in our study, their access types, and cost information (green color highlights the lowest cost, whereas red color highlights the highest cost).

Vendor	LLM	Source Code	Access Type	Cost per 1M Input Tokens	Cost per 1M Output Tokens
Amazon	Nova-Lite	Closed	AWS Bedrock Batch Inference	\$0.03	\$0.12
Amazon	Nova-Micro	Closed	AWS Bedrock Batch Inference	\$0.02	\$0.07
Amazon	Nova-Pro	Closed	AWS Bedrock Batch Inference	\$0.40	\$1.60
Anthropic	Claude 3.5 Haiku	Closed	API	\$0.80	\$4.00
Anthropic	Claude 3.5 Sonnet	Closed	API	\$3.00	\$15.00
DeepSeek	DeepSeek v3 (37B)	Open	Fireworks.ai API	\$0.90	\$0.90
Google	Gemini 1.5 Flash	Closed	Vertex AI Batch Prediction	\$0.04	\$0.15
Google	Gemini 1.5 Pro	Closed	Vertex AI Batch Prediction	\$0.63	\$2.50
Google	Gemini 2.0 Flash	Closed	Vertex AI Batch Prediction	\$0.08	\$0.30
Google	Gemini 2.0 Flash-Lite	Closed	Vertex AI Batch Prediction	\$0.04	\$0.15
Meta	Llama 3.1 (8B)	Open	Groq cloud API	\$0.05	\$0.08
Meta	Llama 3.1 (70B)	Open	AWS Bedrock Batch Inference	\$0.36	\$0.36
Meta	Llama 3.3 (70B)	Open	Groq Cloud API	\$0.59	\$0.79
Mistral AI	Codestral-Mamba-2407 (7B)	Open	API	\$0.30	\$0.90
Mistral AI	Mistral-Large-2407 (123B)	Open	API	\$2.00	\$6.00
Mistral AI	Pixtral-Large-2411 (124B)	Open	API	\$2.00	\$6.00
OpenAI	GPT-3.5 Turbo (175B)	Closed	Batch API	\$0.25	\$0.75
OpenAI	GPT-4 Turbo	Closed	Batch API	\$5.00	\$15.00
OpenAI	GPT-4o	Closed	Batch API	\$1.25	\$5.00
xAI	Grok	Closed	xAI API	\$2.00	\$10.00

3.3 Code Generation

Each LLM receives a standard prompt that consists of the problem statement, input/output specification, constraints, and example test cases (see Appendix for a sample prompt). To ensure **fairness**, all models are tested using the exact same prompt structure. This makes sure that all performance differences stem from the model’s respective behaviors rather than a deviation in the representation of the task itself. For the LLMs, the temperature parameter is set to default values (for Llama-3.1-70B it is 0.5; for Nova, Mistral, Llama-3.1-8B, and Llama-3.3-70B it is 0.7; and for the rest of the models it is 1.0). The model will then produce an initial code solution. To ensure the **correctness** of the generated code prior to measuring efficiency, each solution followed: (1) Syntax check to ensure compilability; (2) Run against 100 test cases, sourced from EffiBench; and (3) Verify against edge cases to confirm robustness. If that solution does not compile or does not pass all 100 test cases for that problem, the LLM is asked to regenerate the solution. During the **regeneration** phase, we provide the model with its original prompt as well as execution feedback on the code it just produced, prompting it to produce a new solution. This process can repeat up to a maximum of 25 iterations per problem, retaining the first solution that returns correct results in the interest of assessing energy and memory usage (see Appendix A and for the details of the code generation workflow).

3.4 Code Energy Consumption Measurements

For collecting energy metrics, we utilize the perf[30] tool’s power monitoring capabilities. Specifically, we use the power/energy-pkg/ for measuring the energy consumption of the entire processor

socket, including all cores and cache; `power/energy-ram/` for measuring the energy consumption of the random access memory (RAM) attached to the integrated memory controller; and `cpu-clock` for measuring the execution time of the code. Our methodical approach consisted of several key steps to ensure the accuracy of the energy measurements: (1) Before running any problem code, we calculate the idle power consumption in the target system for a 30-second period to establish a baseline; (2) For each execution of the problem code, we calculate the adjusted energy consumption by subtracting the baseline idle power; (3) A cooldown period of 10 seconds is implemented between executions to prevent thermal interference; and (4) Each problem code is run 5 separate times in random orders and the results are averaged to ensure statistical validity (see Appendix A.3 and Appendix B.2 for the details of the energy measurement methodology).

3.5 Code Memory Consumption Measurements

For collecting memory metrics, we utilize python library `Memory_Profiler`. This library helps us sample the memory used by the process at the given intervals (in this case 0.001 seconds). For each problem code, we measure the `Average Memory Consumption Over Time`, which is expressed in `Megabytes * seconds` and shows how much memory a process uses and for how long, providing a cumulative view of memory consumption (see Appendix A.3 and Appendix B.3 for the details of the memory consumption measurement methodology).

3.6 Testing Environment

To ensure fairness in our comparative analysis, all models were evaluated under identical conditions. This approach eliminated hardware and software variabilities, allowing for an effective comparison of performance metrics. Our standardized test environment consisted of: (1) **Platform:** Chameleon Cloud [31] ; (2) **Processor:** Intel Xeon Gold 6126 (24 cores); (3) **Memory:** 192 GiB RAM; (4) **Operating System:** Ubuntu 24.04.1 LTS; and (5) **Kernel:** 6.8.0-51-generic.

4 Evaluation and Analysis

In this section, we present the findings of our experimental results. We analyze the results obtained and evaluate the performance of LLMs in terms of energy consumption and cost. We also identify the performance of LLMs compared to canonical solutions written by humans. At the same time, we present the cost breakdown of the LLMs to carry out the tasks.

4.1 Code Generation Accuracy Analysis

Since we do not have direct access to the server-side infrastructure of commercial LLMs to measure their computational resource usage, we develop an alternative approach to estimate the relative inference efficiency of these models during code generation. Our methodology captures both the success rate and the token-based resource consumption which serves as a proxy for computational costs. To perform this assessment across different LLMs, we implement a systematic approach that accounts for both the success rate and the input/output tokens required for successful code generation by each model.

Our analysis procedure follows a structured iteration approach. For each problem, we track the sequence of generation attempts until success. For each problem in our dataset (Table 1), we execute code generation (up to 25 times) across all LLM models under study, until a successful code passing all 100 tests is generated. This repetition allows us to calculate three key metrics:

- (1) **Average Pass @:** This value indicates how many attempts are required before successfully generating a solution that passes all test cases. A lower value suggests more efficient generation.
- (2) **Average Total Input Tokens:** We measure the number of input prompt tokens across successful generations, which directly correlates with API costs when using LLM services.
- (3) **Average Total Output Tokens:** This represents the size of the generated code solutions, which also influences the operational costs of deploying these models.

Table 3 provides comparative performance evaluation across a variety of LLMs through Pass@1, Pass@10, and Pass@25 metrics for our entire problem set (introduced in Table 1). The pass metrics

provide the empirical probability that at least one correct solution is generated within the first, tenth, and twenty-fifth attempt respectively across a common set of problems and provided prompt.

Table 3: Comparative analysis of Large Language Models (LLMs) in terms of Pass@k accuracy and the average number of input and output tokens needed to generate the correct code.

LLM	Pass@1	Pass@10	Pass@25	Avg. Pass@	Avg. Input Tokens	Avg. Output Tokens	Avg. Cost of Code Generation (Cents)
Nova-Lite	42.9%	56.6%	58.8%	2.169	2568.7	545.4	¢0.014
Nova-Micro	33.7%	49.0%	51.4%	2.577	3875.2	602.7	¢0.011
Nova-Pro	60.5%	73.1%	75.2%	1.896	1972.5	388.8	¢0.141
Claude 3.5 Haiku	70.7%	82.4%	85.4%	1.960	2108.4	998.7	¢0.568
Claude 3.5 Sonnet	77.9%	88.0%	89.7%	1.543	1598.3	762.6	¢1.623
DeepSeek v3 (37B)	83.6%	89.7%	91.1%	1.444	1411.5	400.6	¢0.163
Gemini 1.5 Flash	65.9%	75.1%	77.3%	1.704	2122.1	324.7	¢0.013
Gemini 1.5 Pro	79.5%	86.9%	87.5%	1.255	1220.0	243.5	¢0.137
Gemini 2.0 Flash	80.5%	88.2%	89.7%	1.458	1525.9	364.2	¢0.023
Gemini 2.0 Flash-Lite	71.2%	81.9%	84.3%	1.734	1963.7	572.6	¢0.016
Llama 3.1 (8B)	53.2%	59.7%	61.8%	1.974	2251.5	381.0	¢0.014
Llama 3.1 (70B)	54.6%	75.2%	80.9%	2.835	3285.3	846.9	¢0.149
Llama 3.3 (70B)	71.0%	75.2%	82.6%	3.135	1479.2	361.4	¢0.116
Codestral-Mamba-2407 (7B)	43.5%	44.9%	62.4%	7.549	11684.6	1414.1	¢0.478
Mistral-Large-2407 (123B)	64.7%	72.7%	76.1%	1.987	2546.5	342.7	¢0.715
Pixtral-Large-2411 (124B)	56.2%	73.5%	78.2%	2.584	3569.6	512.8	¢1.022
GPT-3.5 Turbo (175B)	56.8%	66.7%	70.7%	2.282	2170.7	401.7	¢0.084
GPT-4 Turbo	56.2%	86.9%	89.3%	2.117	2258.8	604.4	¢2.036
GPT-4o	78.4%	89.7%	92.0%	1.766	2274.5	600.8	¢0.585
Grok	75.2%	83.9%	84.9%	1.415	1380.3	229.1	¢0.505

For all three pass rates, DeepSeek-v3, GPT-4o, Gemini 2.0 Flash, and Claude 3.5 Sonnet consistently position among the best-performing models in terms of the correctness of the code generated, demonstrating reliability with problem-solving accuracy. DeepSeek-v3 has the highest Pass@1 score of 83.6%, whereas both DeepSeek-v3 and GPT-4o have Pass@10 scores of 89.7% and 89.1% respectively, and finally GPT-4o has the highest Pass@25 score of 92.0%. Nova-Micro and Nova-Lite are the worst performers in this experiment, barely exceeding 50% at Pass@25. Models like Gemini 2.0 Flash (¢0.023) and Gemini 2.0 Flash-Lite (¢0.016) demonstrate competitive Pass@10 and Pass@25 rates above 82%, at very low costs, offering more affordable options for large-scale code generation.

4.2 Code Energy Efficiency Analysis

To comprehensively assess the energy efficiency of LLMs, the evaluation was conducted over two distinct benchmark sets. The first set comprises 298 common problems that all 20 LLMs successfully solved, and they formed a relatively equal distribution of algorithmic categories such as Divide & Conquer, Binary Search, and Bit Manipulation. The second benchmark expands the analysis to a larger and more diverse set of 576 common problems that were successfully solved by 11 LLMs, providing insights into how these models handle a wider range of algorithmic complexities and problem difficulties. This provided an overall understanding of how LLMs addressed a broader class of algorithmic complexity and problem difficulty.

For each model, along with the average Pass@ rate, average input token number, and average output token number, the following key efficiency metrics were computed across all common problems:

- (1) **Avg. Cost of Code Generation (Cents):** Represents the average monetary cost required to generate a code solution for each problem using the respective LLM.
- (2) **Avg. Package Energy (Joules):** Energy consumed by the entire processor socket, including all cores and cache.
- (3) **Avg. RAM Energy (Joules):** Energy consumed by the RAM.
- (4) **Avg. Total Energy (Joules):** Represents the combined energy consumption of the processor package and RAM during the execution of generated code. This metric reflects the overall energy consumption of the solution.
- (5) **Avg. Runtime (milliseconds):** Captures the average time required to execute the generated solutions.

(6) **Avg. Memory Consumption (MB-sec)**: Represents the total memory usage over time during code execution, measured as the integral of memory usage over runtime.

4.2.1 Benchmark Set - I: 20 LLMs & 298 Common Problems

Of all 20 models assessed, we recognize a subset of 298 problems from our dataset in which each LLM produces a correct answer passing all tests within the 25-regeneration limit. The algorithm-wise and difficulty-wise distribution of these 298 common problems is provided in Table 4. The majority of the problems fall under the categories of Binary Search (50), Sorting (85), and Bit Manipulation (35). In terms of difficulty, most problems are of medium complexity (179), followed by easy (89) and hard (30) problems. This intersection guarantees that all relative efficiency experiments including energy, memory, token costs, etc. take place with a fair, unambiguous set of problems. By narrowing the evaluation emphasis to the intersection subset of problems, we remove the impact of differing model pass rates to ensure appropriate, consistent, and interpretable comparisons across models.

Table 4: Algorithm and difficulty-wise problem distribution on Benchmark Set - I.

Difficulty	Greedy	DP	Backtracking	Divide & Conquer	DFS	BFS	Binary Search	Two Pointers	Sliding Window	Bit Manip.	Sorting	TOTAL
Easy	14	7	0	1	3	0	13	22	4	18	33	89
Medium	46	49	10	3	15	13	21	28	17	14	51	179
Hard	6	18	1	0	2	3	4	0	2	3	1	30
TOTAL	66	74	11	4	20	16	38	50	23	35	85	298

We present the evaluation results for this subset of problems in this section. The performance and resource utilization of human-written canonical solutions, compared to the LLMs, are illustrated in Table 5. Despite recent advancements in model correctness, as measured by Pass@ rates, the canonical solutions consistently outperform all evaluated LLMs across key sustainability metrics, including energy consumption and memory efficiency.

Average Total Energy Consumption: On average, canonical solutions require only 5.77 J, significantly lower than any LLM-generated solutions. The most efficient LLM, DeepSeek-v3, consumes 5.91 J, while others range from 6.12 J to 12.00 J.

Average Runtime: Human-written code executes in just 74.16 ms, outperforming all LLM-generated solutions, which exhibit runtimes ranging from 75.64 ms (DeepSeek-v3) to 147.95 ms (GPT-4 Turbo).

Average Memory Usage: Canonical solutions also demonstrate superior memory efficiency with an average memory consumption of 8.70 MB-s, lower than nearly all LLM-generated solutions. Only DeepSeek-v3 (8.67 MB-s) achieves comparable memory efficiency, while other LLM-generated solutions exhibit higher memory consumption, ranging from 9.02 MB-s to 11.57 MB-s.

Table 5: Performance and resource usage comparison of LLMs against canonical solutions on Benchmark Set - I.

Model	Avg. Cost of Code Generation (Cents)	Avg. Input Tokens	Avg. Output Tokens	Avg. Pass@	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	—	—	—	—	5.05	0.72	5.77	74.16	8.70
DeepSeek v3	€0.084	789.6	146.0	1.017	5.17	0.74	5.91	75.64	8.67
Gemini 2.0 Flash	€0.012	872.4	166.9	1.020	5.36	0.76	6.12	78.05	9.02
Claude 3.5 Sonnet	€1.029	886.5	508.4	1.047	5.61	0.80	6.41	81.21	9.04
GPT-4o	€0.179	784.0	161.2	1.010	5.93	0.84	6.77	85.54	9.32
Nova-Lite	€0.007	1303.2	267.5	1.409	6.07	0.86	6.93	87.55	9.26
Claude 3.5 Haiku	€0.323	1049.1	597.5	1.191	6.22	0.88	7.10	89.97	9.46
Nova-Pro	€0.080	1147.3	214.7	1.272	6.24	0.88	7.12	90.03	9.58
Gemini 2.0 Flash-Lite	€0.006	934.9	181.2	1.091	6.26	0.88	7.14	90.44	9.56
GPT-3.5 Turbo	€0.042	1129.9	182.3	1.339	6.30	0.89	7.19	91.17	9.66
Pixtral-Large-2411	€0.361	1288.0	173.0	1.188	6.55	0.91	7.46	94.19	9.18
Codestral-Mamba-2407	€0.279	6973.3	773.2	4.379	6.90	0.96	7.86	99.19	9.44
Llama 3.1 (8B)	€0.070	943.7	178.8	1.581	7.11	0.99	8.10	101.88	9.72
Nova-Micro	€0.007	2132.8	438.5	2.067	7.12	0.99	8.11	102.28	10.21
Gemini 1.5 Pro	€0.089	835.1	146.8	1.007	7.60	1.06	8.66	108.32	9.65
Gemini 1.5 Flash	€0.006	1007.3	163.3	1.074	8.38	1.16	9.53	119.33	10.30
Llama 3.3 (70B)	€0.054	1257.2	249.9	1.342	8.60	1.19	9.79	122.35	10.85
Mistral-Large-2407	€0.362	1274.6	177.6	1.228	8.63	1.19	9.82	122.42	10.49
Grok 2	€0.281	799.9	121.2	1.013	8.77	1.21	9.98	124.50	10.11
Llama 3.1 (70B)	€0.006	977.0	159.6	1.185	8.87	1.23	10.10	126.07	10.39
GPT-4 Turbo	€0.729	881.9	192.3	1.091	10.6	1.44	12.00	147.95	11.57

When we analyze the results based on the problem difficulty level, we observe that all LLMs perform similarly to canonical solutions on easy problems. For medium-difficulty problems, solutions generated by DeepSeek-v3 consume approximately 1.02 times the energy of canonical solutions, while

Nova-Lite consumes around 1.20 times. GPT-4 Turbo performs the worst on medium problems, consuming 2.08 times more energy than canonical solutions. For hard problems, DeepSeek-v3 performs comparably to canonical solutions in terms of energy efficiency, while solutions generated by Llama-3.1-70B consume approximately 1.40 times more energy.

Analyzing performance across different algorithmic categories, LLM-generated solutions for problems involving BFS, DFS, and Two-Pointer algorithms achieve energy efficiency similar to canonical solutions. However, LLM-generated solutions for problems involving Sorting and Dynamic Programming consistently require more energy. For Binary Search and Bit Manipulation problems, most LLMs generate code that is as efficient as canonical solutions, except for Llama-3.1-70B and Llama-3.3-70B, which produce solutions consuming significantly more energy. Across all algorithms and difficulty levels, DeepSeek-v3 and GPT-4o consistently outperform other LLMs in terms of energy efficiency and runtime performance (see Appendix D and Appendix E for the detailed results based on the problem difficulty level and across different algorithmic categories).

4.2.2 Benchmark Set - II: 11 LLMs & 576 Common Problems

Table 6 presents the algorithm-wise and difficulty-level breakdown of the 576 problems included in Benchmark Set II. These 576 problems were successfully passed by 11 LLMs within the 25-regeneration limit. A significant portion of these problems fall under the categories of Dynamic Programming (158), Greedy algorithms (149), and Sorting (155). With respect to difficulty, the majority of problems are of medium complexity (347), followed by hard (110) and easy (119).

Table 6: Algorithm and difficulty-wise problem distribution on Benchmark Set - II.

Difficulty	Greedy	DP	Backtracking	Divide & Conquer	DFS	BFS	Binary Search	Two Pointers	Sliding Window	Bit Manip.	Sorting	TOTAL
Easy	28	7	1	3	3	0	16	24	7	22	48	119
Medium	101	98	19	4	27	24	46	37	31	34	89	347
Hard	20	53	5	5	3	6	24	1	10	10	18	110
TOTAL	149	158	25	12	33	30	86	62	48	66	155	576

Table 7 summarizes the performance and resource costs of human-written canonical solutions compared to LLM-generated solutions for the second benchmark set. The problems in this set are more complex, and the canonical solutions consistently outperform the LLM-generated solutions across all relevant efficiency metrics. Moreover, while some LLMs demonstrate better model correctness through higher Pass@ rates, these improvements are often accompanied by significant increases in energy and memory consumption.

Average Total Energy Consumption: On average, canonical solutions require only 5.46 J, substantially lower than any LLM-generated solutions. While DeepSeek-v3 remains the most energy-efficient LLM (6.37 J), it still consumes 16.7% more energy than the canonical solutions. Interestingly, Gemini-1.5-Pro exhibits the best Avg. Pass@ score (1.056) for this set of problems, but its energy consumption is among the highest at 11.15 J.

Average Runtime: Human-written code maintains the lowest average runtime at 69.36 ms, consistently outperforming all LLM-generated solutions. Although smaller models typically demonstrate faster runtimes, some models like Claude-3.5-Haiku still require 88.56 ms. Larger models such as Llama-3.1-70B and Llama-3.3-70B exhibit even higher runtimes at 112.01 ms and 130.02 ms, respectively. The highest runtime is by Gemini 1.5 Pro at 137.14 ms.

Table 7: Performance and resource usage comparison of LLMs against canonical solutions on Benchmark Set - II.

Model	Avg. Cost of Code Generation (Cents)	Avg. Input Tokens	Avg. Output Tokens	Avg. Pass@	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MBs)
Canonical Solution	–	–	–	–	4.78	0.68	5.46	69.36	6.62
DeepSeek v3	¢0.097	889.5	191.0	1.075	5.59	0.78	6.37	80.45	6.90
GPT-4o	¢0.226	934.6	217.7	1.092	5.82	0.81	6.63	83.54	7.44
Claude 3.5 Sonnet	¢1.088	964.0	532.3	1.076	5.91	0.82	6.74	84.60	7.33
Claude 3.5 Haiku	¢0.401	1420.8	718.7	1.415	6.19	0.86	7.05	88.56	7.65
Gemini 2.0 Flash-Lite	¢0.009	1230.1	241.4	1.307	6.42	0.89	7.31	91.91	8.27
Llama 3.1 (70B)	¢0.116	2562.4	644.6	2.309	7.91	1.09	9.00	112.01	8.22
GPT-4 Turbo	¢1.204	1377.8	343.4	1.448	8.27	1.13	9.40	117.10	9.08
Gemini 2.0 Flash	¢0.016	1084.4	231.5	1.151	8.63	1.17	9.80	121.34	7.77
Llama 3.3 (70B)	¢0.097	1248.6	291.4	2.439	9.26	1.26	10.52	130.02	10.73
Grok 2	¢0.352	981.8	156.0	1.146	9.62	1.31	10.93	135.28	9.34
Gemini 1.5 Pro	¢0.102	927.2	174.1	1.056	9.82	1.33	11.15	137.14	8.43

Average Memory Usage: Canonical solutions also demonstrate superior memory efficiency with an average memory consumption of 6.62 MB·s. These values are consistently lower than those of any LLM-generated solutions in the study, where memory usage ranges from 6.90 MB·s (DeepSeek-v3) to a maximum of 10.73 MB·s (Llama-3.3-70B).

When we analyze the results based on difficulty, for easy problems all LLM-generated code performs similarly to that of canonical solutions. Llama-3.1-70B and Llama-3.3-70B models are comparatively better in giving energy-efficient solutions to medium problems than hard problems. Analyzing the results for various algorithms, DeepSeek-v3 consistently performs better than all other LLMs in almost all categories, except for BFS, Backtracking, and Bit Manipulation. Llama models (3.1-70B, 3.3-70B) perform poorly across almost all algorithmic categories. While Grok-2 performs relatively worse than all other LLMs for Dynamic Programming and Binary Search, it gives more energy-efficient solutions to problems involving DFS, Two Pointers, Sorting, and Greedy algorithms. Gemini-1.5 Pro performs poorly in Dynamic Programming and Bit Manipulation while performing relatively well in other categories. GPT-4 Turbo performs poorly in Sorting-based problems while doing better in others.

5 Discussion & Conclusions

This research provides a systematic, empirical approach to comparing energy consumption, runtime, memory usage, and inference costs of code generated by state-of-the-art LLMs and human-generated solutions. 878 coding problems from the EffiBench framework were evaluated, and while they show that LLMs achieve high Pass@N rates and functional correctness, their energy efficiency is always poorer. Our results highlight that LLMs are inefficient mainly due to duplicate logic, inappropriate decisions of algorithms, and excessive memory requirements for trivial tasks. While both DeepSeek-v3 and GPT-4o perform the best across all LLMs used in this study, they still require more energy and memory than human-generated code.

Our comprehensive study shows that LLMs can generate functionally correct code, but they may incur significantly large energy consumption. The concerns for their resource efficiency are influenced by earlier evaluations with token-based energy metrics with Pass@N scores which demonstrated that time taken in latency can be higher for correctness (in terms of larger LLMs), not only due to increased complexity of input, increased code length, and having to repeat many iterations to fix syntactic bugs.

We demonstrate that LLM performance is highly dependent on problem complexity and algorithm type. In Benchmark Set-I, LLMs perform well and produce solutions close to canonical implementations due to the lower problem complexity which is mostly on simpler categories such as Binary Search and Divide and Conquer. However, in Benchmark Set-II, with a higher proportion of complex problems involving Dynamic Programming, Greedy algorithms, and Sorting, the inefficiencies of LLMs become more apparent, which shows their limitations in handling computationally demanding tasks.

To conclude, sustainable software generation requires balancing correctness with computational efficiency. As LLMs become integrated into software development, it is critical to adopt evaluation frameworks that account for energy and memory usage to ensure both functional and environmental viability.

Limitations: Though this work performs a comprehensive study in evaluating LLMs’ ability to generate energy-efficient code, it has some limitations: (1) LLMs are not deterministic. The same LLM might generate a different code, the next time we ask it. (2) Datasets used could have been seen by some LLMs during the training phase, resulting in it memorizing and generating the most efficient solution. (3) This work is currently limited to evaluating codes generated in Python only and does not consider other programming languages.

Future Work: To address the above limitations, future studies can focus on including a diverse range of programming languages and problems that were created recently but not seen by LLMs during their training phase. The impact of various prompt engineering techniques on the code generation aspect of LLMs can also be thoroughly investigated.

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APPENDIX

A Experimentation Details

A.1 End-to-End Experimentation Workflow

The end-to-end experimentation workflow of this study is shown in Figure. 1. We consider 878 problems from EFFIBENCH (detailed in Table 1) and generate solutions using 20 popular LLMs (discussed in Table 2).

The source code of the end-to-end experimentation workflow is made available to the public and it can be found at the following repository: <https://anonymous.4open.science/r/evaluating-the-energy-efficiency-of-the-code-generated-by-llms-0D72>.

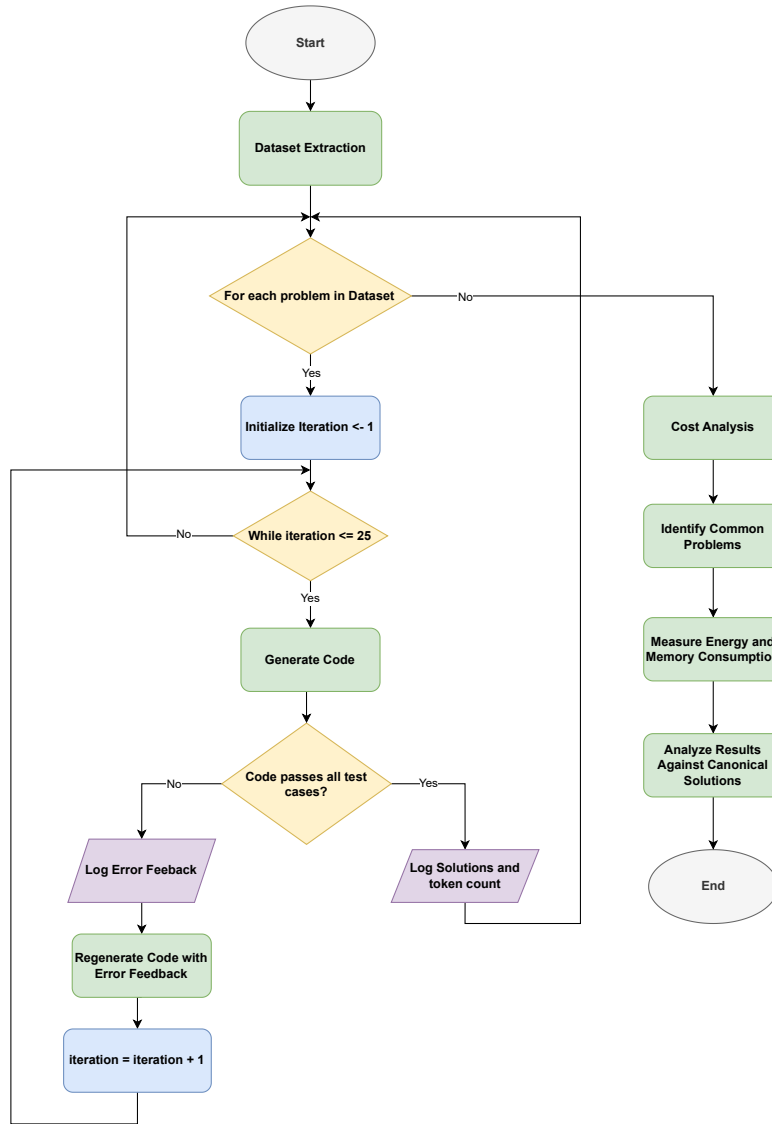


Figure 1: End-to-end experimentation workflow.

A.2 LLM Code Generation

We use a prompt structure similar to the one used in EFFIBENCH, which follows the MBPP code generation prompt, as shown in Figure 2. To ensure fairness, we use the same prompt for all LLMs.

```

Prompt
Problem: Given two sorted arrays nums1 and nums2 of size m and n respectively, return the median of the two sorted arrays. The overall run time complexity should be  $O(\log(m+n))$ .
Example 1:
Input:  nums1 = [1, 3], nums2 = [2]
Output:  2.0
Explanation: Merged array = [1, 2, 3] and median is 2.
Example 2:
Input:  nums1 = [1, 2], nums2 = [3, 4]
Output:  2.5
Explanation: Merged array = [1, 2, 3, 4] and median is (2 + 3) / 2 = 2.5.
Constraints:
nums1.length == m
nums2.length == n
0 ≤ m ≤ 1000
0 ≤ n ≤ 1000
1 ≤ m + n ≤ 2000
-106 ≤ nums1[i], nums2[i] ≤ 106

Test case (Python):
solution = Solution()
assert solution.findMedianSortedArrays([1, 3], [2]) == 2.0
assert solution.findMedianSortedArrays([1, 2], [3, 4]) == 2.5
assert solution.findMedianSortedArrays([0, 0], [0, 0]) == 0.0
assert solution.findMedianSortedArrays([], [1]) == 1.0
assert solution.findMedianSortedArrays([2], []) == 2.0

```

Figure 2: Prompt structure used for code generation.

The methodology followed for generating code with LLMs is shown in Figure 3. We use batch inference wherever possible to save on time and costs associated with code generation. If the LLMs are not able to generate the correct code in the first go, retries are allowed till it generates a correct solution or up to 24 times. After each iteration, python files for each problem are generated, they contain the solution generated by LLMs followed by test cases in the dataset. All the files are then executed and errors are logged. In the next regeneration, the error message is included in the prompt to correct its mistake. To ensure fairness, all models follow the same prompt format. Once a correct solution is generated, that problem will not be considered for regeneration in the next iteration. During each iteration, the number of input tokens and the number of output tokens to LLMs are noted along with the number of problems passed till that iteration. For code regeneration, along with the initial prompt, we also pass the incorrect solution given by LLM, along with the error message, to help it correct the result in the next output.

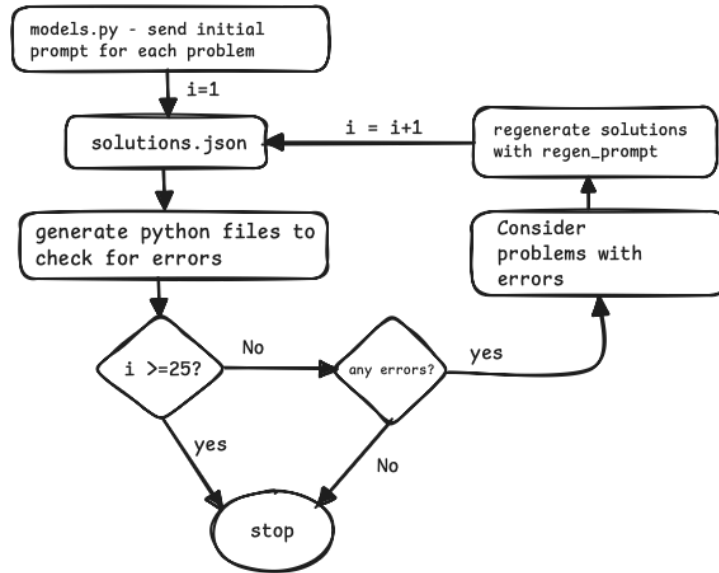


Figure 3: The methodology followed for code generation.

A.3 Energy, Memory, and Runtime Measurements

Figure 4 shows the experimentation process we followed for measuring the runtime, memory, and energy consumed by each tested code.

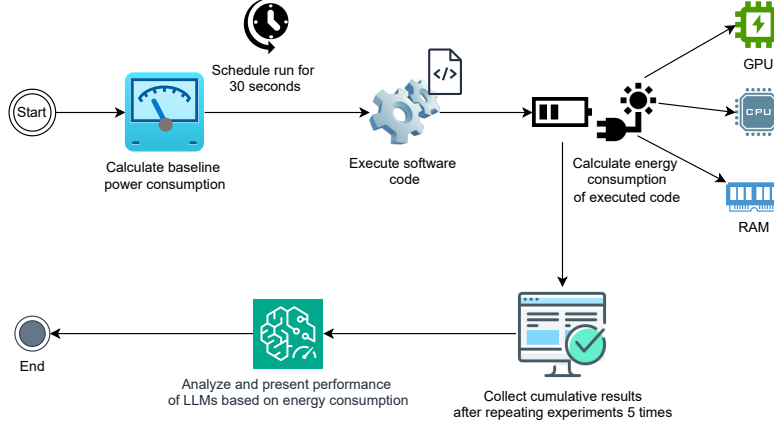


Figure 4: Flowchart showing the experimental process.

For collecting energy metrics, we utilize the `perf` tool’s power monitoring capabilities, specifically the `power/energy-pkg/`, `power/energy-ram/`, and `cpu-clock` packages.

We measure the baseline power consumption of the system while no process is running on it for 30 seconds.

$$P_{\text{baseline}} = \frac{E_{\text{idle}, 30\text{s}}}{30\text{ s}} \quad (1)$$

Then, we calculate the energy consumed by code E_{adjusted} as,

$$E_{\text{adjusted}} = E_{\text{actual}} - P_{\text{baseline}} \times t_{\text{code}} \quad (2)$$

where E_{actual} is the energy reported by Perf while the code runs for t_{code} seconds.

Baseline power consumption is measured for 30 seconds before processing each code, and a cool-down period of 10 seconds is maintained between each run to reduce the effect of previous executions. Each problem code is run 5 separate times in random orders and the results are averaged to ensure statistical validity.

In addition to the above experiment, we calculate the memory used by each solution using the python library `Memory_Profiler`. This library helps us sample the memory used by the process at the given intervals (in this case 0.001 seconds) and store the readings in a .dat file for each solution. This experiment is done 3 times independently of the previous one with perf and the results are averaged to reduce noise.

The measured results are analyzed using the metrics discussed in Appendix B.

B Evaluation Metrics and Measurements

B.1 LLM Inference Cost Analysis

For each LLM model M and problem p , we define the following metrics:

$$\text{Pass}@ (M, p) = \min\{i \in \{1, 2, \dots, 25\} \mid \text{solution at iteration } i \text{ passes all test cases}\} \quad (3)$$

$$\text{InputTokens}(M, p) = \sum_{i=1}^{\text{Pass}@ (M, p)} \text{InputTokens}_i(M, p) \quad (4)$$

$$\text{OutputTokens}(M, p) = \sum_{i=1}^{\text{Pass}@ (M, p)} \text{OutputTokens}_i(M, p) \quad (5)$$

where $\text{InputTokens}_i(M, p)$ represents the number of input tokens for iteration i and $\text{OutputTokens}_i(M, p)$ represents the number of output tokens for iteration i .

The aggregate metrics across all problems P for a model M are computed as:

$$\text{Avg. Pass@}(M) = \frac{1}{|P|} \sum_{p \in P} \text{Pass@}(M, p) \quad (6)$$

$$\text{Avg. InputTokens}(M) = \frac{1}{|P|} \sum_{p \in P} \text{InputTokens}(M, p) \quad (7)$$

$$\text{Avg. OutputTokens}(M) = \frac{1}{|P|} \sum_{p \in P} \text{OutputTokens}(M, p) \quad (8)$$

B.2 Code Energy Consumption Metrics

Execution Time: represents the time taken by the problem to complete execution, represented by T_{code} . It is measured using *perf*.

Average Execution Time: is the sum of the execution times of problems considered for the experiment divided by the number of problems considered (N).

$$\text{Avg. ET} = \frac{1}{N} \sum_{i=1}^N T_{code_i} \quad (9)$$

Package Energy: is the energy consumed by the entire processor socket, including all cores and cache, during the execution of code as measured by *perf*. It is the adjusted package energy calculated using equation 2.

RAM Energy: is the energy consumed by random access memory (RAM) during the execution of the code, measured using *perf*. It is then adjusted considering the baseline power consumption using the equation 2.

Total Energy: is the sum of package energy and RAM energy for a particular problem.

Average Total Energy: is the sum of the total energy consumed by problems considered for the experiment divided by the number of problems considered.

$$\text{Avg. TE} = \frac{1}{N} \sum_{i=1}^N TE_{code_i} \quad (10)$$

B.3 Code Memory Consumption Metrics

Memory Consumption Over Time:

This metric measures how much memory a process uses and for how long, providing a cumulative view of memory consumption:

$$\text{mem-sec} = \sum_{i=1}^{n-1} \left(\frac{M_i + M_{i+1}}{2} \times (T_{i+1} - T_i) \right) \quad (11)$$

Where:

- M_i is the memory consumption at time T_i
- n is the number of sampling points
- The unit is memory-seconds (MB-sec)

The final memory metric for a model M and problem p is derived as:

$$\text{FinalMemory}(M, p) = \frac{1}{3} \sum_{i=1}^3 \text{Memory}_i(M, p) \quad (12)$$

where $\text{Memory}_i(M, p)$ is the memory measurement (either *mem-sec*) from the i^{th} run.

C Comparative Relative Efficiency Analysis

For each LLM-generated code solution and a given resource metric r_i , the relative cost quantifies how many times more or fewer resources the LLM-generated output used compared to the canonical solution.

$$\text{Relative}_{m,r_i} = \frac{V_{m,r_i}}{V_{\text{canonical},r_i}} \quad (13)$$

Where:

- V_{m,r_i} : value of model m for metric r_i
- $V_{\text{canonical},r_i}$: value of the canonical solution for the same metric
- $\text{Relative}_{m,r_i}$: relative cost of the model m compared to the canonical solution

A value greater than 1 indicates that the LLM used more resources (i.e., was less efficient) than the canonical solution. A value less than 1 indicates that the LLM used fewer resources. Values close to 1 reflect near-equivalent cost.

Table 8: Relative cost of LLMs compared to canonical solutions on **Benchmark Set - I**.

Model	Avg. Package Energy	Avg. RAM Energy	Avg. Total Energy	Avg. Runtime	Avg. Memory
DeepSeek v3	1.0238	1.0278	1.0243	1.0200	0.9966
Gemini 2.0 Flash	1.0614	1.0556	1.0607	1.0525	1.0368
Claude 3.5 Sonnet	1.1109	1.1111	1.1109	1.0951	1.0391
GPT-4o	1.1743	1.1667	1.1733	1.1535	1.0713
Nova-Lite	1.2020	1.1944	1.2010	1.1806	1.0644
Claude 3.5 Haiku	1.2307	1.2222	1.2296	1.2131	1.0874
Nova-Pro	1.2356	1.2222	1.2345	1.2132	1.1011
Gemini 2.0 Flash-Lite	1.2396	1.2222	1.2385	1.2195	1.0985
GPT-3.5 Turbo	1.2475	1.2361	1.2470	1.2389	1.1118
Pixtral-Large-2411	1.2970	1.2639	1.2938	1.2704	1.0552
Codestral-Mamba-2407	1.3663	1.3333	1.3629	1.3373	1.0851
Llama 3.1 (8B)	1.4079	1.3750	1.4038	1.3735	1.1172
Nova-Micro	1.4098	1.3750	1.4054	1.3793	1.1713
Gemini 1.5 Pro	1.5040	1.4722	1.5009	1.4609	1.1092
Gemini 1.5 Flash	1.6594	1.6111	1.6516	1.6091	1.1839
Llama 3.3 (70B)	1.7099	1.6528	1.6944	1.6497	1.2471
Mistral-Large-2407	1.7020	1.6528	1.7019	1.6491	1.2069
Grok 2	1.7366	1.6806	1.7301	1.6786	1.1621
Llama 3.1 (70B)	1.7564	1.7083	1.7504	1.7003	1.1943
GPT-4 Turbo	2.0990	2.0000	2.0792	1.9953	1.3299

Table 9: Relative cost of LLMs compared to canonical solutions on **Benchmark Set - II**.

Model	Avg. Package Energy	Avg. RAM Energy	Avg. Total Energy	Avg. Runtime	Avg. Memory
DeepSeek v3	1.1692	1.1493	1.1666	1.1599	1.0423
GPT-4o	1.2171	1.1914	1.2147	1.2043	1.1236
Claude 3.5 Sonnet	1.2361	1.2069	1.2347	1.2196	1.1069
Claude 3.5 Haiku	1.2949	1.2644	1.2911	1.2768	1.1557
Gemini 2.0 Flash-Lite	1.3428	1.3085	1.3388	1.3248	1.2496
Llama 3.1 (70B)	1.6543	1.6026	1.6485	1.6145	1.2424
GPT-4 Turbo	1.7293	1.6618	1.7211	1.6889	1.3722
Gemini 2.0 Flash	1.8086	1.7206	1.7942	1.7491	1.1738
Llama 3.3 (70B)	1.9356	1.8529	1.9258	1.8753	1.6210
Grok 2	2.0127	1.9260	2.0037	1.9516	1.4110
Gemini 1.5 Pro	2.0545	1.9561	2.0431	1.9782	1.2755

D Problem Difficulty-Wise Code Energy Efficiency Analysis

The studied 878 Leetcode problems are divided into three categories (1) easy, (2) medium, and (3) hard problems based on the complexity of the algorithms or data structures required to solve the problems. In the dataset we use (detailed in Table 1), there are 145 easy, 510 medium, and 223 hard problems. In this section, we present the detailed experimental results based on the problem difficulty levels.

D.1 Benchmark Set - I: 20 LLMs & 298 Common Problems

Table 10: Performance and resource usage on **Easy** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.6447	0.6672	5.3119	68.3146	8.3332
Mistral-Large-2407	4.6200	0.6647	5.2847	68.3146	8.3324
Nova-Pro	4.6311	0.6646	5.2957	67.8652	8.3681
Nova-Micro	4.6408	0.6670	5.3078	68.0899	8.3968
Claude 3.5 Haiku	4.6428	0.6674	5.3102	68.4270	8.3103
Pixtral-Large-2411	4.6430	0.6680	5.3110	68.0899	8.3804
DeepSeek v3	4.6451	0.6684	5.3135	68.3146	8.3545
Gemini 1.5 Pro	4.6466	0.6681	5.3147	68.2022	8.3148
Codestral-Mamba-2407	4.6475	0.6674	5.3149	68.3146	8.3639
Llama 3.1 (70B)	4.6471	0.6684	5.3155	68.3146	8.3431
Grok 2	4.6475	0.6688	5.3163	68.0899	8.3666
Nova-Lite	4.6492	0.6687	5.3179	67.9775	8.3496
Gemini 2.0 Flash	4.6525	0.6679	5.3203	68.0899	8.3389
GPT-4o	4.6558	0.6666	5.3225	67.4157	8.3979
Gemini 2.0 Flash-Lite	4.6570	0.6682	5.3252	68.2022	8.3786
Gemini 1.5 Flash	4.6596	0.6700	5.3296	68.2022	8.4905
GPT-4 Turbo	4.6616	0.6696	5.3311	68.2022	8.3600
GPT-3.5 Turbo	4.7419	0.6800	5.4219	69.2135	8.4580
Claude 3.5 Sonnet	5.3321	0.7569	6.0890	77.3034	8.7400
Llama 3.3 (70B)	5.3324	0.7575	6.0899	77.5281	8.8151
Llama 3.1 (8B)	5.4904	0.7793	6.2698	79.5506	8.8789

Table 11: Performance and resource usage on **Medium** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.4982	0.7878	6.2860	80.5028	10.0253
Nova-Lite	5.5962	0.7995	6.3957	81.4525	10.3356
DeepSeek v3	5.6428	0.8065	6.4493	82.5140	9.9460
Claude 3.5 Haiku	5.8471	0.8351	6.6822	85.1397	10.6977
Nova-Pro	5.8991	0.8411	6.7402	85.5866	10.8609
Gemini 2.0 Flash-Lite	5.9157	0.8435	6.7592	86.0894	10.8333
GPT-3.5 Turbo	5.9468	0.8491	6.7959	86.8156	10.9531
Gemini 2.0 Flash	5.9648	0.8500	6.8148	86.5922	10.5324
Claude 3.5 Sonnet	6.0437	0.8587	6.9023	87.3743	10.3755
Pixtral-Large-2411	6.3934	0.9042	7.2977	92.3464	10.1944
GPT-4o	6.7210	0.9499	7.6709	96.8715	10.9429
Codestral-Mamba-2407	6.9753	0.9806	7.9559	100.7263	10.6409
Llama 3.1 (8B)	7.0516	0.9901	8.0417	101.3966	10.9040
Nova-Micro	7.3587	1.0334	8.3920	106.0894	11.9066
Llama 3.1 (70B)	7.4142	1.0420	8.4562	106.3687	11.3072
Gemini 1.5 Pro	8.1617	1.1371	9.2988	115.9777	11.0047
Gemini 1.5 Flash	9.4430	1.3084	10.7514	134.3575	11.9996
Llama 3.3 (70B)	9.5988	1.3296	10.9284	136.3128	12.8081
Mistral-Large-2407	9.8755	1.3639	11.2394	139.3296	12.4016
Grok 2	10.1078	1.3955	11.5033	143.0168	11.7598
GPT-4 Turbo	13.0738	1.7823	14.8561	181.7877	14.1855

Table 12: Performance and resource usage on **Hard** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	3.6287	0.5133	4.1420	53.6667	1.8960
Gemini 2.0 Flash	3.8263	0.5380	4.3643	56.6667	1.9679
Claude 3.5 Sonnet	3.8613	0.5410	4.4023	56.0000	1.9753
DeepSeek v3	3.9007	0.5477	4.4483	56.3333	1.9838
GPT-4o	4.9540	0.6860	5.6400	71.6667	2.3810
Llama 3.1 (8B)	12.3187	1.6310	13.9497	171.0000	5.1774
Llama 3.3 (70B)	12.3737	1.6427	14.0163	172.0000	5.2305
Grok 2	13.0240	1.7383	14.7623	181.3333	5.4729
Gemini 1.5 Flash	13.0550	1.7417	14.7967	181.3333	5.4979
GPT-3.5 Turbo	13.0660	1.7320	14.7980	182.3333	5.4916
GPT-4 Turbo	13.0720	1.7373	14.8093	182.6667	5.5109
Gemini 1.5 Pro	13.0773	1.7323	14.8097	181.6667	5.5012
Nova-Pro	13.0793	1.7377	14.8170	182.3333	5.5022
Claude 3.5 Haiku	13.0810	1.7400	14.8210	182.6667	5.5168
Nova-Lite	13.0793	1.7423	14.8217	182.0000	5.5190
Nova-Micro	13.0870	1.7380	14.8250	181.0000	5.5033
Mistral-Large-2407	13.0980	1.7320	14.8300	182.0000	5.5305
Codestral-Mamba-2407	13.1023	1.7413	14.8437	181.6667	5.4850
Gemini 2.0 Flash-Lite	13.1087	1.7380	14.8467	182.3333	5.5093
Pixtral-Large-2411	13.1167	1.7473	14.8640	182.6667	5.5145
Llama 3.1 (70B)	30.0567	3.9837	34.0403	415.0000	11.0132

D.2 Benchmark Set - II: 11 LLMs & 576 Common Problems

Table 13: Performance and resource usage on **Easy** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.4834	0.6386	5.1220	64.8739	6.5104
Claude 3.5 Haiku	4.4797	0.6379	5.1176	65.1261	6.5318
Grok 2	4.4999	0.6415	5.1414	65.2101	6.5511
DeepSeek v3 (37B)	4.5446	0.6466	5.1913	65.7143	6.5245
Gemini 2.0 Flash	4.5621	0.6474	5.2095	65.8824	6.5310
Gemini 1.5 Pro	4.5654	0.6489	5.2143	65.7143	6.5549
GPT-4o	4.5882	0.6517	5.2399	66.1345	6.5589
Gemini 2.0 Flash-Lite	4.5886	0.6526	5.2412	66.4706	6.5649
GPT-4 Turbo	4.5966	0.6534	5.2501	66.3025	6.5687
Llama 3.1 (70B)	4.6179	0.6566	5.2745	66.3866	6.5949
Claude 3.5 Sonnet	5.0890	0.7186	5.8076	73.0252	6.8626
Llama 3.3 (70B)	5.1242	0.7218	5.8460	73.5294	6.8738

Table 14: Performance and resource usage on **Medium** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.1280	0.7258	5.8538	74.1787	7.7783
Claude 3.5 Haiku	6.2490	0.8718	7.1208	89.5389	8.5283
DeepSeek v3	6.3454	0.8831	7.2285	90.8646	8.2535
Gemini 2.0 Flash-Lite	6.4084	0.8924	7.3007	92.0749	8.8409
GPT-4o	6.4459	0.8973	7.3432	92.3631	8.6318
Claude 3.5 Sonnet	6.6971	0.9293	7.6264	95.5620	8.8311
Llama 3.1 (70B)	7.7076	1.0615	8.7691	109.4236	9.1444
Llama 3.3 (70B)	9.3395	1.2749	10.6145	131.6427	10.1128
GPT-4 Turbo	9.5619	1.3073	10.8692	135.1297	10.3171
Gemini 2.0 Flash	11.2547	1.5145	12.7692	156.9452	9.2581
Grok 2	11.5037	1.5532	13.0570	160.9510	9.7341
Gemini 1.5 Pro	12.1494	1.6327	13.7821	168.9049	9.3706

Table 15: Performance and resource usage on **Hard** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.0241	0.5670	4.5911	59.0000	3.0738
Claude 3.5 Sonnet	4.3294	0.6046	4.9340	62.5455	3.1147
DeepSeek v3 (37B)	4.3489	0.6075	4.9565	63.5455	3.0378
Gemini 2.0 Flash	4.7688	0.6631	5.4319	69.0000	4.3946
GPT-4o	5.1903	0.7158	5.9061	74.5455	4.6173
Claude 3.5 Haiku	7.8569	1.0631	8.9200	110.8182	6.0918
Gemini 1.5 Pro	8.1489	1.0985	9.2474	114.1818	7.5059
GPT-4 Turbo	8.1596	1.1035	9.2631	115.1818	7.8800
Gemini 2.0 Flash-Lite	8.4450	1.1413	9.5863	118.9091	8.3057
Grok 2	9.2089	1.2430	10.4519	130.0909	11.1074
Llama 3.1 (70B)	12.0945	1.6356	13.7301	169.5455	7.0872
Llama 3.3 (70B)	13.4854	1.7825	15.2679	186.0000	16.8674

E Algorithm-Wise Code Energy Efficiency Analysis

The studied dataset includes twelve algorithmic methods, which are Greedy, Dynamic Programming (DP), Backtracking, Divide and Conquer, Depth-First Search (DFS), Breadth-First Search (BFS), Binary Search, Two Pointers, Sliding Window, Bit Manipulation, and Sorting (detailed in Table 1). In this section, we present the detailed experimental results based on each algorithmic category.

E.1 Benchmark Set - I: 20 LLMs & 298 Common Problems

Table 16: Performance and resource usage on **Greedy** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.1920	0.6050	4.7970	61.5152	7.5404
Pixtral-Large-2411	4.1347	0.5974	4.7321	60.7576	7.2395
Mistral-Large-2407	4.1361	0.5968	4.7329	60.4545	7.1168
Gemini 1.5 Pro	4.1398	0.5979	4.7377	60.4545	7.2002
Grok 2	4.1426	0.5977	4.7403	60.4545	7.1998
DeepSeek v3	4.1420	0.5985	4.7405	60.7576	7.1993
Gemini 2.0 Flash	4.1648	0.6009	4.7658	60.7576	7.3499
Claude 3.5 Haiku	4.1885	0.6048	4.7933	61.3636	7.4778
GPT-4o	4.1909	0.6036	4.7945	60.9091	7.4988
Codestral-Mamba-2407	4.2542	0.6112	4.8655	62.4242	7.9851
Claude 3.5 Sonnet	4.2982	0.6185	4.9167	62.5758	8.0772
Gemini 2.0 Flash-Lite	4.3129	0.6208	4.9336	63.0303	8.1648
Llama 3.1 (8B)	4.3511	0.6271	4.9782	63.7879	8.4561
Llama 3.3 (70B)	4.3515	0.6271	4.9786	63.7879	8.4575
Nova-Pro	4.3588	0.6259	4.9847	63.3333	8.4165
Nova-Lite	4.3591	0.6271	4.9862	63.1818	8.4439
Llama 3.1 (70B)	4.3661	0.6289	4.9950	63.4848	8.4499
GPT-3.5 Turbo	4.3691	0.6295	4.9986	63.9394	8.4216
Nova-Micro	4.4288	0.6383	5.0671	65.3030	8.8569
Gemini 1.5 Flash	4.4659	0.6411	5.1070	65.3030	8.4453
GPT-4 Turbo	8.0168	1.1027	9.1195	113.9394	8.7471

Table 17: Performance and resource usage on **DP** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.0514	0.5678	4.6192	59.7297	2.0289
DeepSeek v3	4.6659	0.6492	5.3151	68.2432	2.2492
Gemini 2.0 Flash	5.2708	0.7312	6.0020	76.2162	3.5364
Claude 3.5 Sonnet	5.3718	0.7416	6.1134	77.7027	2.4968
GPT-4o	7.2693	0.9959	8.2653	103.3784	4.2553
Nova-Lite	8.0426	1.0877	9.1303	113.9189	3.5552
Gemini 1.5 Pro	8.0938	1.0900	9.1838	113.7838	3.5782
Pixtral-Large-2411	8.1832	1.1054	9.2886	115.4054	3.5840
GPT-4 Turbo	8.2824	1.1161	9.3985	117.5676	3.6257
Gemini 2.0 Flash-Lite	8.7188	1.1781	9.8969	123.5135	4.8863
Nova-Pro	8.7930	1.1885	9.9815	124.4595	4.8438
Claude 3.5 Haiku	8.8465	1.1959	10.0424	125.0000	4.9631
GPT-3.5 Turbo	8.8945	1.2007	10.0951	125.8108	4.9758
Llama 3.3 (70B)	10.1141	1.3597	11.4738	141.8919	5.3765
Mistral-Large-2407	10.6577	1.4330	12.0907	149.7297	5.5846
Gemini 1.5 Flash	11.1853	1.5042	12.6895	157.0270	4.6200
Llama 3.1 (8B)	11.2842	1.5046	12.7888	157.7027	4.6872
Codestral-Mamba-2407	11.4876	1.5392	13.0268	161.0811	4.6953
Nova-Micro	11.7234	1.5686	13.2920	164.1892	4.7946
Llama 3.1 (70B)	11.9942	1.6122	13.6064	168.3784	4.9080
Grok 2	13.1142	1.7599	14.8741	183.5135	5.2539

Table 18: Performance and resource usage on **Backtracking** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.6818	0.6509	5.3327	70.9091	2.2505
Nova-Lite	4.4455	0.6173	5.0627	63.6364	2.1453
Gemini 1.5 Pro	4.5591	0.6318	5.1909	66.3636	2.2002
GPT-4 Turbo	7.1027	0.9627	8.0655	101.8182	3.0507
DeepSeek v3	7.0991	0.9691	8.0682	101.8182	2.9887
Llama 3.1 (70B)	7.4118	1.0091	8.4209	107.2727	3.1304
Nova-Pro	9.3491	1.2864	10.6355	133.6364	10.8562
Gemini 2.0 Flash	9.4955	1.3036	10.7991	135.4545	10.8023
Claude 3.5 Haiku	9.7991	1.3509	11.1500	140.0000	11.6377
Llama 3.3 (70B)	9.8800	1.3555	11.2355	140.0000	11.6134
Mistral-Large-2407	9.8855	1.3591	11.2445	140.0000	11.6881
GPT-3.5 Turbo	9.9427	1.3655	11.3082	140.0000	11.5888
Gemini 2.0 Flash-Lite	10.1800	1.3973	11.5773	144.5455	11.4508
Claude 3.5 Sonnet	11.0155	1.4764	12.4918	153.6364	4.4692
GPT-4o	12.6900	1.7182	14.4082	179.0909	12.4071
Pixtral-Large-2411	19.9027	2.6409	22.5436	277.2727	7.4959
Gemini 1.5 Flash	25.2555	3.3664	28.6218	354.5455	9.1733
Codestral-Mamba-2407	27.3227	3.6236	30.9464	380.0000	9.8519
Nova-Micro	27.9064	3.6991	31.6055	387.2727	10.1196
Llama 3.1 (8B)	28.2391	3.7136	31.9527	389.0909	10.6508
Grok 2	28.9127	3.8382	32.7509	400.9091	10.4245

Table 19: Performance and resource usage on **Divide & Conquer** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.8525	0.6750	5.5275	70.0000	2.8257
Llama 3.1 (8B)	4.6625	0.6500	5.3125	67.5000	2.7171
GPT-4o	4.7700	0.6575	5.4275	70.0000	2.7633
Pixtral-Large-2411	4.9050	0.6750	5.5800	70.0000	2.8561
Nova-Micro	5.0000	0.6975	5.6975	72.5000	2.8611
GPT-4 Turbo	5.0250	0.6950	5.7200	77.5000	2.9864
Nova-Pro	5.0600	0.7075	5.7675	75.0000	2.9898
Gemini 2.0 Flash	5.1250	0.7125	5.8375	75.0000	2.9920
Claude 3.5 Sonnet	5.1625	0.7100	5.8725	72.5000	2.9603
DeepSeek v3	5.1700	0.7150	5.8850	75.0000	3.0432
Gemini 1.5 Pro	5.3100	0.7375	6.0475	77.5000	3.1163
Claude 3.5 Haiku	5.3200	0.7425	6.0625	80.0000	3.1131
Llama 3.3 (70B)	5.4025	0.7450	6.1475	77.5000	3.1728
Gemini 1.5 Flash	5.4175	0.7475	6.1650	77.5000	3.1688
Nova-Lite	5.4800	0.7525	6.2325	80.0000	3.2003
Codestral-Mamba-2407	5.4775	0.7550	6.2325	80.0000	3.1819
Mistral-Large-2407	5.6025	0.7675	6.3700	80.0000	3.2742
Grok 2	5.7350	0.7875	6.5225	82.5000	3.4081
Gemini 2.0 Flash-Lite	5.7700	0.7925	6.5625	82.5000	3.3522
Llama 3.1 (70B)	5.8300	0.8025	6.6325	85.0000	3.4416
GPT-3.5 Turbo	6.8925	0.9375	7.8300	100.0000	4.0938

Table 20: Performance and resource usage on **DFS** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.4550	0.6455	5.1005	69.0000	3.5409
Gemini 2.0 Flash-Lite	4.0690	0.5865	4.6555	62.0000	3.1474
GPT-4o	4.0695	0.5875	4.6570	62.5000	3.1620
Pixtral-Large-2411	4.0715	0.5865	4.6580	62.5000	3.1565
GPT-4 Turbo	4.0765	0.5875	4.6640	62.0000	3.1682
Llama 3.3 (70B)	4.0760	0.5885	4.6645	62.5000	3.1440
Mistral-Large-2407	4.0775	0.5875	4.6650	62.5000	3.1600
Gemini 1.5 Flash	4.0790	0.5885	4.6675	63.0000	3.1439
Codestral-Mamba-2407	4.0865	0.5885	4.6750	62.5000	3.1324
Llama 3.1 (70B)	4.0890	0.5890	4.6780	62.5000	3.1718
GPT-3.5 Turbo	4.0890	0.5890	4.6780	62.5000	3.1471
Gemini 2.0 Flash	4.0915	0.5895	4.6810	62.0000	3.1579
Nova-Pro	4.0965	0.5890	4.6855	62.0000	3.1583
Grok 2	4.0990	0.5890	4.6880	61.5000	3.1433
Nova-Lite	4.1070	0.5920	4.6990	62.0000	3.1634
DeepSeek v3	4.1085	0.5910	4.6995	61.0000	3.1516
Gemini 1.5 Pro	4.1085	0.5915	4.7000	61.5000	3.1616
Nova-Micro	4.1135	0.5905	4.7040	61.5000	3.1423
Llama 3.1 (8B)	4.1305	0.5930	4.7235	62.0000	3.1516
Claude 3.5 Haiku	4.2700	0.6115	4.8815	64.5000	3.1951
Claude 3.5 Sonnet	4.5315	0.6505	5.1820	67.0000	3.5600

Table 21: Performance and resource usage on **BFS** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.0531	0.7281	5.7812	76.2500	4.0769
Mistral-Large-2407	4.9769	0.7169	5.6938	75.0000	4.0199
Gemini 2.0 Flash-Lite	4.9831	0.7169	5.7000	74.3750	4.0258
Llama 3.3 (70B)	4.9819	0.7194	5.7012	75.0000	4.0185
GPT-3.5 Turbo	4.9869	0.7169	5.7038	74.3750	3.9910
Gemini 1.5 Flash	5.0075	0.7188	5.7263	74.3750	4.0083
Gemini 1.5 Pro	5.0069	0.7200	5.7269	73.7500	4.0188
Gemini 2.0 Flash	5.0094	0.7194	5.7288	74.3750	4.0175
Codestral-Mamba-2407	5.0131	0.7194	5.7325	75.0000	3.9936
Llama 3.1 (70B)	5.0150	0.7206	5.7356	74.3750	4.0448
Nova-Lite	5.0156	0.7213	5.7369	74.3750	4.0365
Nova-Micro	5.0212	0.7188	5.7400	73.1250	4.0069
Llama 3.1 (8B)	5.0288	0.7213	5.7500	74.3750	4.0200
Grok 2	5.0506	0.7231	5.7738	74.3750	4.0383
GPT-4 Turbo	5.0575	0.7244	5.7819	74.3750	4.0674
Nova-Pro	5.0712	0.7256	5.7969	75.0000	4.0737
GPT-4o	5.0675	0.7325	5.8000	75.0000	4.0718
Claude 3.5 Haiku	5.3544	0.7650	6.1194	78.7500	4.1307
DeepSeek v3	5.3781	0.7725	6.1506	78.7500	4.1291
Claude 3.5 Sonnet	5.4075	0.7725	6.1800	80.0000	4.1781
Pixtral-Large-2411	5.7119	0.8150	6.5269	83.7500	4.2429

Table 22: Performance and resource usage on **Binary Search** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	10.9111	1.5847	12.4958	158.4211	35.3952
Mistral-Large-2407	10.8992	1.5853	12.4845	158.4211	35.4054
DeepSeek v3	10.9147	1.5858	12.5005	158.4211	35.4106
Gemini 2.0 Flash	10.9171	1.5879	12.5050	159.2105	35.3539
Codestral-Mamba-2407	10.9192	1.5874	12.5066	158.4211	35.4220
Pixtral-Large-2411	10.9284	1.5892	12.5176	158.6842	35.4368
Claude 3.5 Sonnet	10.9432	1.5863	12.5295	157.3684	35.2925
Nova-Lite	10.9426	1.5871	12.5297	157.6316	35.5502
Nova-Pro	10.9450	1.5866	12.5316	157.1053	35.4164
GPT-4o	10.9468	1.5861	12.5329	156.5789	35.3753
Gemini 1.5 Pro	10.9426	1.5911	12.5337	158.4211	35.4047
Claude 3.5 Haiku	10.9529	1.5916	12.5445	158.6842	35.4130
Gemini 2.0 Flash-Lite	10.9555	1.5897	12.5453	157.8947	35.3401
Grok 2	10.9550	1.5911	12.5461	157.8947	35.4858
Gemini 1.5 Flash	10.9918	1.5987	12.5905	159.7368	35.6661
GPT-4 Turbo	11.0218	1.5989	12.6208	159.2105	35.9505
GPT-3.5 Turbo	11.1471	1.6184	12.7655	161.3158	35.7040
Llama 3.3 (70B)	11.1613	1.6195	12.7808	161.8421	36.7364
Llama 3.1 (8B)	11.2816	1.6371	12.9187	163.4211	35.8710
Nova-Micro	11.5818	1.6789	13.2608	167.3684	39.5061
Llama 3.1 (70B)	24.5637	3.3911	27.9547	345.5263	40.9890

Table 23: Performance and resource usage on **Two Pointers** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	6.7030	0.9758	7.6788	97.8000	21.1321
Grok 2	6.6762	0.9720	7.6482	96.8000	20.7135
DeepSeek v3	6.6846	0.9726	7.6572	97.4000	20.6268
Mistral-Large-2407	6.7170	0.9768	7.6938	97.6000	20.6131
Gemini 1.5 Pro	6.7312	0.9786	7.7098	97.4000	20.7130
Claude 3.5 Haiku	6.7298	0.9806	7.7104	98.2000	21.0926
Gemini 2.0 Flash	6.7488	0.9818	7.7306	98.2000	20.8350
GPT-4o	6.8024	0.9872	7.7896	98.0000	20.9696
Pixtral-Large-2411	6.8050	0.9884	7.7934	98.4000	20.7085
Codestral-Mamba-2407	6.8074	0.9866	7.7940	98.4000	21.6941
Claude 3.5 Sonnet	6.8930	0.9990	7.8920	99.6000	21.7388
GPT-3.5 Turbo	6.9266	1.0064	7.9330	100.6000	22.2774
Nova-Pro	6.9366	1.0064	7.9430	100.0000	22.2237
Nova-Lite	6.9404	1.0052	7.9456	100.4000	22.3925
Llama 3.1 (8B)	6.9444	1.0092	7.9536	100.6000	22.4614
Gemini 2.0 Flash-Lite	6.9490	1.0072	7.9562	100.4000	21.9128
Gemini 1.5 Flash	6.9918	1.0136	8.0054	101.8000	22.1877
GPT-4 Turbo	7.0012	1.0136	8.0148	101.4000	21.5005
Llama 3.3 (70B)	7.2122	1.0442	8.2564	104.4000	23.2472
Llama 3.1 (70B)	7.2118	1.0466	8.2584	104.2000	23.3472
Nova-Micro	7.6618	1.1070	8.7688	110.6000	25.9528

Table 24: Performance and resource usage on **Sliding Window** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	7.3565	1.0691	8.4257	105.2174	26.9084
GPT-3.5 Turbo	7.3248	1.0700	8.3948	106.5217	26.8932
Mistral-Large-2407	7.3365	1.0704	8.4070	106.0870	26.9404
DeepSeek v3	7.3435	1.0687	8.4122	106.0870	26.7775
Pixtral-Large-2411	7.3435	1.0717	8.4152	106.0870	26.7335
GPT-4o	7.3483	1.0683	8.4165	105.2174	26.6089
Gemini 2.0 Flash	7.3465	1.0700	8.4165	106.0870	26.7481
Nova-Pro	7.3483	1.0717	8.4200	105.6522	26.7771
Claude 3.5 Haiku	7.3530	1.0726	8.4257	105.6522	26.9961
Claude 3.5 Sonnet	7.3565	1.0696	8.4261	106.0870	26.6658
Llama 3.1 (8B)	7.3617	1.0739	8.4357	105.6522	27.1564
Gemini 2.0 Flash-Lite	7.3709	1.0717	8.4426	106.0870	26.7718
Codestral-Mamba-2407	7.3752	1.0730	8.4483	105.2174	26.8745
Gemini 1.5 Pro	7.3809	1.0739	8.4548	106.0870	26.9190
Gemini 1.5 Flash	7.3839	1.0739	8.4578	105.2174	26.6743
Nova-Lite	7.3870	1.0722	8.4591	106.0870	27.0621
Grok 2	7.3961	1.0752	8.4713	105.6522	26.9730
GPT-4 Turbo	7.4917	1.0904	8.5822	108.2609	27.7598
Llama 3.3 (70B)	7.7465	1.1243	8.8709	111.3043	28.7879
Llama 3.1 (70B)	7.7552	1.1283	8.8835	110.8696	29.0314
Nova-Micro	8.4552	1.2248	9.6800	121.3043	33.5166

Table 25: Performance and resource usage on **Bit Manipulation** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	3.0623	0.4354	3.4977	45.1429	1.6504
Claude 3.5 Haiku	2.9423	0.4203	3.3626	44.0000	1.6011
GPT-4o	2.9443	0.4209	3.3651	44.2857	1.6155
DeepSeek v3	2.9451	0.4211	3.3663	44.2857	1.6093
Mistral-Large-2407	2.9503	0.4200	3.3703	43.7143	1.6112
Claude 3.5 Sonnet	2.9514	0.4209	3.3723	43.7143	1.6081
Codestral-Mamba-2407	2.9826	0.4249	3.4074	44.2857	1.6116
GPT-3.5 Turbo	2.9871	0.4257	3.4129	44.0000	1.6220
Gemini 2.0 Flash	2.9974	0.4271	3.4246	44.2857	1.6277
Gemini 2.0 Flash-Lite	3.0003	0.4257	3.4260	44.0000	1.6259
Nova-Micro	3.0114	0.4294	3.4409	44.5714	1.6232
GPT-4 Turbo	3.0380	0.4337	3.4717	45.1429	1.6416
Nova-Pro	3.0654	0.4360	3.5014	45.4286	1.6584
Nova-Lite	3.0689	0.4360	3.5049	44.8571	1.6566
Llama 3.1 (8B)	3.1029	0.4429	3.5457	46.2857	1.6706
Llama 3.1 (70B)	3.1137	0.4417	3.5554	45.4286	1.6677
Pixtral-Large-2411	7.1914	0.9760	8.1674	101.7143	3.0908
Grok 2	15.6151	2.0931	17.7083	216.2857	7.5604
Gemini 1.5 Flash	15.6614	2.1029	17.7643	216.8571	7.6045
Gemini 1.5 Pro	16.4140	2.1906	18.6046	227.1429	7.3323
Llama 3.3 (70B)	18.2411	2.4380	20.6791	252.2857	8.6808

Table 26: Performance and resource usage on **Sorting** problems from **Benchmark Set - I**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	6.5265	0.9441	7.4706	94.8235	17.3111
Pixtral-Large-2411	6.5282	0.9449	7.4732	94.8235	17.0698
DeepSeek v3	6.5451	0.9465	7.4915	95.4118	17.0882
Gemini 2.0 Flash	6.6494	0.9607	7.6101	96.4706	17.1853
Gemini 1.5 Pro	6.6761	0.9633	7.6394	96.4706	17.0801
GPT-4o	6.6835	0.9633	7.6468	96.0000	17.4976
Grok 2	6.6864	0.9659	7.6522	97.0588	17.1309
Claude 3.5 Haiku	6.6978	0.9691	7.6668	97.6471	17.6077
Codestral-Mamba-2407	6.7938	0.9780	7.7718	98.8235	17.7396
Nova-Pro	6.8233	0.9831	7.8064	98.5882	18.0333
Gemini 2.0 Flash-Lite	6.8932	0.9925	7.8856	99.8824	17.9685
GPT-3.5 Turbo	6.9145	0.9968	7.9113	100.4706	18.1414
Nova-Lite	6.9166	0.9960	7.9126	100.1176	18.0759
Gemini 1.5 Flash	7.0067	1.0073	8.0140	101.4118	18.1709
Nova-Micro	7.2829	1.0486	8.3315	105.8824	20.2935
Claude 3.5 Sonnet	7.4954	1.0695	8.5649	107.5294	18.1460
Llama 3.1 (8B)	7.5456	1.0794	8.6251	108.8235	18.5860
Llama 3.3 (70B)	7.6629	1.0959	8.7588	110.5882	19.0995
Llama 3.1 (70B)	9.5380	1.3485	10.8865	136.2353	19.7630
Mistral-Large-2407	13.6091	1.8732	15.4822	190.1176	20.6693
GPT-4 Turbo	22.2915	3.0160	25.3075	306.0000	26.0765

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Table 27: Performance and resource usage on **Greedy** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	3.6603	0.5175	4.1778	53.2215	4.1165
Grok 2	3.6160	0.5127	4.1287	52.8859	3.9836
DeepSeek v3 (37B)	3.6323	0.5140	4.1464	52.4832	3.9999
GPT-4o	3.6930	0.5221	4.2150	53.6242	4.1181
Gemini 1.5 Pro	3.7479	0.5287	4.2765	54.2282	4.0302
Claude 3.5 Sonnet	3.8555	0.5423	4.3978	55.5034	4.4288
Claude 3.5 Haiku	3.8604	0.5430	4.4034	55.4362	4.1778
Llama 3.1 (70B)	3.8611	0.5439	4.4050	56.0403	4.6114
Gemini 2.0 Flash-Lite	3.8744	0.5455	4.4199	56.0403	4.4935
Gemini 2.0 Flash	3.8809	0.5462	4.4272	56.1745	4.1288
Llama 3.3 (70B)	3.9405	0.5539	4.4944	57.1141	4.6310
GPT-4 Turbo	5.3377	0.7378	6.0755	76.4430	4.6970

Table 28: Performance and resource usage on **DP** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.1146	0.5721	4.6867	59.6154	2.7721
DeepSeek v3 (37B)	6.3665	0.8607	7.2272	90.3205	3.8131
GPT-4o	6.9045	0.9315	7.8360	97.2436	5.4728
Claude 3.5 Sonnet	7.0043	0.9426	7.9469	98.6538	4.7442
GPT-4 Turbo	7.8680	1.0578	8.9258	110.2564	6.7915
Claude 3.5 Haiku	8.3847	1.1260	9.5108	117.6923	6.3315
Gemini 2.0 Flash-Lite	9.2200	1.2338	10.4538	129.0385	8.3407
Llama 3.1 (70B)	11.0878	1.4747	12.5625	153.8462	6.4045
Llama 3.3 (70B)	15.7245	2.0661	17.7906	216.1538	15.1335
Gemini 2.0 Flash	17.4983	2.2915	19.7897	239.6795	6.8631
Grok 2	18.2125	2.3948	20.6073	251.3462	11.3735
Gemini 1.5 Pro	18.7244	2.4491	21.1735	256.2821	8.0891

Table 29: Performance and resource usage on **Backtracking** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	8.9544	1.2652	10.2196	127.2000	21.9081
GPT-4 Turbo	11.8400	1.6328	13.4728	166.4000	23.5252
GPT-4o	15.0500	2.0664	17.1164	210.8000	27.6705
Claude 3.5 Sonnet	15.3848	2.0932	17.4780	216.0000	24.7516
Gemini 2.0 Flash-Lite	17.1360	2.3276	19.4636	239.2000	28.3890
Claude 3.5 Haiku	17.5416	2.3788	19.9204	244.0000	28.2667
DeepSeek v3 (37B)	19.0252	2.5568	21.5820	264.0000	25.6659
Llama 3.1 (70B)	24.5892	3.2872	27.8764	340.4000	27.7724
Llama 3.3 (70B)	55.8324	7.2816	63.1140	756.8000	74.2700
Grok 2	66.9000	8.7356	75.6356	913.6000	36.2330
Gemini 1.5 Pro	79.7148	10.3496	90.0644	1077.6000	32.5344
Gemini 2.0 Flash	82.4440	10.7056	93.1496	1114.4000	36.8112

Table 30: Performance and resource usage on **Divide & Conquer** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	3.8542	0.5350	4.3892	55.8333	2.0303
Claude 3.5 Haiku	3.8808	0.5375	4.4183	56.6667	2.0862
Grok 2	3.9375	0.5450	4.4825	56.6667	2.1585
DeepSeek v3 (37B)	4.4425	0.6108	5.0533	64.1667	2.2794
Claude 3.5 Sonnet	4.4492	0.6117	5.0608	64.1667	2.2634
GPT-4 Turbo	4.4583	0.6142	5.0725	65.0000	2.2651
Gemini 2.0 Flash	4.5067	0.6192	5.1258	65.8333	2.2838
Llama 3.3 (70B)	4.5083	0.6217	5.1300	65.0000	2.3204
Gemini 1.5 Pro	4.5183	0.6192	5.1375	64.1667	2.2972
GPT-4o	4.5700	0.6267	5.1967	66.6667	2.2528
Gemini 2.0 Flash-Lite	4.7267	0.6458	5.3725	66.6667	2.4001
Llama 3.1 (70B)	4.7467	0.6517	5.3983	69.1667	2.4406

Table 31: Performance and resource usage on **DFS** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	6.1661	0.8848	7.0509	91.5152	6.8849
Grok 2	5.9167	0.8482	6.7648	88.1818	6.6496
Gemini 1.5 Pro	5.9215	0.8482	6.7697	87.8788	6.6613
DeepSeek v3 (37B)	5.9264	0.8470	6.7733	87.5758	6.6432
GPT-4 Turbo	5.9336	0.8503	6.7839	88.1818	6.6526
GPT-4o	5.9548	0.8509	6.8058	88.4848	6.6690
Gemini 2.0 Flash-Lite	5.9630	0.8542	6.8173	89.3939	6.6983
Llama 3.1 (70B)	5.9776	0.8545	6.8321	88.7879	6.6550
Gemini 2.0 Flash	5.9885	0.8564	6.8448	88.1818	6.7327
Claude 3.5 Haiku	6.0476	0.8639	6.9115	90.3030	6.7167
Llama 3.3 (70B)	6.0609	0.8667	6.9276	89.3939	6.7028
Claude 3.5 Sonnet	6.1588	0.8827	7.0415	90.9091	6.8542

Table 32: Performance and resource usage on **BFS** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	7.6440	1.0747	8.7187	110.6667	7.9833
Gemini 2.0 Flash	10.1163	1.4137	11.5300	148.0000	7.9332
Gemini 2.0 Flash-Lite	10.1893	1.4207	11.6100	148.3333	7.9233
Llama 3.3 (70B)	10.2653	1.4310	11.6963	149.0000	7.9710
GPT-4o	10.5053	1.4613	11.9667	152.0000	8.0799
Claude 3.5 Sonnet	10.6250	1.4807	12.1057	154.0000	8.0730
GPT-4 Turbo	10.6593	1.4837	12.1430	154.6667	8.1395
Gemini 1.5 Pro	10.6823	1.4873	12.1697	154.0000	8.1141
Grok 2	10.7960	1.5027	12.2987	156.0000	8.1800
DeepSeek v3 (37B)	10.8820	1.5113	12.3933	157.0000	8.1797
Claude 3.5 Haiku	10.9117	1.5113	12.4230	157.6667	8.2380
Llama 3.1 (70B)	11.0823	1.5393	12.6217	160.0000	8.3741

Table 33: Performance and resource usage on **Binary Search** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	7.4294	1.0772	8.5066	108.3721	17.6033
DeepSeek v3 (37B)	7.3084	1.0566	8.3650	106.2791	17.2535
Claude 3.5 Sonnet	7.3731	1.0691	8.4422	107.3256	17.3487
GPT-4o	7.8806	1.1320	9.0126	113.9535	18.9988
Gemini 2.0 Flash	7.9167	1.1374	9.0542	114.4186	19.0329
Claude 3.5 Haiku	8.1220	1.1638	9.2858	117.5581	19.7633
Gemini 1.5 Pro	8.7494	1.2470	9.9964	125.9302	21.6781
Llama 3.3 (70B)	8.8747	1.2641	10.1387	128.6047	22.3635
GPT-4 Turbo	8.9222	1.2700	10.1922	128.8372	22.3864
Gemini 2.0 Flash-Lite	8.9279	1.2709	10.1988	129.0698	22.5757
Grok 2	10.1612	1.4328	11.5940	146.0465	26.1733
Llama 3.1 (70B)	13.8681	1.9417	15.8099	197.7907	21.7054

Table 34: Performance and resource usage on **Two Pointers** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.9835	0.8606	6.8442	86.6129	16.5701
Grok 2	5.9560	0.8579	6.8139	85.6452	16.1937
DeepSeek v3 (37B)	5.9782	0.8585	6.8368	85.4839	16.3254
Claude 3.5 Haiku	5.9985	0.8610	6.8595	86.6129	16.5482
Gemini 1.5 Pro	6.0013	0.8621	6.8634	86.2903	16.2923
Gemini 2.0 Flash	6.0294	0.8673	6.8966	86.7742	16.4732
GPT-4o	6.0713	0.8711	6.9424	87.0968	16.5650
Claude 3.5 Sonnet	6.1439	0.8827	7.0266	88.3871	17.1383
Gemini 2.0 Flash-Lite	6.1844	0.8869	7.0713	88.7097	17.3136
GPT-4 Turbo	6.2097	0.8897	7.0994	89.0323	16.9718
Llama 3.1 (70B)	6.3985	0.9147	7.3132	91.4516	18.4823
Llama 3.3 (70B)	6.3977	0.9161	7.3139	91.7742	18.4822

Table 35: Performance and resource usage on **Sliding Window** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.2135	0.7477	5.9613	74.5833	13.2610
Claude 3.5 Haiku	5.2219	0.7479	5.9698	75.4167	13.2504
Claude 3.5 Sonnet	5.3706	0.7698	6.1404	76.8750	13.1980
DeepSeek v3 (37B)	5.3906	0.7698	6.1604	77.2917	13.3448
GPT-4o	5.4254	0.7744	6.1998	77.7083	13.3001
Gemini 1.5 Pro	5.4296	0.7746	6.2042	77.9167	13.3303
Gemini 2.0 Flash-Lite	5.4321	0.7763	6.2083	78.3333	13.2615
GPT-4 Turbo	5.4715	0.7798	6.2513	77.7083	13.7686
Grok 2	5.5013	0.7850	6.2863	78.3333	13.2852
Llama 3.3 (70B)	5.6110	0.8029	6.4140	80.8333	14.4033
Llama 3.1 (70B)	5.6512	0.8065	6.4577	80.8333	14.3844
Gemini 2.0 Flash	6.1148	0.8648	6.9796	87.0833	13.6598

Table 36: Performance and resource usage on **Bit Manipulation** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	4.7403	0.6727	5.4130	68.4848	8.9917
GPT-4o	5.1327	0.7223	5.8550	73.6364	9.0154
GPT-4 Turbo	5.1361	0.7235	5.8595	73.7879	9.1655
Claude 3.5 Sonnet	5.7236	0.8000	6.5236	81.6667	9.4019
Claude 3.5 Haiku	6.1771	0.8589	7.0361	88.1818	9.3643
Gemini 2.0 Flash-Lite	6.2344	0.8670	7.1014	89.3939	9.5377
DeepSeek v3 (37B)	7.7945	1.0650	8.8595	109.8485	9.9943
Llama 3.1 (70B)	9.7048	1.3150	11.0198	135.6061	10.7411
Grok 2	28.7344	3.7917	32.5261	394.6970	15.7563
Llama 3.3 (70B)	29.1011	3.8211	32.9221	395.7576	30.5932
Gemini 2.0 Flash	31.2664	4.0761	35.3424	424.5455	12.9024
Gemini 1.5 Pro	38.0906	4.9780	43.0686	516.2121	15.7420

Table 37: Performance and resource usage on **Sorting** problems from **Benchmark Set - II**.

Model	Avg. Pkg Energy (J)	Avg. RAM Energy (J)	Avg. Total Energy (J)	Avg. Runtime (ms)	Avg. Mem (MB-s)
Canonical Solution	5.2085	0.7427	5.9512	75.2903	9.9341
DeepSeek v3 (37B)	5.2352	0.7472	5.9824	75.9355	9.8572
Gemini 2.0 Flash	5.2943	0.7539	6.0483	76.5161	9.9365
Grok 2	5.3334	0.7601	6.0934	77.2258	9.8291
GPT-4o	5.3683	0.7632	6.1315	77.8065	10.1040
Claude 3.5 Haiku	5.3702	0.7627	6.1329	77.2258	10.1022
Gemini 1.5 Pro	5.3963	0.7659	6.1622	77.7419	9.8676
Gemini 2.0 Flash-Lite	5.5224	0.7842	6.3066	79.8065	10.3771
Claude 3.5 Sonnet	5.8338	0.8249	6.6587	83.6774	10.4589
Llama 3.3 (70B)	6.0050	0.8481	6.8531	86.4516	11.0881
Llama 3.1 (70B)	6.9970	0.9767	7.9737	99.4839	11.3818
GPT-4 Turbo	13.7246	1.8608	15.5854	192.6452	14.9146

F Code Analysis for Different LLMs

This section compares the code generated by different LLMs and analyzes the reasons behind their varying levels of energy efficiency compared to a canonical solution. The most energy-inefficient code is observed in algorithm categories such as Dynamic Programming, Backtracking, and Bit Manipulation. In these cases, the main cause of increased energy consumption is the absence of optimization techniques such as pruning. Without pruning, redundant computations are repeatedly executed, leading to higher computational load and memory usage. This, in turn, results in longer execution times and consequently higher energy consumption.

F.1 Case I: Large Differences in Energy Consumption

To evaluate this case, we take the solution generated for **LeetCode Problem 2305**. The problem details are as follows:

Problem Name: Fair Distribution of Cookies

Algorithm Categories: Dynamic Programming, Backtracking, Bit Manipulation

Problem Description: The task is to distribute the cookie bags as part of `cookies` list among `k` children as fairly as possible. The cookie bags should be distributed in such a way that all the cookies in the selected bag go to the same child. After distributing the cookies fairly, the program should return the minimum unfairness value which is the maximum number of cookies that a single child received during distribution.

Input: `cookies` (List of integers of length n , where $2 \leq n \leq 8$ and $1 \leq \text{cookies}[i] \leq 10^5$), `k` (An integer representing the number of children, where $2 \leq k \leq n$)

Output: The minimum unfairness value

The following are our observations.

1. The **best solution** is the solution generated by LLMs **Claude Haiku** and **GPT-4 Turbo** as they apply effective pruning strategies to eliminate redundant calculations.
2. The **Canonical Solution** has a **slightly higher** energy consumption than the best solution as it misses one pruning strategy of eliminating redundant calculation of symmetric paths.
3. **GPT-4o** and **Gemini 2.0 Flash Lite** generate solutions that closely resemble the canonical version, and therefore demonstrate similar energy consumption profiles.
4. **Claude 3.5 Sonnet** produces a solution that has **15 times** higher energy consumption as compared to the best solution as it uses a minimum unfairness value that resets with each recursive call and lacks

other checks that can reduce redundant computations. However, it does apply the pruning strategy to remove redundant calculation of symmetric paths.

5. **DeepSeek v3** produces a **slightly worse solution** than the canonical solution. This solution uses a minimum unfairness value that resets with each recursive call and lacks the symmetric path check, leading to more unnecessary computations, and thus resulting in energy consumption nearly **39 times** more than the best solution.
6. **LLaMA 3.3 70B** produces an **even worse solution** than **DeepSeek v3**. Although the logic produced by both LLMs is very similar, LLaMA 3.3 70B does more redundant calculations by evaluating the branches with the same values. This results in energy consumption which is **3 times** more than the DeepSeek v3 solution and **129 times** more than the best solution.
7. **Gemini 1.5 Pro** and **Gemini 2.0 Flash** generate the **worst solutions**. Both LLMs generate the same solution, which does not have any pruning logic in place, resulting in up to **450 times** the energy consumption of the **canonical solution** and **548 times** the energy consumption of the **best solution**.

Figure 5 presents both the canonical solution and the representative outputs of selected LLMs, effectively highlighting the differences in energy consumption and supporting our performance analysis.

GPT-4 Turbo	Canonical Solution
Total Energy Consumption: 3.51 J	Total Energy Consumption: 4.28 J
<pre> class Solution: def distributeCookies(self, cookies, k): n = len(cookies) self.bestMax = float('inf') def backtrack(i, dist): if i == n: self.bestMax = min(self.bestMax, max(dist)) return if max(dist) >= self.bestMax: return for child in range(k): dist[child] += cookies[i] backtrack(i + 1, dist) dist[child] -= cookies[i] if dist[child] == 0: break distributions = [0] * k backtrack(0, distributions) return self.bestMax </pre>	<pre> class Solution: def distributeCookies(self, cookies: List[int], k: int) -> int: def dfs(i): if i >= len(cookies): nonlocal ans ans = max(cnt) return for j in range(k): if cnt[j] + cookies[i] >= ans or (j and cnt[j] == cnt[j - 1]): continue cnt[j] += cookies[i] dfs(i + 1) cnt[j] -= cookies[i] ans = inf cnt = [0] * k cookies.sort(reverse=True) dfs(0) return ans </pre>
Claude 3.5 Sonnet	DeepSeek v3
Total Energy Consumption: 53.54 J	Total Energy Consumption: 139.66 J
<pre> class Solution: def distributeCookies(self, cookies: list[int], k: int) -> int: n = len(cookies) children = [0] * k def backtrack(index: int, count: int) -> int: remaining = n - index if k - count > remaining: return float('inf') if index == n: return max(children) ans = float('inf') for j in range(k): add = 1 if children[j] == 0 else 0 children[j] += cookies[index] ans = min(ans, backtrack(index + 1, count + add)) children[j] -= cookies[index] if index == 0: break return ans return backtrack(0, 0) </pre>	<pre> from typing import List class Solution: def distributeCookies(self, cookies: List[int], k: int) -> int: def backtrack(index, distribution): if index == len(cookies): return max(distribution) min_unfairness = float('inf') for i in range(k): distribution[i] += cookies[index] if distribution[i] < min_unfairness: current_unfairness = backtrack(index + 1, distribution) if current_unfairness < min_unfairness: min_unfairness = current_unfairness distribution[i] -= cookies[index] return min_unfairness return backtrack(0, [0] * k) </pre>
LLaMA 3.3 70B	Gemini 1.5 Pro
Total Energy Consumption: 456.16 J	Total Energy Consumption: 1922.22 J
<pre> class Solution: def distributeCookies(self, cookies, k): n = len(cookies) total_cookies = sum(cookies) def backtrack(idx, child_cookies): if idx == n: return max(child_cookies) res = float('inf') for i in range(k): if child_cookies[i] + cookies[idx] <= res: child_cookies[i] += cookies[idx] res = min(res, backtrack(idx+1, child_cookies)) child_cookies[i] -= cookies[idx] return res return backtrack(0, [0]*k) </pre>	<pre> class Solution: def distributeCookies(self, cookies: List[int], k: int) -> int: n = len(cookies) self.ans = float('inf') dist = [0] * k def backtrack(index): if index == n: self.ans = min(self.ans, max(dist)) return for i in range(k): dist[i] += cookies[index] backtrack(index + 1) dist[i] -= cookies[index] # backtrack backtrack(0) return self.ans </pre>

Figure 5: The above figure shows the canonical solution and the code generated by different LLMs along with their respective energy consumptions for LeetCode Problem 2305.

F.2 Case II: Comparable Difference in Energy Consumption

To evaluate this case, we take the solution generated for **LeetCode Problem 740**. The problem details are as follows:

Problem Name: Delete and Earn

Categories: Dynamic Programming.

Problem Description: Given a list of integers `nums`, the goal is to earn the maximum number of points by repeatedly performing the following operation: select any element `nums[i]` from the list, earn points equal to its value, and then remove that element along with all elements equal to `nums[i] - 1` and `nums[i] + 1` from the list.

Input: `nums` (List of integers containing the number of points where $1 \leq \text{nums.length} \leq 2 \times 10^4$, $1 \leq \text{nums}[i] \leq 10^4$).

Output: The maximum number of points that can be earned.

Figure 6 showcases the canonical solution to LeetCode Problem 740, along with representative outputs from selected LLMs, highlighting our comparative analysis.

GPT-4o	Canonical Solution
Total Energy Consumption: 3.29 J	Total Energy Consumption: 15.73 J
<pre> class Solution: def deleteAndEarn(self, nums: List[int]) -> int: if not nums: return 0 points = defaultdict(int) for num in nums: points[num] += num unique_nums = sorted(points.keys()) prev_num = None prev_two_earnings = 0 prev_earnings = 0 for num in unique_nums: if num - 1 == prev_num: current_earnings = max(prev_earnings, prev_two_earnings + points[num]) else: current_earnings = prev_earnings + points[num] prev_two_earnings, prev_earnings = prev_earnings, current_earnings prev_num = num return prev_earnings </pre>	<pre> class Solution: def deleteAndEarn(self, nums: List[int]) -> int: mx = -inf for num in nums: mx = max(mx, num) total = [0] * (mx + 1) for num in nums: total[num] += num first = total[0] second = max(total[0], total[1]) for i in range(2, mx + 1): cur = max(first + total[i], second) first = second second = cur return second </pre>
Gemini 1.5 Pro	Claude 3.5 Sonnet
Total Energy Consumption: 21.90 J	Total Energy Consumption: 28.77 J
<pre> from typing import List class Solution: def deleteAndEarn(self, nums: List[int]) -> int: points = [0] * 10001 for num in nums: points[num] += num dp = [0] * 10001 dp[1] = points[1] for i in range(2, 10001): dp[i] = max(dp[i-1], dp[i-2] + points[i]) return dp[10000] </pre>	<pre> from typing import * from collections import Counter class Solution: def deleteAndEarn(self, nums: List[int]) -> int: count = Counter(nums) max_num = max(nums) dp = [0] * (max_num + 1) dp[1] = count[1] * 1 if max_num >= 2: dp[2] = max(dp[1], count[2] * 2) for i in range(3, max_num + 1): dp[i] = max(dp[i-1], dp[i-2] + count[i] * i) return dp[max_num] </pre>

Figure 6: The above figure shows the canonical solution and the code generated by different LLMs along with their respective energy consumptions for LeetCode Problem 740.

The following are our observations.

1. The **best solution** is generated by **GPT-4o**, **Grok2**, **LLaMA 3.1 70B**, and **Gemini 2.0 Flash-Lite**. These models use an optimal approach using a few variables to iteratively compute the result. Their solutions achieve a time complexity of $\mathcal{O}(\text{len}(\text{nums}))$, resulting in the **lowest energy consumption** across all models evaluated.
2. The **Canonical solution** produces a solution that consumes **5 times** more energy than the best solution. This implementation relies on constructing a list with a size proportional to the maximum value in the input array, resulting in a time complexity of $\mathcal{O}(\text{max}(\text{nums}))$. This increased both memory usage and computational cost.
3. **Gemini 1.5 Pro** produces a solution with energy consumption roughly **7 times** greater than the best solution. Similar to the canonical approach, it uses a list-based method to accumulate points. However, the list is statically sized to a fixed upper bound of 10,000, irrespective of the actual maximum value in `nums`. This leads to a suboptimal time complexity of $\mathcal{O}(10^4)$.

4. The **worst solution** is produced by **Claude-Sonnet** and **LLaMA 3.1 70B**. While structurally similar to the canonical approach in utilizing a list indexed by element values, their implementations introduce additional redundant multiplications during the computation. These unnecessary operations further increase computational overhead, resulting in energy consumption nearly **9 times** higher than the best solution.