

This is the DEDICATION:
you can write whatever you want here,
or nothing at all . . .

Introduction

This is the introduction

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Chapter 1

Experimental Evaluation

1.1 Methodology

In this section, the focus is on outlining the foundational decisions required to establish an initial benchmark. This benchmark serves as the basis for refining subsequent experiments and assessing both the current capabilities and future potential of the solver.

The section is structured into four subsections, each addressing a key preliminary choice. The first subsection discusses the selection of large language models used as candidates for the agentic component. The second details the initial prompt-engineering strategy needed to define a clean, consistent prompt format for evaluation. The third presents the rationale behind the selection of benchmark problems used to test model performance. The fifth explains the metrics adopted to evaluate how effectively each model could operate as a meta-solver. The final subsection explains the pre-processing methods adopted to make automatic testing possible.

1.1.1 Provider Choice

To build the proposed Agentic Solver (AS), the first requirement is the availability of an LLM capable of orchestrating the system and acting as the agent. Given the limited computational resources available during the testing phase, we had to rely on externally hosted LLMs accessed through usage-based APIs. The selection prioritized generous free tiers, permissive rate limits, and straightforward integration. This led to the choice of the following providers:

- **Gemini API v1** [1], offered by Google DeepMind. Gemini is a family of large language models with multiple sizes and capabilities. This provider was selected for its strong reasoning abilities, robust tool-use features, and overall high-quality text generation. For the purpose of this research, the version v1 [2] was preferred as it is more stable and our only concern is its text generation capability.
- **Groq API** [3], provided by Groq. Groq offers high-performance inference solutions through its specialized hardware architecture. The Groq API exposes a selection of LLMs through

a simple and lightweight interface, enabling fast and low-latency experimentation.

Both APIs were selected for their ease of use, flexibility, overall performance, and, critically, their comparatively generous rate limits relative to competing services, in Table 1.2 and Table 1.1 are displayed rate limits of both APIs. From the leftmost column of the table, there are: Model containing the names of each one of the available LLMs (for the purpose of this paper, only text generation models were selected), moving to the right *RPM* contains the maximum number of requests in a minute, *RPD* contains the maximum number of requests per day, *TPM* contains the maximum number of requested tokens per minute, and finally *TPD* contains the maximum number of tokens per day.

| Model | RPM | RPD | TPM | TPD |
|---|-----|-------|-------|--------|
| allam-2-7b | 30 | 7000 | 6000 | 500000 |
| deepseek-r1-distill-llama-70b | 30 | 1000 | 6000 | 100000 |
| gemma2-9b-it | 30 | 14400 | 15000 | 500000 |
| groq/compound | 30 | 250 | 70000 | – |
| groq/compound-mini | 30 | 250 | 70000 | – |
| llama-3.1-8b-instant | 30 | 14400 | 6000 | 500000 |
| llama-3.3-70b-versatile | 30 | 1000 | 12000 | 100000 |
| meta-llama/llama-4-maverick-17b-128e-instruct | 30 | 1000 | 6000 | 500000 |
| meta-llama/llama-4-scout-17b-16e-instruct | 30 | 1000 | 30000 | 500000 |
| meta-llama/llama-guard-4-12b | 30 | 14400 | 15000 | 500000 |
| meta-llama/llama-prompt-guard-2-22m | 30 | 14400 | 15000 | 500000 |
| meta-llama/llama-prompt-guard-2-86m | 30 | 14400 | 15000 | 500000 |
| moonshotai/kimi-k2-instruct | 60 | 1000 | 10000 | 300000 |
| moonshotai/kimi-k2-instruct-0905 | 60 | 1000 | 10000 | 300000 |
| openai/gpt-oss-120b | 30 | 1000 | 8000 | 200000 |
| openai/gpt-oss-20b | 30 | 1000 | 8000 | 200000 |
| playai-tts | 10 | 100 | 1200 | 3600 |
| playai-tts-arabic | 10 | 100 | 1200 | 3600 |
| qwen/qwen3-32b | 60 | 1000 | 6000 | 500000 |

Table 1.1: Rate limits - Groq models [4]:

This table shows all the offered models from Groq API, in leftmost column and each relative rate limit.

| Model | RPM | RPD | TPM | TPD |
|-----------------------|-----|------|---------|-----|
| gemini-2.5-pro | 5 | 100 | 250000 | – |
| gemini-2.5-flash | 10 | 250 | 250000 | – |
| gemini-2.5-flash-lite | 15 | 1000 | 250000 | – |
| gemini-2.0-flash | 15 | 200 | 1000000 | – |
| gemini-2.0-flash-lite | 30 | 200 | 1000000 | – |

Table 1.2: Rate limits - Gemini models [5]

This table shows all the offered models from Gemini API, in leftmost column and each relative rate limit.

1.1.2 Large Language Models Selection

Both providers offer a broad set of LLMs with varying capabilities and constraints, so an initial filtering step was required. Several options were excluded immediately because they are not designed for text generation, which is essential for the proposed AS. In particular, `playai-tts` and `playai-tts-arabic` are text-to-speech LLMs available only on Groq’s platform and therefore unsuitable for remote testing.

Additional LLMs were removed because they are currently decommissioned or unavailable: `deepseek-r1-distill-llama-70b`, `gemini-2.0-flash-lite`, and `gemma2-9b-it`.

Two more LLMs were excluded due to insufficient context window size. Although their rate limits were acceptable, their token capacity was too small to accommodate even a single full MiniZinc model as input: `meta-llama/llama-prompt-guard-2-22m` and `meta-llama/llama-prompt-guard-2-86m`.

Finally, `allam-2-7b` was removed because it failed to follow instructions consistently, often producing incomplete, inconsistent, or unreadable outputs.

After this filtering stage, 18 LLMs remained as a stable base for the evaluation phase.

1.1.3 Prompt General Structure

To determine which LLM would be best suited for building an AS, it was necessary to design a consistent prompt format to query each model. The primary objective was to define a structure that was as short and clean as possible, for two main reasons:

- Minimize prompt-induced bias: A highly descriptive or too long and complex prompt could influence LLMs negatively. As we could encounter problems as “context rot” [6] - a progressive decay in accuracy as prompts grow longer.
- Reduce token usage: Since the testing setup depends on API limits, keeping the prompt compact minimizes token consumption.

Output Structure

Ensuring a standardized output format was equally important: Automated testing requires that model outputs follow a strict and predictable format. Any deviation introduces ambiguity during parsing and prevents reliable extraction of solver selections. Maintaining this structure is therefore essential to ensure consistent and fully automated evaluation.

Large or verbose responses also impose practical limitations on the available context window. Because each message contributes to the total token count, excessively long outputs reduce the room available for subsequent turns and larger prompts.

For these reasons, the output format was fixed as an array of three strings:

$$[“1^{st}Solver“, “2^{nd}Solver“, “3^{rd}Solver“]$$

Selecting the top three solvers enables two forms of evaluation:

- Single-solver evaluation: Measures whether the solver chosen by the LLM is the single best solver for the given instance. If it is not, the evaluation can quantify how close its performance is to the optimal solver.
- Parallel-solver evaluation: Measures the effectiveness of running the top three solvers selected by the LLM in parallel. The best result among the three is considered, allowing assessment of whether any of them corresponds to the single best solver for the instance, or, if not, how close the best among the three comes to the optimal performance.

The metrics used for these evaluations will be detailed in subsection 1.1.5.

After all of this considerations, the resulting prompt structure is the one displayed in Figure 1.1

1.1.4 Problem Selection

A crucial component of the testing pipeline is the problem selection. Consistent and meaningful evaluation requires a set of benchmark problems that are reliable, diverse, and representative of real solver behavior. To meet these requirements, the problem set should satisfy the following criteria:

- Extensive prior testing: The problems must be validated and associated with reliable solver performance data, preferably obtained from recent evaluations of state-of-the-art solvers.
- Diversity: The set must include a varied mix of problem types-combinatorial problems, real-world applications, and puzzle-like tasks-covering all major categories: Maximization, Minimization and Satisfaction.

This ensures that LLM performance can be assessed across different solving paradigms.

Prompt Structure

MiniZinc model:

...Minizinc problem model (.mzn content) ...

MiniZinc data:

...Instance relative data (.dzn or .json content) ...

The goal is to determine which constraint programming solver would be best suited for this problem, considering the following options:

– s_1 ,

– s_2 ,

...

– s_n

where $s_{1...n} \in \text{SolverList}$ Answer only with the name of the 3 best solvers inside square brackets separated by comma and nothing else.

Figure 1.1: Example of prompt

- Complexity: The problems must be sufficiently challenging so that solver selection is non-trivial and the LLM’s reasoning abilities are meaningfully tested.

Following these criteria, the selected benchmark was the problem set from the *MiniZinc Challenge 2025* [9] [7] [8]. These problems are specifically curated to benchmark the strongest solvers of the year and therefore represent an ideal test bed for evaluating the proposed Agentic Solver.

The problem set contains twenty problems: 1 satisfaction problem, 3 maximization problems, 16 minimization problems.

Each problem is a combination of a `.mzn` file containing the Minizinc [10] model made of the high-level description of the problem (variables, constraints and objective function). Every problem also is also accompanied by five corresponding data instances each of them contained either in a `.dzn` or a `.json` file containing specific parameters and constants, yielding a total of 100 testable, diverse, and complex scenarios.

1.1.5 Test Metrics

In order to actually evaluate model performance, it is necessary to chose a standard metric for answer evaluation, other than that, it is necessary to have a metric to evaluate how an AS controlled by the given LLM would perform against the current Single Best Solver (SBS).

Before analysing the evaluation metrics, we must first define the systems to which these metrics will be applied. Namely, the solvers. In our context, a solver is a program that takes as input the description of a computational problem in a given language and returns an observable outcome providing zero or more solutions for the given problem. For example, for

decision problems, the outcome may be simply “yes“ or “no“ while for optimization problems, we might be interested in the best solutions found along the search. An evaluation metric, or performance metric, is a function mapping the outcome of a solver on a given instance to a number representing “how good“ the solver is on this instance. An evaluation metric is often not just defined by the output of the solver. Indeed, it can be influenced by other actors, such as the computational resources available, the problems on which we evaluate the solver, and the other solvers involved in the evaluation. For example, it is often unavoidable to set a **timeout** τ on the solver’s execution when there is no guarantee of termination in a reasonable amount of time (e.g. NP-hard problems). Timeouts make the evaluation feasible but inevitably couple the evaluation metric to the execution context. For this reason, the evaluation of a meta-solver should also consider the scenario that encompasses the solvers to evaluate, the instances used for the validation, and the timeout. Formally, at least for the purposes of this paper, we can define a scenario as a triple $(\mathcal{I}, \mathcal{S}, \tau)$, where: \mathcal{I} is a set of problem instances, \mathcal{S} is a set of individual solvers, $\tau \in (0, +\infty)$ is a timeout such that the outcome of solvers $s \in \mathcal{S}$ Solver instance $i \in \mathcal{I}$ is always measured in the time interval $[0, \tau]$. Evaluating meta-solvers over heterogeneous scenarios $(\mathcal{I}_1, \mathcal{S}_1, \tau_1)$, $(\mathcal{I}_2, \mathcal{S}_2, \tau_2)$, \dots , is complicated by the fact that the sets of instances \mathcal{I}_k , the sets of solvers \mathcal{S}_k and the timeouts τ_k can be very different. And things could get even more complicated in scenarios including optimization problems.

For those objectives two separate metrics were chosen

Metric for Solver Score

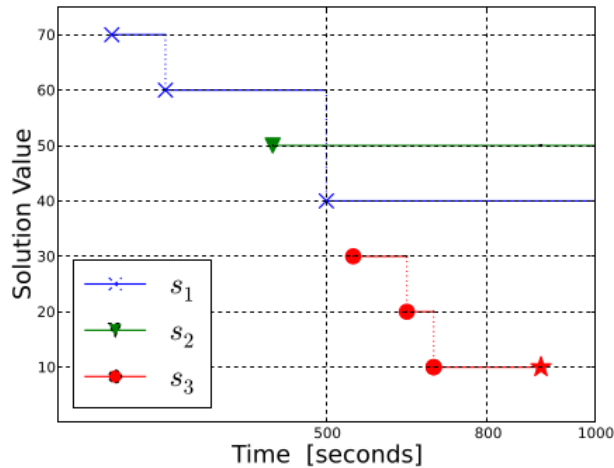


Figure 1.2: Solver performances example

We are now ready to associate to every instance i and solver s a weight that quantitatively represents how good is s when solving i over time T . We define the scoring value of s (shortly, score) on the instance i at a given time t as a function $\text{score}_{\alpha, \beta}$ [11] [12] defined as follows:

$$\text{score}_{\alpha,\beta}(s, i, t) = \begin{cases} 0, & \text{if } \text{sol}(s, i, t) = \text{unk}, \\ 1, & \text{if } \text{sol}(s, i, t) \in \{\text{opt}, \text{uns}\}, \\ \beta, & \text{if } \text{sol}(s, i, t) = \text{sat} \\ & \text{and } \text{MIN}(i) = \text{MAX}(i), \\ \max\left\{0, \beta - (\beta - \alpha) \frac{\text{val}(s, i, t) - \text{MIN}(i)}{\text{MAX}(i) - \text{MIN}(i)}\right\}, & \text{if } \text{sol}(s, i, t) = \text{sat} \\ & \text{and } i \text{ is a minimization problem}, \\ \max\left\{0, \alpha + (\beta - \alpha) \frac{\text{val}(s, i, t) - \text{MIN}(i)}{\text{MAX}(i) - \text{MIN}(i)}\right\}, & \text{if } \text{sol}(s, i, t) = \text{sat} \\ & \text{and } i \text{ is a maximization problem}. \end{cases}$$

Here, $\text{MIN}(i)$ and $\text{MAX}(i)$ denote the minimal and maximal objective function values found by any solver s at the time limit T .

As an example, consider the scenario in Figure 1.2 showing three different solvers on the same minimization problem. Let $T = 500$, $\alpha = 0.25$, $\beta = 0.75$. Solver s_1 finds the optimal value (40), therefore it receives score 0.75. Solver s_2 finds the maximal value (50), hence score 0.25. Solver s_3 does not find a solution in time, giving score 0. If instead $T = 800$, the value of s_1 becomes 0.375 and s_3 gets 0.75. If $T = 1000$, since s_3 improves the objective to 10 (marked with a star in the figure), it receives the highest score.

The parameter used for score calculation in testing are: $T = 1200000$ (1200000ms = 20 minutes, which is the time limit used solver evaluation in the MiniZinc Challenge) $\alpha = 0.25$ $\beta = 0.75$.

Closed Gap

Once the evaluation metric for solver score has been defined, we also need a comparative metric after score calculation. For this objective, we have chosen to use *closed-gap* [11] as the evaluation metric. Which is a relative and meta-solver-specific measure, adopted in the 2015 ICON and 2017 OASC [13] challenges to handle the disparate nature of the scenarios, is the closed gap score. This metric assigns to a meta-solver a value in $(-\infty, 1]$ proportional to how much it closes the gap between the best individual solver available, or single best solver (SBS), and the virtual best solver (VBS), i.e., an oracle-like meta-solver always selecting the best individual solver. The closed gap is actually a “meta-metric“, defined in terms of another evaluation metric m to minimize, which in this case is the scoring metric defined earlier. Formally, if (I, S, τ) is a scenario then

$$m(i, \text{VBS}, \tau) = \min\{m(i, s, \tau) \mid s \in S\} \quad \text{for each } i \in I,$$

and

$$\text{SBS} = \arg \min_{s \in S} \sum_{i \in I} m(i, s, \tau).$$

With these definitions, *Closed-gap* can be defined as follows: Let (\mathcal{I}, S, τ) be a scenario and

$$m : \mathcal{I} \times (S \cup \{S, \text{VBS}\}) \times [0, \tau] \rightarrow \mathbb{R}$$

an evaluation metric to minimize for that scenario, where S is a meta-solver over the solvers of S . Let

$$m_\sigma = \sum_{i \in \mathcal{I}} m(i, \sigma, \tau) \quad \text{for } \sigma \in \{S, \text{SBS}, \text{VBS}\}.$$

The closed gap of S with respect to m on that scenario is

$$\frac{m_{\text{SBS}} - m_S}{m_{\text{SBS}} - m_{\text{VBS}}}.$$

The assumption $m_{\text{VBS}} > m_{\text{SBS}}$ is required, i.e., no single-solver can be the VBS (otherwise, no algorithm selection would be needed, given that its objective is to reach the VBS). Unlike other scores, the closed gap is designed specifically for meta-solvers. Applying it to individual solvers would assign 0 to the SBS and a negative score to the remaining solvers, proportional to their performance difference with respect to the SBS and the gap $m_{\text{SBS}} - m_{\text{VBS}}$, which makes little sense for individual solvers, as it wouldn't reflect their actual performance overall.

1.1.6 Experiment Setup

We have defined both the structure of the queries posed to the LLMs (Section 1.1.4) and the way in which these queries are formulated (Section 1.1.3). The remaining challenge is to evaluate them automatically over the full set of selected instances. To this end, we designed an automated testing pipeline that parallelizes execution by assigning one thread per LLM. For each model, requests are issued sequentially, with five requests per problem, each containing a MiniZinc model and a single instance encoded as shown in Figure 1.1.

Despite preliminary prompt engineering and model filtering, several MiniZinc models, particularly their associated data files, still exceed the providers' rate limits. Since these limits are strict, additional mechanisms were required to prevent limit violations while still allowing evaluation over the complete instance set.

Script Manipulation

The most direct way to address oversized requests is to reduce their length. As the prompt itself was already minimal, this required direct manipulation of the MiniZinc model (`.mzn`) and data files.

A first step consisted in removing all non-essential elements, such as comments (starting with `%` [10]), tabs, and unnecessary whitespace. While this helps reduce token usage and standardizes script formatting, it is insufficient on its own. The main contributor to token overflow is the presence of large data arrays, which not only increase message length but may also pollute the context, “distracting” the LLM from the most relevant information [14].

To mitigate this issue, data arrays were truncated to a fixed maximum length of 30 elements, with an inline comment indicating the original size:

```
[e1, e2, ..., e30// array too long to display, dimensions: (150)]
```

While effective for simple arrays of scalar values, this approach does not account for the complexity of individual elements and performs poorly on more structured data. For this reason, a second truncation mechanism was introduced based on raw character length. Arrays exceeding 90 characters were truncated accordingly, using the same annotation to preserve information about the original size.

Custom Delays

Since each experiment involves multiple problems and multiple sequential requests per LLM, rate limits can still be exceeded even when individual requests are within bounds. To handle this, custom delays were introduced into the experiment orchestration logic.

When an error message is received, for example:

```
Error code: 413 - Request too large for model 'openai/gpt-oss-120b' in organization 'org_01k9qqesvte4d9h5jnhmzvbm4' service tier 'on_demand' on tokens per minute (TPM): Limit 8000, Requested 8939, please reduce your message size and try again. Need more tokens? Upgrade to Dev Tier today at https://console.groq.com/settings/billing
```

```
Error code: 429 - Rate limit reached for model 'openai/gpt-oss-120b' in organization 'org_01k9qqesvte4d9h5jnhmzvbm4' service tier 'on_demand' on tokens per day (TPD): Limit 200000, Used 193047, Requested 10632. Please try again in 26m29.328s. Need more tokens? Upgrade to Dev Tier today at https://console.groq.com/settings/billing
```

Its code is inspected. Errors 413 and 429 indicate that a rate limit has been exceeded. The error message is then parsed to identify the specific limit involved. If the limit concerns tokens per minute (TPM) or requests per minute (RPM), the system pauses execution for 60 seconds before retrying. If the exceeded limit is tokens per day (TPD) or requests per day (RPD), the message is further analyzed to extract the cooldown duration, typically expressed in the form $XXh, XXm, XX.XXs$ where h stands for hours, m for minutes and s for seconds. The required delay is then computed from this value, after which the request is retried.

1.2 Experiments

In this section we are gonna show and explain al the experiments that led to the final choice of the context information and overall setup of the agentic solver. ...structure description ...

1.2.1 Preliminary tests

The first experiments were conducted using the unedited problems. Each LLM was provided with the original MiniZinc model (.mzn) together with the corresponding instance data (in either .dzn or .json format), following the prompt structure defined in Section 1.1.3.

| Model | Single Score | Parallel Score | Closed Gap |
|---|--------------|----------------|------------|
| gemini-2.5-flash-lite | 64.363 | 69.040 | -1.047 |
| gemini-2.5-flash | 60.962 | 69.426 | -1.330 |
| moonshotai/kimi-k2-instruct-0905 | 59.680 | 66.186 | -1.436 |
| moonshotai/kimi-k2-instruct | 58.609 | 65.816 | -1.525 |
| openai/gpt-oss-120b | 58.166 | 64.508 | -1.562 |
| openai/gpt-oss-20b | 57.154 | 63.329 | -1.646 |
| meta-llama/llama-4-maverick-17b-128e-instruct | 56.297 | 63.549 | -1.717 |
| meta-llama/llama-4-scout-17b-16e-instruct | 54.305 | 57.815 | -1.883 |
| gemini-2.0-flash | 43.413 | 53.748 | -2.788 |
| qwen/qwen3-32b | 42.117 | 48.018 | -2.895 |
| gemini-2.5-pro | 37.641 | 41.594 | -3.267 |
| llama-3.1-8b-instant | 36.082 | 56.228 | -3.397 |
| groq/compound-mini | 25.423 | 29.623 | -4.282 |
| llama-3.3-70b-versatile | 7.455 | 9.496 | -5.775 |
| groq/compound | 5.197 | 8.246 | -5.963 |

Table 1.3: Initial tests giving plain scripts to all the LLMs, In this table:column "Model" contains the names of each tested LLM, "Total Score" represents the sum of the score reached in every instance, in this table "Total Score" represents the sum of the score reached in every instance, score was calculated by summing the performance of what was suggested to be the best solver on the given instance by each of the LLMs, "Parallel Score" represents the sum of the score reached in every instance, score was calculated in parallel-solver setup, so taking the 3 best solvers given by the LLM, calculate the score of all the 3, and take the maximum out of the three, and finally "Closed Gap" displays the closed gap score calculated over "Single Score" by using the formula explained in Section 1.1.5.

As reported in Table 1.3, (and more in depth in Table 1.10, Table 1.9 and Table 1.11) for both single-solver evaluation and parallel-solver evaluation, the scores are all under 70, meaning a lower performance than 3 of the single solvers from free category, and 4 of the single solvers

from open category, and clearly a negative closed gap for all of the LLMs. While part of this outcome can be attributed to the deliberately simple formulation of the requests, a major limiting factor is the presence of strict rate limits, which prevent many instances from being processed by some, if not all, of the LLMs, due to the script length alone exceeding TPM (showed in Table 1.2 and Table 1.1). This problem is predominant in problems with large instance data, such as: `ihc-2024-marte` or `gt-sort`

These constraints motivated both the adoption of script manipulation techniques, as described in Section 1.1.6, and, simple time issues due to tests taking even up to 48 hours, the decision to restrict subsequent experiments to the five best-performing LLMs identified in this preliminary phase, namely: `gpt-oss-120b`, `gemini-2,5-flash`, `gemini-2,5-flash-lite`, `kimi-k2-instruct-0905` and `kimi-k2-instruct`.

1.2.2 Single Request Experiments

After establishing a stable experimental pipeline, we repeated the evaluation on the full set of 100 instances. All experiments in this phase adopt a single-request setup, where each prompt is processed independently: the LLM receives the input and produces an answer without access to any prior interaction history or retained context.

Base Setup

As a baseline, the LLMs were first evaluated under the same conditions as the preliminary experiments, using only the raw MiniZinc and data scripts.

| Model | Single Score | Parallel Score | Closed Gap |
|----------------------------------|--------------|----------------|------------|
| openai/gpt-oss-120b | 74.488 | 82.227 | -0.206 |
| moonshotai/kimi-k2-instruct-0905 | 71.623 | 82.657 | -0.444 |
| moonshotai/kimi-k2-instruct | 70.939 | 83.268 | -0.501 |
| gemini-2.5-flash-lite | 70.145 | 80.741 | -0.567 |
| gemini-2.5-flash | 69.763 | 79.105 | -0.598 |

Table 1.4: Tests on sanitized scripts given to the 5 best performing LLMs, columns content is calculated as in Table 1.3.

As shown in Table 1.4 and Table 1.12, performance in the parallel-solver evaluation is generally strong. All tested LLMs outperform every individual solver except `or-tools_cp-sat-par`, which corresponds to the single best solver (SBS) in the open category and remains clearly dominant, with a substantial margin over both the LLM-based meta-solvers and the remaining individual solvers.

Greater variability emerges in the single-solver evaluation (Table 1.13). In this case, only `gpt-oss-120b` consistently outperforms all individual solvers other than the SBS in the free category (`or-tools-cp-sat-free`), as will be later reported in Table 1.25 and Figure 1.5b. The remaining LLMs still achieve competitive results compared to most standalone solvers, but a significant performance gap remains, as highlighted by the closed-gap scores, also reported more in depth in Table 1.14.

Problem Description

The results of the baseline experiments indicate that further improvements to the Agentic Solver are necessary. A natural approach is to provide the LLM with additional contextual information. However, as discussed previously, excessively large contexts can be counterproductive, potentially distracting the model and degrading performance rather than improving it [6, 14]. This trade-off motivates a more careful investigation into which types of information are most beneficial for LLM-based solver selection.

As a first step, we augmented the prompt with a concise problem description (PD): a short textual summary of the MiniZinc model’s semantics. These descriptions were automatically generated using another LLM (GPT-5.1) and subsequently refined manually to correct minor inaccuracies, e.g.:

- **atsp**: “Scheduling and resource allocation problem involving moulds, colors, and production jobs. The goal is to minimize makespan, tardiness, and waste while respecting compatibility and demand constraints.”
- **black-hole**: “A constraint model for solving the Black Hole Patience solitaire game. Cards must be arranged so that the sequence follows game rules using global constraints.”

The PD was incorporated into the prompt structure (Figure 1.1) as:

| Model | Single Score | Parallel Score | Closed Gap |
|----------------------------------|--------------|----------------|------------|
| moonshotai/kimi-k2-instruct-0905 | 72.605 | 83.182 | -0.362 |
| openai/gpt-oss-120b | 70.741 | 83.250 | -0.517 |
| gemini-2.5-flash-lite | 69.043 | 82.621 | -0.658 |
| moonshotai/kimi-k2-instruct | 67.555 | 81.890 | -0.782 |
| gemini-2.5-flash | 49.897 | 59.154 | -2.249 |

Table 1.5: Test on sanitized scripts combined with textual problem description. Columns are calculated as in Table 1.3.

Prompt Structure

Prompt description:

...Textual problem description ...

MiniZinc model:

...Minimizing problem model (.mzn content) ...

MiniZinc data:

...Instance relative data (.dzn or .json content) ...

The goal is to determine which constraint programming solver would be best suited for this problem, considering the following options:

- s_1 ,
- s_2 ,
- ...
- s_n where $s_1 \dots s_n \in \text{SolverList}$.

Answer only with the name of the 3 best solvers inside square brackets separated by comma and nothing else.

As shown in Table 1.5, single-solver performance consistently degrades, while parallel-solver evaluation shows modest improvements, with three out of the five tested LLMs achieving better results than in the base configuration. This divergence suggests that additional context can aid diversification in solver selection, even if, in this case, it does not reliably improve the choice of an optimal solver.

As can be deduced from the results, all the closed gap scores are negatives even after improving the context.

1.2.3 Multi-turn Experiments

What we discussed so far indicate that the contextual information provided to the LLMs is either insufficient or, in some cases, not beneficial overall. A natural next step is therefore to explore alternative forms of context. However, this introduces two practical issues. First, the single-request setup already operates close to the maximum allowed tokens per minute (TPM), making it infeasible to simply add more information without violating rate limits. Second, the existing setup is inefficient in terms of token usage, as it repeatedly supplies redundant information.

More specifically, for each problem we evaluate five different instances, each with distinct data, while the underlying MiniZinc model and the associated problem description remain unchanged. Re-sending this invariant information with every request unnecessarily consumes tokens. Given the limited API resources available, addressing both constraints is essential. To this end, we transitioned to a multi-turn (chat-like) experimental setup.

Setup Explanation

The core idea of the multi-turn setup is to partition the interaction using role-based formatting [15]. In the context of LLMs, messages are explicitly associated with roles, typically **system**, **user**, and **assistant**. Which helps the LLM distinguish between instructions, inputs, and generated outputs, while also maintaining conversational state across turns.

In our experiments, the **system** role is used to convey all invariant and high-level information, namely the MiniZinc model (**.mzn**) content, the textual descriptions, and the expected format of the answers. The **user** role is then reserved for instance-specific inputs, containing the data associated with each instance (in **.dzn** or **.json** format). This separation allows us to avoid repeatedly transmitting redundant context, significantly reducing token consumption per instance.

An additional advantage of the multi-turn setup is that it enables the handling of larger instance data by distributing content across multiple messages, while relying on the LLM’s ability to retain previously supplied information within the same conversation. As a result, the system can accommodate longer and more complex inputs without exceeding rate limits.

Solvers Description

The increased efficiency of the multi-turn setup also makes it possible to enrich the contextual information with new textual data: solver descriptions. For each solver under consideration, a short textual description was generated and provided to the LLM within the **system** prompt, with the aim of improving the model’s awareness of the available solver options and their respective characteristics.

To better understand the importance of this information, we experimented with two different configurations: one in which solver descriptions were combined with all previously provided contextual elements, and another in which the solvers descriptions constituted the only additional textual information alongside the MiniZinc model and the instance data. This design allows us to assess the contribution of solver-specific knowledge to the overall performance of the Agentic Solver.

| Model | Single Score | Parallel Score | Closed Gap |
|---|---------------|----------------|--------------|
| moonshotai/kimi-k2-instruct | 76.964 | 82.236 | 0.000 |
| moonshotai/kimi-k2-instruct-0905 | 76.964 | 82.489 | 0.000 |
| gemini-2.5-flash | 71.687 | 83.137 | -0.439 |
| openai/gpt-oss-120b | 70.974 | 78.800 | -0.498 |
| gemini-2.5-flash-lite | 54.714 | 77.747 | -1.849 |

Table 1.6: Test with sanitized scripts combined with solvers description in a multi turn setup. Columns are calculated as in Table 1.3.

In the parallel-solver evaluation (Table 1.18), providing only solver descriptions does not lead to systematic improvements. The sole exception is **gemini-2.5-flash** although its score is still under that of the single best solver (SBS) in the open category.

On the other hand, the effects are more pronounced in the single-solver evaluation, displayed in Table 1.6Table 1.19. Two models, **moonshotai/kimi-k2-instruct-0905** and **moonshotai/kimi-k2-instruct**, exhibit a substantial improvement, reaching the SBS score and thus achieving a closed-gap value of zero for the first time. A closer inspection of their outputs, however, reveals that this result is achieved by consistently selecting the same solver, namely **or-tools_cp-sat-free**, which is itself the SBS. This behavior effectively bypasses the decision-making role of the LLM, thereby undermining the intended purpose of employing an LLM in the first place.

Solver Description and Problem Description

Following this observation, we evaluated the configuration combining both forms of textual context: solver descriptions and problem descriptions. In this setup, each LLM is provided with the largest amount of contextual information until now.

| Model | Single Score | Parallel Score | Closed Gap |
|----------------------------------|---------------|----------------|--------------|
| openai/gpt-oss-120b | 77.261 | 80.296 | 0.025 |
| moonshotai/kimi-k2-instruct-0905 | 76.964 | 82.219 | 0.000 |
| moonshotai/kimi-k2-instruct | 74.464 | 80.417 | -0.208 |
| gemini-2.5-flash | 73.552 | 83.651 | -0.284 |
| gemini-2.5-flash-lite | 63.063 | 78.148 | -1.155 |

Table 1.7: Test with sanitized scripts combined with both solvers description, and problem description in a multi turn setup. Columns are calculated as in Table 1.3.

In the parallel-solver evaluation, this configuration yields the highest scores observed so far, again driven primarily by **gemini-2.5-flash**. However, otehr LLMs score is slightly lower than in the previous setups, and all of the reached scores are still under the open-category SBS.

In the single-solver evaluation, **moonshotai/kimi-k2-instruct-0905** continues to default to selecting the SBS exclusively. Nevertheless, improvements emerge for two other models, namely **gemini-2.5-flash** and **gpt-oss-120b**. In particular, **gpt-oss-120b** achieves the first strictly positive closed-gap score, surpassing **or-tools_cp-sat-free**.

Basic Tests Evaluation

In this initial testing phase, a positive closed gap has been achieved, showing an agentic solver with better performance than the single best solver. Moreover, when we put the perfor-

mance respect to the “non-best solvers“, these primitive configurations of agentic solvers still hold fairly competitive results.

To better display single LLMs performances, all variants scores are put together against one another, using histograms for better visualization in Figure 1.3. In Figure 1.3a for parallel-solver evaluation, Figure 1.3b for single-solver evaluation and Figure 1.3c for closed gap evaluation.

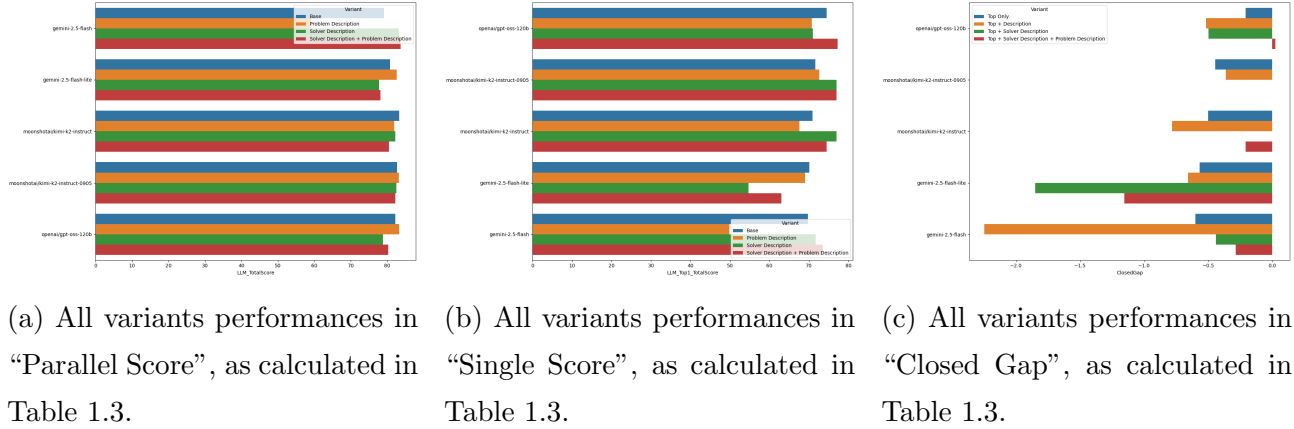


Figure 1.3: Histograms displaying the performances of all the solver variants in “Single Score” evaluation, “Parallel Score” evaluation and “Closed Gap” evaluation.

To give results another point of view, the performance of each agentic solver configuration is displayed against the single solvers of the corresponding category. In Table 1.24 and Figure 1.5a are shown the performance of all the configurations, scored with parallel-solvers evaluation, when put against single solvers from the open category. On the other hand, looking at Table 1.25 and Figure 1.5b, the resulting score of single-solver evaluation of all the variants is put against all the single solvers from free category.

1.2.4 Feature Employment

In the last section, we exposed the importance of textual informations, and giving a richer context to the LLM instead of relying on its understanding of a `.mzn` script. Even though a closed gap was already reached in previous experiments, relying on context information such as the problem description is a strong limitation for the solver, given those data need to be supervised, if not entirely rewritten by hand, due to the high variability, especially when extracted on new problems. This limitation highlights the necessity of a mean to extract informations automatically, in a controlled and predictable way.

Another problem is the one concerning script dimensions: programs with longer scripts need some techniques like sanitization, as previously stated in Section 1.1.6, these type of technique, makes it possible to work with longer scripts and context data. But is still penalizing towards longer problems, raising the risk of hallucination [16], due to the forced removal of elements in data, leaving incomplete arrays as input.

For these tasks we decided to employ a feature-extractor [17], which allows to extract an extensive set of 95 features from a Constraint (Satisfaction/Optimization) Problem defined in possibly different modelling languages: MiniZinc, FlatZinc or XCSP. Designed to be independent from the particular machine on which it is run as well as from the specific global redefinitions of a given solver. The employed version was already used in other projects [18] [19] [20].

Tool Description

The tool `mzn2feat` is designed to extract a set of 155 features from a MiniZinc model. Of these, 144 are static features derived through syntactic analysis of the source problem instance, while 11 are dynamic features obtained via a short execution of the Gecode solver. Due to the complexity of the MiniZinc language, particularly the presence of control-flow constructs, direct extraction of syntactic features from MiniZinc models is nontrivial. To address this, models are first compiled into FlatZinc, a lower-level language whose syntax is largely a subset of MiniZinc. This translation is performed using the `mzn2fzn` tool provided within the MiniZinc toolchain.

The compilation step employs Gecode-specific redefinitions of global constraints. This preserves information about the presence and type of global constraints without decomposing them into primitive constraints. Such preservation is relevant because, in the absence of solver-specific redefinitions, certain global constraints (e.g., `alldifferent`) are typically decomposed into sets of simpler constraints, from which the original high-level constraint cannot be uniquely reconstructed.

Static feature extraction from the resulting FlatZinc model is performed using `fzn2feat`, a parser implemented with Flex and Bison. Dynamic features are obtained by executing the Gecode FlatZinc interpreter (`fz`) for a fixed time budget of two seconds on the compiled model.

In summary, given a MiniZinc model M , the `mzn2feat` workflow consists of three stages. First, M is translated into a FlatZinc model F_M using Gecode global constraint redefinitions. Second, static features are extracted from F_M via `fzn2feat`. Third, dynamic features are extracted from F_M through a bounded run of the Gecode interpreter. The static feature extraction stage is applicable to any FlatZinc model, although solver-specific redefinitions that are not recognized may be ignored. The static and dynamic feature extraction procedures are independent, allowing them to be executed in parallel or in arbitrary order. For example, static feature computation may be omitted if the instance is solved during the dynamic feature collection phase.

For a better understanding of all of the features, refer to Table 1.26 for the description by category, and to 1.1 as an example output.

Testing and Results

To understand the potential of the feature extractor we tried to use the pretty-print output (like the one in 1.1) combined with the context informations given until now. So we tried

testing:

- Only `mzn2feat` output.
- `mzn2feat` output and problem text description.
- `mzn2feat` output, problem text description and solvers text description.

And then tried those setup, adding first the `.mzn` problems only, and finally also the sanitized data scripts (`.dzn/.json`).

| Variant | Single Score | Parallel Score | Closed Gap |
|---|--------------|----------------|------------|
| Features + Solver Description + Problem Description | 75.659731 | 83.731582 | -0.108399 |
| Features + Solver Description | 75.390197 | 82.994278 | -0.130793 |
| Features + Problem Description | 74.829813 | 83.289246 | -0.177354 |
| Features | 73.600955 | 82.259760 | -0.279455 |
| Features + <code>.mzn</code> + Problem Description | 71.916389 | 78.530605 | -0.419420 |
| Features + <code>.mzn</code> | 70.368365 | 78.371276 | -0.548041 |
| Features + <code>.mzn</code> + Instance Data | 68.422708 | 74.803213 | -0.709699 |
| Features + <code>.mzn</code> + Instance Data + Solver Description | 63.585459 | 66.346631 | -1.111610 |
| Features + <code>.mzn</code> + Instance Data + Problem Description | 62.516550 | 69.284744 | -1.200422 |
| Features + <code>.mzn</code> + Solver Description | 61.687990 | 66.874762 | -1.269264 |
| Features + <code>.mzn</code> + Solver Description + Problem Description | 58.576543 | 64.774159 | -1.527784 |
| Features + <code>.mzn</code> + Instance Data + Solver Description + Problem Description | 54.188182 | 59.410873 | -1.892398 |

Table 1.8: Test with all the possible combinations involving features extracted using `mzn2feat` [17], all the tests have been made using `gpt-oss-120b` as it’s the only model that produced a positive closed gap until this point. Columns are calculated as in Table 1.3.

As displayed in Table 1.8, the best performing instances are the ones combining features and textual informations, while adding `.mzn` or instance data is consistently lowering score, most probably because of some problems explained earlier such as context rot [6].

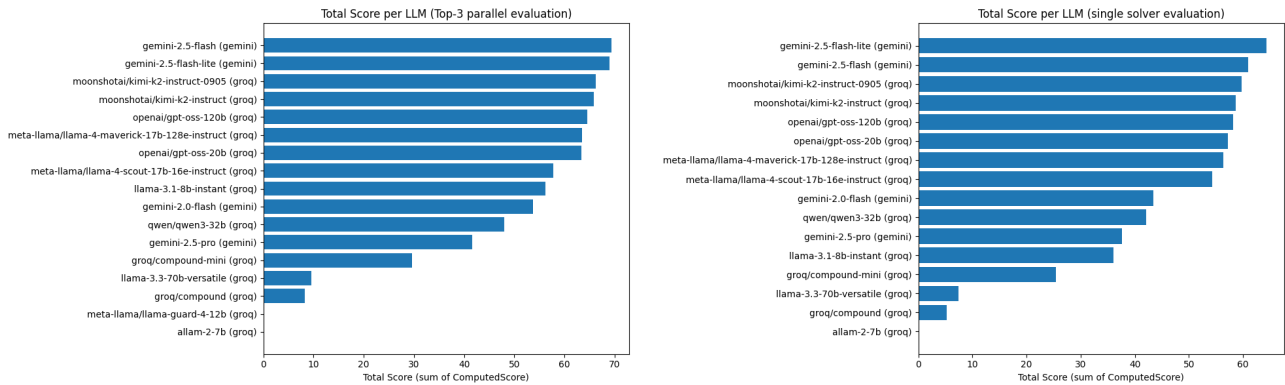
Appendix

| Model | Total Score | Instances Covered | Average Score |
|---|-------------|-------------------|---------------|
| gemini-2.0-flash | 53.748 | 67 | 0.802 |
| gemini-2.5-flash | 69.426 | 86 | 0.807 |
| gemini-2.5-flash-lite | 69.040 | 85 | 0.812 |
| gemini-2.5-pro | 41.594 | 51 | 0.815 |
| allam-2-7b | 0.0 | 10 | 0.0 |
| groq/compound | 8.246 | 9 | 0.916 |
| groq/compound-mini | 29.623 | 35 | 0.846 |
| llama-3.1-8b-instant | 56.228 | 72 | 0.780 |
| llama-3.3-70b-versatile | 9.496 | 10 | 0.949 |
| meta-llama/llama-4-maverick-17b-128e-instruct | 63.548 | 72 | 0.882 |
| meta-llama/llama-4-scout-17b-16e-instruct | 57.814 | 69 | 0.837 |
| meta-llama/llama-guard-4-12b | 0.0 | 77 | 0.0 |
| moonshotai/kimi-k2-instruct | 65.816 | 75 | 0.877 |
| moonshotai/kimi-k2-instruct-0905 | 66.186 | 75 | 0.882 |
| openai/gpt-oss-120b | 64.508 | 74 | 0.871 |
| openai/gpt-oss-20b | 63.328 | 75 | 0.844 |
| qwen/qwen3-32b | 48.018 | 65 | 0.738 |

Table 1.9: Initial tests giving plain scripts to all the LLMs, In this table: column "Model" contains the names of each tested LLM, "Total Score" is the equivalent of "Parallel Score" as explained in Table 1.3, "Instances Covered" contains the amount of instances that gave a viable result so the ones that did not exceed the token limitations portrayed in Table 1.1 and Table 1.2, "Average Score" represents $\frac{TotalScore}{InstancesCovered}$ to show the solver performance in the evaluated instances.

| Model | Total Score | Instances Covered | Average Score |
|---|-------------|-------------------|---------------|
| gemini-2.5-flash-lite | 64.363 | 85 | 0.794 |
| gemini-2.5-flash | 60.962 | 85 | 0.734 |
| moonshotai/kimi-k2-instruct-0905 | 59.680 | 75 | 0.817 |
| moonshotai/kimi-k2-instruct | 58.609 | 75 | 0.837 |
| openai/gpt-oss-120b | 58.166 | 74 | 0.796 |
| openai/gpt-oss-20b | 57.154 | 75 | 0.828 |
| meta-llama/llama-4-maverick-17b-128e-instruct | 56.297 | 72 | 0.804 |
| meta-llama/llama-4-scout-17b-16e-instruct | 54.305 | 69 | 0.798 |
| gemini-2.0-flash | 43.412 | 67 | 0.700 |
| qwen/qwen3-32b | 42.116 | 65 | 0.779 |
| gemini-2.5-pro | 37.640 | 51 | 0.738 |
| llama-3.1-8b-instant | 36.082 | 72 | 0.546 |
| groq/compound-mini | 25.422 | 35 | 0.726 |
| llama-3.3-70b-versatile | 7.454 | 10 | 0.745 |
| groq/compound | 5.197 | 9 | 0.577 |
| allam-2-7b | 0.0 | 4 | 0.0 |

Table 1.10: Initial tests giving plain scripts to all the LLMs, in this table “Total Score” is the equivalent of “Single Score” as explained in Table 1.3. “Instances Covered” and “Average Score” are calculated the same way as in Table 1.9



(a) Scores obtained by all of the considered LLM from parallel-solver evaluation, “Total Score” is the equivalent of “Single Score” as explained in Table 1.3.

(b) Scores obtained by all of the considered LLM from single-solver evaluation, “Total Score” is the equivalent of “Parallel Score” as explained in Table 1.3

Figure 1.4: Histograms displaying performances of All the LLMs with plain scripts

| model | InstancesCovered | AS | SBS | VBS | ClosedGap |
|---|------------------|--------|--------|--------|-----------|
| gemini-2.5-flash-lite | 85 | 64.363 | 76.964 | 89.000 | -1.047 |
| gemini-2.5-flash | 85 | 60.962 | 76.964 | 89.000 | -1.330 |
| moonshotai/kimi-k2-instruct-0905 | 75 | 59.680 | 76.964 | 89.000 | -1.436 |
| moonshotai/kimi-k2-instruct | 75 | 58.609 | 76.964 | 89.000 | -1.525 |
| openai/gpt-oss-120b | 74 | 58.166 | 76.964 | 89.000 | -1.562 |
| openai/gpt-oss-20b | 75 | 57.154 | 76.964 | 89.000 | -1.646 |
| meta-llama/llama-4-maverick-17b-128e-instruct | 72 | 56.297 | 76.964 | 89.000 | -1.717 |
| meta-llama/llama-4-scout-17b-16e-instruct | 69 | 54.305 | 76.964 | 89.000 | -1.883 |
| gemini-2.0-flash | 67 | 43.413 | 76.964 | 89.000 | -2.788 |
| qwen/qwen3-32b | 65 | 42.117 | 76.964 | 89.000 | -2.895 |
| gemini-2.5-pro | 51 | 37.641 | 76.964 | 89.000 | -3.267 |
| llama-3.1-8b-instant | 72 | 36.082 | 76.964 | 89.000 | -3.397 |
| groq/compound-mini | 35 | 25.423 | 76.964 | 89.000 | -4.282 |
| llama-3.3-70b-versatile | 10 | 7.455 | 76.964 | 89.000 | -5.775 |
| groq/compound | 9 | 5.197 | 76.964 | 89.000 | -5.963 |

Table 1.11: Initial tests giving plain scripts to all the LLMs, in this table: “Instances Covered” is the same as in Table 1.9, “AS” is the same as the “Single Score” explained in Table 1.3, “SBS” displays the sum of all the scores obtained by the single best solver (namely, `or-tools_cp-sat-free`) in every instance, and “VBS” displays the score obtained with the use of an hypothetical virtual best solver, giving the maximum obtainable score on every instance. Finally, “Closed Gap” is calculated as in Table 1.3

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| gemini-2.5-flash | 79.105 | 100 | 0.791 |
| gemini-2.5-flash-lite | 80.740 | 100 | 0.807 |
| moonshotai/kimi-k2-instruct | 83.268 | 100 | 0.832 |
| moonshotai/kimi-k2-instruct-0905 | 82.656 | 100 | 0.826 |
| openai/gpt-oss-120b | 82.226 | 100 | 0.822 |

Table 1.12: Tests on sanitized scripts given to the 5 best performing LLMs, parallel-solver evaluation. Columns are calculated as in Table 1.9

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| openai/gpt-oss-120b | 74.488 | 100 | 0.744 |
| moonshotai/kimi-k2-instruct-0905 | 71.622 | 100 | 0.753 |
| moonshotai/kimi-k2-instruct | 70.939 | 100 | 0.723 |
| gemini-2.5-flash-lite | 70.145 | 100 | 0.738 |
| gemini-2.5-flash | 69.763 | 98 | 0.742 |

Table 1.13: Tests on sanitized scripts given to the 5 best performing LLMs, single-solver evaluation. Columns are calculated as in Table 1.10

| Model | Instances Covered | AS | SBS | VBS | Closed Gap |
|----------------------------------|-------------------|--------|--------|------|------------|
| openai/gpt-oss-120b | 100 | 74.488 | 76.964 | 89.0 | -0.205 |
| moonshotai/kimi-k2-instruct-0905 | 100 | 71.622 | 76.964 | 89.0 | -0.443 |
| moonshotai/kimi-k2-instruct | 100 | 70.939 | 76.964 | 89.0 | -0.500 |
| gemini-2.5-flash-lite | 100 | 70.145 | 76.964 | 89.0 | -0.566 |
| gemini-2.5-flash | 98 | 69.763 | 76.964 | 89.0 | -0.598 |

Table 1.14: Tests on sanitized scripts given to the 5 best performing LLMs, closed gap. Columns are calculated as in Table 1.11

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| gemini-2.5-flash | 59.154 | 75 | 0.788 |
| gemini-2.5-flash-lite | 82.620 | 100 | 0.826 |
| moonshotai/kimi-k2-instruct | 81.889 | 100 | 0.818 |
| moonshotai/kimi-k2-instruct-0905 | 83.182 | 100 | 0.831 |
| openai/gpt-oss-120b | 83.249 | 100 | 0.832 |

Table 1.15: Test on sanitized scripts combined with textual problem description, parallel-solver evaluation. Columns are calculated as in Table 1.9

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| moonshotai/kimi-k2-instruct-0905 | 72.605 | 100 | 0.748 |
| openai/gpt-oss-120b | 70.740 | 100 | 0.721 |
| gemini-2.5-flash-lite | 69.042 | 100 | 0.719 |
| moonshotai/kimi-k2-instruct | 67.554 | 100 | 0.718 |
| gemini-2.5-flash | 49.896 | 73 | 0.723 |

Table 1.16: Test on sanitized scripts combined with textual problem description, single-solver evaluation. Columns are calculated as in Table 1.10

| Model | Instances Covered | AS | SBS | VBS | Closed Gap |
|----------------------------------|-------------------|--------|--------|------|------------|
| moonshotai/kimi-k2-instruct-0905 | 100 | 72.605 | 76.964 | 89.0 | -0.362 |
| openai/gpt-oss-120b | 100 | 70.740 | 76.964 | 89.0 | -0.517 |
| gemini-2.5-flash-lite | 100 | 69.042 | 76.964 | 89.0 | -0.658 |
| moonshotai/kimi-k2-instruct | 100 | 67.554 | 76.964 | 89.0 | -0.781 |
| gemini-2.5-flash | 73 | 49.896 | 76.964 | 89.0 | -2.248 |

Table 1.17: Test on sanitized scripts combined with textual problem description, closed gap. Columns are calculated as in Table 1.11

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| gemini-2.5-flash | 83.137 | 100 | 0.831 |
| gemini-2.5-flash-lite | 77.746 | 100 | 0.777 |
| moonshotai/kimi-k2-instruct | 82.236 | 100 | 0.822 |
| moonshotai/kimi-k2-instruct-0905 | 82.488 | 100 | 0.824 |
| openai/gpt-oss-120b | 78.799 | 100 | 0.787 |

Table 1.18: Test with sanitized scripts combined with solvers description in a multi turn setup, parallel-solver evaluation. Columns are calculated as in Table 1.9

| Model | Total Score | Instances Covered | Average Score | |
|----------------------------------|-----------------------|-------------------|---------------|-------|
| moonshotai/kimi-k2-instruct | 76.964 | 100 | 0.769 | |
| moonshotai/kimi-k2-instruct-0905 | 76.964 | 100 | 0.769 | |
| gemni | gemini-2.5-flash | 71.686 | 100 | 0.716 |
| openai/gpt-oss-120b | 70.974 | 100 | 0.716 | |
| gemni | gemini-2.5-flash-lite | 54.713 | 100 | 0.552 |

Table 1.19: Test with sanitized scripts combined with solvers description in a multi turn setup, single-solver evaluation. Columns are calculated as in Table 1.10

| Model | Instances Covered | AS | SBS | VBS | Closed Gap |
|----------------------------------|-------------------|--------|--------|------|------------|
| moonshotai/kimi-k2-instruct | 100 | 76.964 | 76.964 | 89.0 | 0.0 |
| moonshotai/kimi-k2-instruct-0905 | 100 | 76.964 | 76.964 | 89.0 | 0.0 |
| gemini-2.5-flash | 100 | 71.686 | 76.964 | 89.0 | -0.438 |
| openai/gpt-oss-120b | 100 | 70.974 | 76.964 | 89.0 | -0.497 |
| gemini-2.5-flash-lite | 100 | 54.713 | 76.964 | 89.0 | -1.848 |

Table 1.20: Test with sanitized scripts combined with solvers description in a multi turn setup, closed gap. Columns are calculated as in Table 1.11

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| gemini-2.5-flash | 83.650 | 100 | 0.836 |
| gemini-2.5-flash-lite | 78.147 | 100 | 0.781 |
| moonshotai/kimi-k2-instruct | 80.417 | 99 | 0.812 |
| moonshotai/kimi-k2-instruct-0905 | 82.218 | 100 | 0.822 |
| openai/gpt-oss-120b | 80.295 | 100 | 0.802 |

Table 1.21: Test with sanitized scripts combined with both solvers description, and problem description in a multi turn setup, parallel-solver evaluation. Columns are calculated as in Table 1.9

| Model | Total Score | Instances Covered | Average Score |
|----------------------------------|-------------|-------------------|---------------|
| openai/gpt-oss-120b | 77.260 | 100 | 0.780 |
| moonshotai/kimi-k2-instruct-0905 | 76.964 | 100 | 0.769 |
| moonshotai/kimi-k2-instruct | 74.464 | 99 | 0.752 |
| gemini-2.5-flash | 73.551 | 100 | 0.750 |
| gemini-2.5-flash-lite | 63.062 | 100 | 0.630 |

Table 1.22: Test with sanitized scripts combined with both solvers description, and problem description in a multi turn setup, single-solver evaluation. Columns are calculated as in Table 1.10

| Model | Instances Covered | AS | SBS | VBS | Closed Gap |
|----------------------------------|-------------------|--------|--------|------|------------|
| openai/gpt-oss-120b | 100 | 77.260 | 76.964 | 89.0 | 0.024 |
| moonshotai/kimi-k2-instruct-0905 | 100 | 76.964 | 76.964 | 89.0 | 0.0 |
| moonshotai/kimi-k2-instruct | 99 | 74.464 | 76.964 | 89.0 | -0.207 |
| gemini-2.5-flash | 100 | 73.551 | 76.964 | 89.0 | -0.283 |
| gemini-2.5-flash-lite | 100 | 63.062 | 76.964 | 89.0 | -1.155 |

Table 1.23: Test with sanitized scripts combined with both solvers description, and problem description in a multi turn setup, closed gap. Columns are calculated as in Table 1.11

| Type | Solver | Total Score |
|-------------|--|-------------|
| Solver | or-tools_cp-sat-par | 88.117 |
| LLM Variant | gemini-2.5-flash (Solvers Description + Problem Description) | 83.650 |
| LLM Variant | moonshotai/kimi-k2-instruct | 83.268 |
| LLM Variant | openai/gpt-oss-120b (Problem Description) | 83.249 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Problem Description) | 83.182 |
| LLM Variant | gemini-2.5-flash (Solvers Description) | 83.137 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 | 82.656 |
| LLM Variant | gemini-2.5-flash-lite (Problem Description) | 82.620 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Solvers Description) | 82.488 |
| LLM Variant | moonshotai/kimi-k2-instruct (Solvers Description) | 82.236 |
| LLM Variant | openai/gpt-oss-120b | 82.226 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Solvers Description + Problem Description) | 82.218 |
| LLM Variant | moonshotai/kimi-k2-instruct (Problem Description) | 81.889 |
| LLM Variant | gemini-2.5-flash-lite | 80.740 |
| LLM Variant | openai/gpt-oss-120b (Solvers Description + Problem Description) | 80.295 |
| LLM Variant | gemini-2.5-flash | 79.105 |
| LLM Variant | openai/gpt-oss-120b (Solvers Description) | 78.799 |
| LLM Variant | gemini-2.5-flash-lite (Solvers Description + Problem Description) | 78.147 |
| LLM Variant | gemini-2.5-flash-lite (Solvers Description) | 77.746 |
| Solver | chuffed-free | 74.819 |
| Solver | picatsat-free | 70.647 |
| Solver | huub-free | 68.784 |
| Solver | gurobi-par | 61.081 |
| Solver | cplex-par | 60.301 |
| Solver | choco-solver_cp-par | 59.365 |
| Solver | izplus-par | 58.216 |
| Solver | pumpkin-free | 57.681 |
| Solver | choco-solver_cp-sat-par | 56.896 |
| Solver | gencode-par | 54.283 |
| Solver | cp_optimizer-par | 53.877 |
| Solver | gencode_dexter-open | 47.304 |
| Solver | or-tools_cp-sat_ls-par | 46.292 |
| Solver | jacop-free | 44.373 |
| Solver | sicstus_prolog-free | 43.548 |
| Solver | yuck-par | 38.321 |
| Solver | scip-par | 36.675 |
| Solver | highs-par | 33.598 |
| Solver | cbc-par | 26.334 |
| Solver | atlantis-free | 1.555 |

Table 1.24: Table displaying all the different LLM variants results from parallel-solver evaluation, “Total Score” is calculated as “Parallel Score” in Table 1.3, and compared to all of the single solvers in open category of the MiniZinc Challenge [8]

| Type | Solver | TotalScore |
|--------------------|--|---------------|
| LLM Variant | openai/gpt-oss-120b (Solvers Description + Problem Description) | 77.260 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Solvers Description + Problem Description) | 76.964 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Solvers Description) | 76.964 |
| LLM Variant | moonshotai/kimi-k2-instruct (Solvers Description) | 76.964 |
| Solver | or-tools_cp-sat-free | 76.964 |
| LLM Variant | openai/gpt-oss-120b (Simple) | 74.488 |
| LLM Variant | moonshotai/kimi-k2-instruct (Solvers Description + Problem Description) | 74.464 |
| Solver | chuffed-free | 74.456 |
| LLM Variant | gemini-2.5-flash (Solvers Description + Problem Description) | 73.551 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Problem Description) | 72.605 |
| LLM Variant | gemini-2.5-flash (Solvers Description) | 71.686 |
| LLM Variant | moonshotai/kimi-k2-instruct-0905 (Simple) | 71.622 |
| LLM Variant | openai/gpt-oss-120b (Solvers Description) | 70.974 |
| LLM Variant | moonshotai/kimi-k2-instruct (Simple) | 70.939 |
| Solver | picatsat-free | 70.933 |
| LLM Variant | openai/gpt-oss-120b (Problem Description) | 70.740 |
| LLM Variant | gemini-2.5-flash-lite (Simple) | 70.145 |
| LLM Variant | gemini-2.5-flash (Simple) | 69.763 |
| LLM Variant | gemini-2.5-flash-lite (Problem Description) | 69.042 |
| Solver | huub-free | 68.497 |
| LLM Variant | moonshotai/kimi-k2-instruct (Problem Description) | 67.554 |
| LLM Variant | gemini-2.5-flash-lite (Solvers Description + Problem Description) | 63.062 |
| Solver | choco-solver_cp-sat-free | 60.808 |
| Solver | izplus-free | 58.672 |
| Solver | pumpkin-free | 58.543 |
| Solver | choco-solver_cp-free | 58.404 |
| Solver | gurobi-free | 55.384 |
| LLM Variant | gemini-2.5-flash-lite (Solvers Description) | 54.713 |
| Solver | cp_optimizer-free | 50.992 |
| Solver | gecode-fd | 50.073 |
| LLM Variant | gemini-2.5-flash (Problem Description) | 49.896 |
| Solver | cplex-free | 48.514 |
| Solver | sicstus_prolog-free | 44.592 |
| Solver | jacop-free | 44.549 |
| Solver | or-tools_cp-sat_ls-free | 43.222 |
| Solver | scip-free | 36.902 |
| Solver | yuck-free | 34.715 |
| Solver | highs-free | 34.418 |
| Solver | cbc-free | 22.615 |
| Solver | atlantis-free | 1.5 |

Table 1.25: Table displaying all the first LLM variants results given single-solver evaluation, “Total Score” is calculated as “Single Score” in Table 1.3, and compared to all of the single solvers in free category of the MiniZinc Challenge [8]

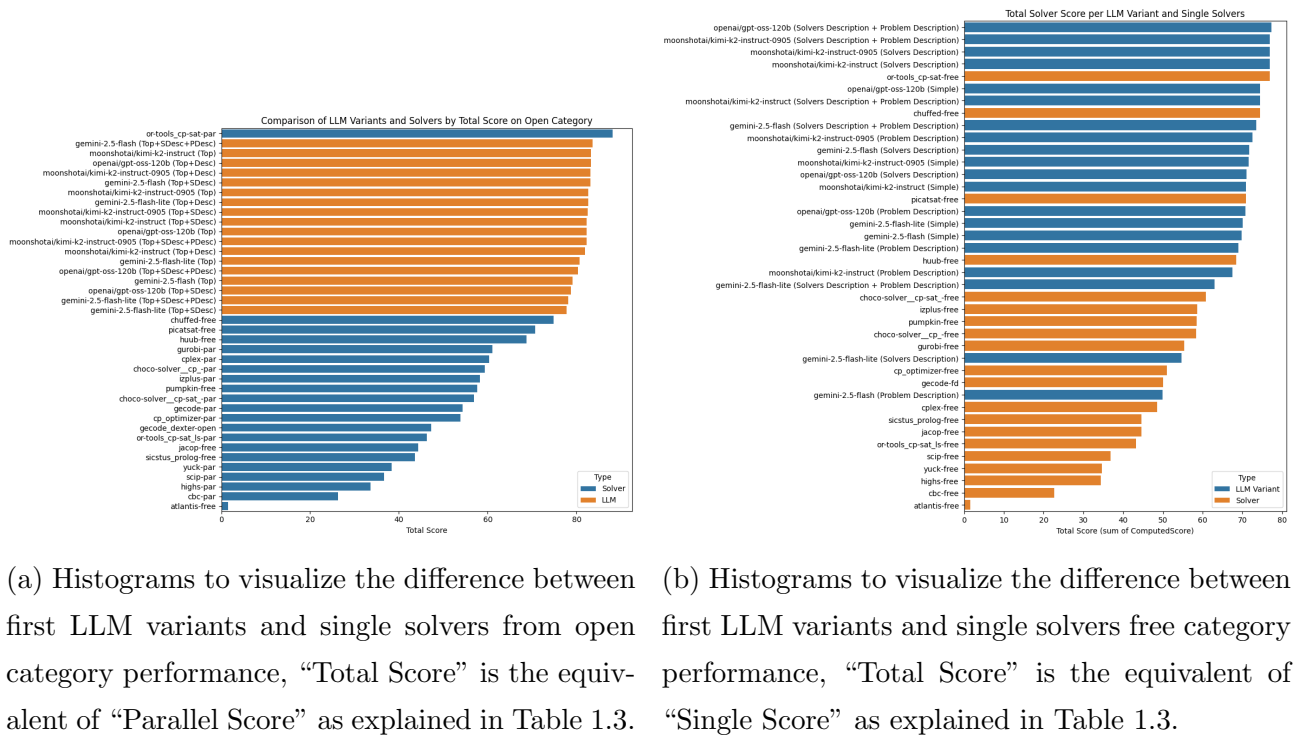


Figure 1.5: Histograms to visualize the difference between first LLM variants and single solvers

| Category | Number | Description (summary) |
|--------------------|--------|--|
| Variables | 27 | Counts of variables (including constants, aliases, defined and introduced variables), ratios involving N_V and N_C , and statistics of domain size, degree, and domain/degree ratio. |
| Domains | 18 | Counts and ratios of variables by type (Boolean, integer, float, set) and constraints by type (Boolean, integer, float, set, array). |
| Constraints | 27 | Total N_C , ratios with N_V , annotation usage, and statistics of constraint domain, degree, and domain/degree ratio. |
| Global constraints | 29 | Total number and ratio of global constraints, plus counts per equivalence class of Gecode-supported globals. |
| Graphs | 20 | Statistics on structural properties of the constraint graph and variable graph (degree, clustering coefficient, diameter). |
| Solving | 11 | Information from the solve item, including labeled variables, goal type, and counts of search and heuristic annotations. |
| Objective | 12 | Domain, degree, and graph-related measures of the objective variable, including normalized and standardized forms relative to global domain and degree statistics. |
| Static total | 144 | Extracted from the FlatZinc model via syntactic and structural analysis. |
| Dynamic | 11 | Runtime indicators from short Gecode executions: solutions found, propagations, nodes, failures, search depth, memory usage, and timing measures for translation and feature extraction. |

Table 1.26: The table shows a quick explanation of the features that can be extracted using the tool `mzn2feat` [17], divided per category, and counted.

Listing 1.1: Example output using `mzn2feat` [17] pretty print option on `EchoSched.mzn`, instance 14-10-0-2_1.

| IDENTIFIER | VALUE | DESCRIPTION |
|---------------------------------|-------------|---|
| ===== | | |
| <code>c_avg_deg_cons</code> | 3.11367 | Average of the constraints degree |
| <code>c_avg_dom_cons</code> | 20.3934 | Average of the constraints domain |
| <code>c_avg_domdeg_cons</code> | 5.85385 | Average of the ratio constraints domain/degree |
| <code>c_bounds_d</code> | 0 | No of constraints using 'boundsD' annotation |
| <code>c_bounds_r</code> | 0 | No of constraints using 'boundsR' annotation |
| <code>c_bounds_z</code> | 0 | No of constraints using 'boundsZ' or 'bounds' annotation |
| <code>c_cv_deg_cons</code> | 0.963493 | Coefficient of Variation of constraints degree |
| <code>c_cv_dom_cons</code> | 1.50739 | Coefficient of Variation of constraints domain |
| <code>c_cv_domdeg_cons</code> | 0.566571 | Coefficient of Variation of the ratio constraints domain/degree |
| <code>c_domain</code> | 0 | No of constraints using 'domain' annotation |
| <code>c_ent_deg_cons</code> | 1.60699 | Entropy of constraints degree |
| <code>c_ent_dom_cons</code> | 5.54008 | Entropy of constraints domain |
| <code>c_ent_domdeg_cons</code> | 2.58764 | Entropy of the ratio constraints domain/degree |
| <code>c_logprod_deg_cons</code> | 6021.66 | Logarithm of the product of constraints degree |
| <code>c_logprod_dom_cons</code> | 14249.3 | Logarithm of the product of constraints domain |
| <code>c_max_deg_cons</code> | 141 | Maximum of the constraints degree |
| <code>c_max_dom_cons</code> | 1724.64 | Maximum of the constraints domain |
| <code>c_max_domdeg_cons</code> | 12.2315 | Maximum of the ratio constraints domain/degree |
| <code>c_min_deg_cons</code> | 1 | Minimum of the constraints degree |
| <code>c_min_dom_cons</code> | 1 | Minimum of the constraints domain |
| <code>c_min_domdeg_cons</code> | 1 | Minimum of the ratio constraints domain/degree |
| <code>c_num_cons</code> | 3906 | Total no of constraints |
| <code>c_priority</code> | 0 | No of constraints using 'priority' annotation |
| <code>c_ratio_cons</code> | 1.49426 | Ratio no of constraints / no of variables |
| <code>c_sum_ari_cons</code> | 13031 | Sum of constraints arity |
| <code>c_sum_dom_cons</code> | 79656.6 | Sum of constraints domain |
| <code>c_sum_domdeg_cons</code> | 22865.2 | Sum of the ratio constraints domain/degree |
| <code>d_array_cons</code> | 1 | No of array constraints |
| <code>d_bool_cons</code> | 910 | No of boolean constraints |
| <code>d_bool_vars</code> | 1820 | No of boolean variables |
| <code>d_float_cons</code> | 0 | No of float constraints |
| <code>d_float_vars</code> | 0 | No of float variables |
| <code>d_int_cons</code> | 2591 | No of integer constraints |
| <code>d_int_vars</code> | 794 | No of integer variables |
| <code>d_ratio_array_cons</code> | 0.000256016 | Ratio array constraints / total no of constraints |
| <code>d_ratio_bool_cons</code> | 0.232975 | Ratio boolean constraints / total no of constraints |
| <code>d_ratio_bool_vars</code> | 0.696251 | Ratio boolean variables / total no of variables |
| <code>d_ratio_float_cons</code> | 0 | Ratio float constraints / total no of constraints |
| <code>d_ratio_float_vars</code> | 0 | Ratio float variables / total no of variables |
| <code>d_ratio_int_cons</code> | 0.663338 | Ratio integer constraints / total no of constraints |
| <code>d_ratio_int_vars</code> | 0.303749 | Ratio integer variables / total no of variables |
| <code>d_ratio_set_cons</code> | 0 | Ratio set constraints / total no of constraints |
| <code>d_ratio_set_vars</code> | 0 | Ratio set variables / total no of variables |
| <code>d_set_cons</code> | 0 | No of set constraints |
| <code>d_set_vars</code> | 0 | No of set variables |
| <code>gc_diff_globs</code> | 1 | No of different global constraints |
| <code>gc_global_cons</code> | 404 | Total no of global constraints |
| <code>gc_ratio_diff</code> | 0.00247525 | Ratio different global constraints / no of global constraints |
| <code>gc_ratio_globs</code> | 0.103431 | Ratio no of global constraints / total no of constraints |
| <code>o_deg</code> | 1 | Degree of the objective variable |
| <code>o_deg_avg</code> | 0.214932 | Ratio degree of the objective variable / average of var degree |
| <code>o_deg_cons</code> | 0.000256016 | Ratio degree of the objective variable / number of constraints |
| <code>o_deg_std</code> | -0.442948 | Standardization of the degree of the objective variable |
| <code>o_dom</code> | 6685 | Domain size of the objective variable |

| | | |
|--------------------|-------------|--|
| o_dom_avg | 12.79 | Ratio domain of the objective variable / average of var domain |
| o_dom_deg | 6685 | Ratio domain of the objective variable / degree of the obj var |
| o_dom_std | 4.13516 | Standardization of the domain of the objective variable |
| s_bool_search | 0 | Number of 'bool_search' annotations |
| s_first_fail | 1 | Number of 'int_search' annotations |
| s_goal | 2 | Solve goal (1 = satisfy, 2 = minimize, 3 = maximize) |
| s_indomain_max | 0 | Number of 'indomain_max' annotations |
| s_indomain_min | 1 | Number of 'indomain_min' annotations |
| s_input_order | 0 | Number of 'input_order' annotations |
| s_int_search | 1 | Number of 'int_search' annotations |
| s_labeled_vars | 1 | Number of variables to be assigned |
| s_other_val | 0 | Number of other value search heuristics |
| s_other_var | 0 | Number of other variable search heuristics |
| s_set_search | 0 | Number of 'set_search' annotations |
| v_avg_deg_vars | 4.65264 | Average of the variables degree |
| v_avg_dom_vars | 522.674 | Average of the variables domain |
| v_avg_domdeg_vars | 141.005 | Average of the ratio variables domain/degree |
| v_cv_deg_vars | 1.77237 | Coefficient of Variation of variables degree |
| v_cv_dom_vars | 2.85116 | Coefficient of Variation of variables degree |
| v_cv_domdeg_vars | 3.94885 | Coefficient of Variation of the ratio variables domain/degree |
| v_def_vars | 2334 | Number of defined variables |
| v_ent_deg_vars | 1.0029 | Entropy of variables degree |
| v_ent_dom_vars | 2.09955 | Entropy of variables domain |
| v_ent_domdeg_vars | 1.83264 | Entropy of the ratio variables domain/degree |
| v_intro_vars | 2753 | Number of introduced variables |
| v_logprod_deg_vars | 3665.47 | Logarithm of the product of variables degree |
| v_logprod_dom_vars | 6788.52 | Logarithm of the product of variables domain |
| v_max_deg_vars | 36 | Maximum of the variables degree |
| v_max_dom_vars | 6685 | Maximum of the variables domain |
| v_max_domdeg_vars | 6685 | Maximum of the ratio variables domain/degree |
| v_min_deg_vars | 0 | Minimum of the variables degree |
| v_min_dom_vars | 2 | Minimum of the variables domain |
| v_min_domdeg_vars | 0.1 | Minimum of the ratio variables domain/degree |
| v_num_aliases | 700 | Number of alias variables |
| v_num_consts | 10 | Number of constant variables |
| v_num_vars | 2614 | Total no of variables variables |
| v_ratio_bounded | 0.271614 | Ratio (aliases + constants) / total no of variables |
| v_ratio_vars | 0.669227 | Ratio no of variables / no of constraints |
| v_sum_deg_vars | 12162 | Sum of variables degree |
| v_sum_dom_vars | 1.36627e+06 | Sum of variables domain |
| v_sum_domdeg_vars | 368586 | Sum of the ratio variables domain/degree |

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