# Towards Understanding Differences Between Modelling Pipelines: a Modelers Perspective

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#### 9 — Abstract -

In this work we aim to investigate the capabilities of the MiniZinc and Savile Row constraint 10 programming pipelines from the user's perspective. We evaluate their modelling and reformulation 11 capabilities on a selection of six diverse problem classes using the commonly supported Chuffed 12 solver. Our preliminary findings show that both pipelines are very competitive in performance. 13 However, they seem to cater to distinct user preferences. MiniZinc allows better modeler control, 14 and provides a slightly more expressive language due to the facilities for code organization and 15 reusability. Conversely, Savile Row provides a solid set of default settings and a more consistent 16 performance profile. 17

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#### <sup>21</sup> Introduction

As with imperative programming languages like C, the process from writing out the problem constraints to arriving at a solution involves a pipeline of translation from a high-level language to a low-level language that can be directly interpreted by the solver. Modelling problems to be efficiently solved is no trivial task, and as a result there are automated modelling assistants who tailor the models to the required input to specific solvers. More concretely, we consider tailoring as the process of translating the constraint model with given input parameters (an instance) to a form readable by a specific constraint solver.

In this work we are going to focus on two well-known pipelines: MiniZinc [12] and its 29 homonymous language, and Savile Row [14] and its Essence' [13] language. Both MiniZinc 30 and Essence' are high-level constraint modelling languages. The Savile Row modelling 31 assistant was developed between the University of York and St Andrews. MiniZinc is an 32 open-source language, developed at Monash University in collaboration with Data61 Decision 33 Sciences and the University of Melbourne. Similarly, it has its own modelling assistant to 34 tailor the input for the solvers. The following steps describe the usual workflow for a problem 35 to be able to be solved using these two pipelines: 1. Using a high-level constraint modelling 36 language, a problem is modelled. 2. The constraints are merged with the instance data and 37 tailored to be fed as input to a specified constraint solver. **3**. The constraint solver reads the 38 low-level description and searches for solutions. 4. If a solution is found, the solution is then 39 translated back to a user-readable form. We have decided to focus on Chuffed [5], as the 40 solver is used by both pipelines, given its robustness, performance and for the maturity of its 41 support by both pipelines. 42

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We selected a set of 6 diverse problems from CSPLib [7] and the Minizinc Challenges [17]. 43 While the benchmarks for these problems already existed encoded in either MiniZinc or 44 Essence', no direct detailed comparison has been made between the two due to models 45 not being available in both languages. In addition, to our knowledge our work is unique in 46 considering the full pipeline: from modelling, translation and optimisation, to the effects 47 upon the solver. Further, while two models for the same problem may arrive at the same 48 solution, variations in a model, such as a different viewpoint, can result in great variations in 49 solving time [9]. Our objective is to manually create models as similar as possible to try to 50 isolate the pipeline effects as much as possible. 51

In summary, our contributions are as follows: (i) new models in both Essence' and MiniZinc of existing problems which allow to directly compare the considered pipelines, (ii) a discussion on how both languages compare when modelling the selected problems, (iii) an empirical evaluation of the pipelines performance over 3 different optimisation levels.

#### 56 2 The Models

We now present the models for the categories and problems which we chose for this work: mathematical objects (Quasigroup Completion [15]), packing problems (Wordpress [4]), scheduling problems (Rotating Rostering [18] and Travelling Tournament Problem with Predefined Values [16]), planning problems (Multi-Skilled Project Scheduling Problem) and routing problems (Capacitated Vehicle Routing Problem with Time Windows). All models can be found at https://github.com/stacs-cp/modref2024-pipeline-comparison.

MiniZinc has predicates and further rich functionality and syntax that Essence' is 63 lacking. However, in all cases an equivalent expression can be created and run in Essence' 64 to produce valid solutions. The main difference in both pipelines is the treatment of the 65 search order. MiniZinc has an extensive number of search orders it may impose upon the 66 variables, for example searching through an array of variables from the maximum of the 67 domain to the minimum. Essence' on the other hand provides similar functionality for 68 the target solver Minion with search heuristics, but these fall short in control compared to 69 MiniZinc. We have tried to recreate the MiniZinc search order through a rough translation 70 by specifying which variables to branch on first, but there is little control in how to perform 71 the search over the variables and their respective domains. 72

#### 73 2.1 Quasigroup Completion

<sup>74</sup> In Quasigroup Completion CSPLib [15], an order n quasigroup can be viewed as a size n<sup>75</sup> Latin square, where a Latin square is a  $n \times n$  table of numbers ranging from 1 up to n<sup>76</sup> inclusive. The table's rows and columns must be distinct in numbers. The Quasigroup <sup>77</sup> Completion problem gives an incomplete quasigroup table and requires the remaining empty <sup>78</sup> cells to be filled in with numbers.

The provided MiniZinc model on CSPLib uses an explicit representation, making use of the allDifferent constraint to ensure columns and rows are distinct. The allDifferent constraint takes in an array, and imposes that every element appears at most once in the array. Given the simplicity of the problem and its reliance upon allDifferent through the explicit model, an equivalent occurrence model was created (for both pipelines). The occurrence model represents numbers through an array of zeros and ones [8].

To impose allDifferent upon an occurrence representation, either allDifferent\_except or sum could be used. Rather than compare slight variations of allDifferent, the interest

is in comparing the difference between using a simple operator such as sum, and a powerful
optimised propagator such as allDifferent.

There does not exist an Essence' model for Quasigroup Completion on CSPLib, so one needed to be created. The explicit model follows the MiniZinc model exactly, except Essence' has a nice spread operator for slicing columns and rows from matrices instead of list comprehensions. In Essence' we represent the occurrence model, by finding a three

 $_{93}$  dimensional 0,1 matrix and using a sum constraint.

#### <sup>94</sup> 2.2 Wordpress Application Deployment in the Cloud

Wordpress Application Deployment in the Cloud [4] was used in the 2022 MiniZinc chal-95 lenge [10] with minor adaptations. Wordpress is an application used to create websites and 96 needs to be deployed to the cloud with a set of hardware and virtual machines (VMs). The 97 goal is to deploy several Wordpress instances while minimising the cost of hardware, VM 98 configurations and providers to deploy the instances into the cloud. The Wordpress problem 99 is an example of a bin packing problem, a common problem in combinatorial optimization 100 ranging over many applications such as loading trucks or graphics card resource allocation. 101 The MiniZinc model used is taken from the MiniZinc challenge 2022 [10]. The original 102 MiniZinc model [6], which the MiniZinc challenge model is based on, included variables not 103

<sup>104</sup> used within the input files given. More concretely, FVariables and FVInstances are Fixed <sup>105</sup> Variables and Fixed Variable Instances respectively and were used to determine the effects of <sup>106</sup> fixing certain variables otherwise left to be optimized and found. The paper also originally <sup>107</sup> left the number of VMs as a decision variable, however the MiniZinc challenge model has an <sup>108</sup> input parameter for the upper bound on the number of VMs to use. This restricts the search <sup>109</sup> space on the number of VMs and focusing on the objective of minimising the cost.

The Essence' model is a one-to-one translation of the MiniZinc model. Note the 110 MiniZinc model does not break symmetry upon the distribution of hardware on the VMs. 111 The hardware deployed on a VM can be swapped to any other VM for an equivalent 112 solution, resulting in the symmetry of the problem. The original model [6] does break 113 the symmetry of the problem, using multiple different methods such as pricing and the 114 lexicographical assignment of hardware on machines among others. This change from the 115 paper to the MiniZinc challenge model might have been done to test a solvers ability to 116 recognize symmetry and break it. 117

While the non-symmetric version of the problem is of interest following the MiniZinc challenge to compare to, the symmetric model is more attuned to how a modeller would write this given problem. We created a version of the problem in Essence' that breaks the aforementioned symmetries. To remain fair, an equivalent symmetry breaking version of the MiniZinc model was created to compare the symmetry breaking version of the Essence' model. Both the symmetry-breaking and non symmetry-breaking models will be compared.

#### 124 2.3 Rotating Rostering Problem

The Rotating Rostering Problem [18] generalises many real life rostering problems, such as nurse rostering. The goal is to find a satisfiable assignment of shifts for each day to fulfill the shifts requirements and avoid conflicts. A shift type may either be a day off, a morning shift, a late shift, or a night shift. The shifts are ordered such that the following constraints are satisfied: 1. The number of staff required for a day is satisfied as needed. 2. There is a min and max number of consecutive shift assignments for the same shift type. 3. The shift ordering is forward rotating; a shift must be proceeded by a larger or equal shift type, or a

rest day. 4. Weekends (Saturday Sunday) have the same shift type. 5. At least two days
must be rest days every 14 days.

When converting the MiniZinc model over to Essence', we identified what we believe 134 is an overlooked edge case. Incorrect solutions rarely appeared, but surfaced when running 135 generated instance solutions through a solution checker. The issue related to the minimum 136 number of shift assignments mandated by the constraints. As part of the original constraints, 137 if the shift type of one day is different to the next day, the following days must meet the 138 minimum number of consecutive shifts. This works well, until the edge case of the very 139 first shift forgoing the minimum number of consecutive shifts, as the constraints ensure the 140 following days meet the minimum number of consecutive shifts as seen in Listing 1. To fix 141 this, we simply an extra constraint from the very first shift as seen in Listing 2. 142

**Listing 1** MiniZinc minimum number of consecutive shifts constraint

```
143
144 constraint forall(day in 1..numberOfDays - s_min) (
145 plan1d[day] != plan1d[day+1] -> all_equal(plan1d[day+1..day+s_min]));
```

Listing 2 MiniZinc minimum number of consecutive shifts additional constraint

```
148
149 constraint(all_equal(plan1d[1..s_min]));
```

147

#### <sup>150</sup> 2.4 Traveling Tournament Problem with Predefined Venues

The Traveling Tournament Problem with Predefined Venues (TTPPV) [16], is a specialisation of the Traveling Tournament Problem. A set of teams playing in a tournament is organized as a simple round robin schedule, with each game playing at different venues. The objective is to minimize the distance travelled by the teams between different venues.

The difference to the Traveling Tournament Problem is that in TTPPV the venues of each game are predefined. This means if team a plays against team b, the venue is predefined as being at either a's home or b's home. With the predefined venues, the problem lies in the scheduling of the games and minimizing the sum of the traveling distances of the teams. The problem is further specialised by using circular distances between the venues for simplicity.

The regular predicate is used within the MiniZinc model to assert there are at most 3 consecutive home games and at most 3 consecutive away games. More generally, the regular predicate asserts that a sequence of variables take a value from a finite automaton, where the automaton in the MiniZinc model asserts at most two consecutive away or home games. When translating the regular predicate to Essence', we use a forAll statement, checking that there are not four consecutive assignments.

## <sup>166</sup> 2.5 Capacitated Vehicle Routing problem with Time Windows, Service <sup>167</sup> Times and Pickup and Deliveries

The Capacitated Vehicle Routing problem with Time Windows, Service Times and Pickup and Deliveries (CVRPTW) is an example of a routing problem which specialises the Capacitated Vehicle Routing Problem [19] and was sourced from the 2022 MiniZinc challenge [17]. It is defined as follows: there are several vehicles with a given capacity for goods, and there are a number of pickup and drop-off locations of customers to deliver to. These pickup and delivery locations have an associated demand for the goods the vehicles need to pick up or deliver. As an added constraint, there are specified time windows for the deliveries to each

<sup>175</sup> customer such that the delivery truck must arrive and leave within this time window from
<sup>176</sup> the delivery location. The route chosen may not take any sub-tours for any route it takes.
<sup>177</sup> As part of the MiniZinc model, the circuit predicate is used to ensure the vehicle
<sup>178</sup> delivery routes do not take sub-tours in their route and visits each location uniquely for
<sup>179</sup> optimisation. A circuit is such that the cell value of an array points to the index of the next

number, and this forms a circuit that continues around. For the translation to Essence',
we used the decomposition of the circuit predicate from the MiniZinc library <sup>2</sup>.

To create the equivalent expression of circuit in Essence', a new variable is introduced to determine and constrain the ordering of values to form the circuit. The Essence' equivalent of circuit for the decision variable successor in the model is as follows in Listing 3.

Listing 3 Essence' circuit predicate equivalent

```
185
     allDiff(successor),
186
     forAll i : NODES . successor[i] != i,
187
     allDiff(successorOrder),
188
     successorOrder[1] = 1,
189
     forAll i : NODES .
190
         (successorOrder[i] = maxNodes -> successorOrder[successor[i]] = 1) /\
191
         (successorOrder[i] != maxNodes -> successorOrder[successor[i]] =
192
             successorOrder[i] + 1)
183
```

#### <sup>195</sup> 2.6 Multi-Skilled Project Scheduling Problem

The Multi-Skilled Project Scheduling Problem (MSPSP) is a variation on the basic resourceconstraint project scheduling problem [1] used in the 2012 Minizinc Challenge. In this problem there are a series of workers, with each worker having a specific skill set. There are several activities with an associated skill requiring completion to finish the project, and the overall goal is to minimize the project time.

The MiniZinc formulation uses set variables, where Essence' (unlike Essence [3]) lacks 201 modelling support for them. To overcome this limitation, the sets from MiniZinc were 202 translated into the occurrence representation of the numbers. This allowed for each matrix to 203 be equivalent in size to satisfy the Essence' language limitations. A disadvantage of using 204 this method is that by using the occurrence representation the parameter files become larger. 205 The MiniZinc model also makes use of letting to create variables within constraints, 206 but Essence' cannot do the same. As a result, an equivalent expression is created. On Line 4 207 of Listing 4, a new Boolean variable is introduced into the scope of the constraint. This 208 variable acts like a normal decision variable, with the goal of assigning a satisfiable value. In 209 Line 5 and Line 6 the Boolean variable before in combination with an implication ensures 210 at least one of the expressions following the implication is true. This can be compactly 211 expressed in Essence' by using an or, as shown in Listing 5 on Line 5. 212

Listing 4 Usage of MiniZinc letting in MSPSP

```
213
214
constraint
215
forall (i, j in Tasks where i < j /\ not(j in suc[i]) /\ not(i in suc[j]))(
216
if exists( k in Skills )( rr[k,i] + rr[k,j] > rc[k] ) then
217
let { var bool: before } in (
```

2 3

6

<sup>&</sup>lt;sup>2</sup> fzn\_circuit.mzn in [11]

```
218 (before -> s[i] + d[i] <= s[j])
219 /\ (not(before) -> s[j] + d[j] <= s[i]) )
220 else true endif);</pre>
```

**Listing 5** Essence' letting equivalent to Listing 4

```
223 forAll i : Tasks . forAll j : Tasks .
224 (i < j /\ suc[i,j] = 0 /\ suc[j,i] = 0) ->
225 ((exists k : Skills .
226 rr[k,i] + rr[k,j] > rc[k]) ->
227 ((s[i] + d[i] <= s[j]) \/ (s[j] + d[j] <= s[i]))),</pre>
```

The MiniZinc model (Listing 6) has a series of further lettings: WTasks and TWorkers. WTasks and TWorkers are sets, where WTasks is the set of tasks where a skill for that task exists, and TWorkers is the set of workers who have an existing skill required. To create an equivalent in Essence', a single variable is introduced, TWorkers, encompassing WTasks and TWorkers together in a 2d matrix. This is expressed in Listing 7.

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**Listing 6** Additional MiniZinc lettings in MSPSP

```
let { set of int: WTasks =
        { i | i in Tasks where exists(k in has_skills[j])(rr[k, i] > 0) }
in...
let { set of int: TWorkers =
        { j | j in Workers where exists(k in has_skills[j])(rr[k, i] > 0) }
in...
```

**Listing 7** Essence' equivalent to Listing 6

```
242
243 forAll i : Tasks . forAll j : Workers .
244 TWorkers[j, i] = 1 <->
245 exists k : Skills . has_skills[j, k] = 1 /\ rr[k,i] > 0,
```

TWorkers is then leveraged in all further constraints equivalent to the lettings of TWorkers and WTasks as seen in Listing 8. Listing 8 constraints the number of workers with a set skill working upon a task to satisfy the requirements. Using the TWorkers variable created in Listing 7, the equivalent of the MiniZinc Listing 8 is created for Essence' in Listing 9.

```
Listing 8 MiniZinc letting over TWorkers
```

```
constraint forall ( i in Tasks ) (
253
        let {
254
            set of int: TWorkers =
255
                { j | j in Workers where exists(k in has_skills[j])(rr[k, i] > 0) }
256
        } in (
257
            forall ( k in Skills where rr[k, i] > 0 )
258
                (sum(j in TWorkers where k in has_skills[j])(
259
                bool2int(w[j, i])) >= rr[k, i])
260
         /\ forall ( j in Workers where not(j in TWorkers) )
261
             (w[j, i] = false)));
262
263
```

**Listing 9** Essence' equivalent to Listing 8

222

234

252

The cumulative predicate is used to determine if the cumulative resource usage is within 272 bounds. That is, a set of tasks with start times, durations, and resource requirements, never 273 exceed the global resource bound at any time. The cumulative predicate is a common 274 predicate used in scheduling problems and is therefore optimized in most solvers such as 275 Chuffed. In the translation to Essence' we used the default MiniZinc decomposition of 276 cumulative<sup>3</sup>. The cumulative predicate is used twice in the MSPSP MiniZinc model, both 277 with letting statements. The first cumulative imposes that at least one worker fulfills the 278 task assignment while respecting the duration and timings. The second cumulative ensures 279 the resources requirements is exceeded or equaled by workers while respecting durations and 280 orderings. The equivalent Essence' is created in Listing 10. 281

Listing 10 Essence' equivalent of cumulative in MSPSP

```
forAll work : Workers .
283
                                             sum(TWorkers[work,..]) > 1 ->
284
                                                                  (forAll j : Tasks .
285
                                                                                    1 >= sum([(TWorkers[work, j] = 1) / (TWorkers[work, i] = 1) / (TWork
286
                                                                                                       (s[i] <= s[j]) /\ (s[j] < (s[i] + d[i]))
287
                                                                                                      /\ w[work,i] | i : Tasks])),
288
                        forAll k : Skills .
289
                                             (sum([rr[k,i] > 0 | i : Tasks]) > 1 /\
290
                                                 sum([rr[k,i] | i : Tasks, rr[k,i] > 0]) > rc[k]) ->
291
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   9
                                                               forAll j : Tasks .
292
                                                                                   rr[k,j] > 0 ->
293
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   11
                                                                                                      rc[k] >= sum([(s[i] <= s[j] /\ s[j] < (s[i] + d[i]))*rr[k,i] | i :</pre>
294
                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   12
                                                                                                                             Tasks, rr[k,i] > 0]),
295
```

#### <sup>297</sup> **3** Experiments

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Our experiments aim to identify performance differences between Savile Row 1.9.1 and 298 MiniZinc 2.7.5. The experiments were run using 3 different optimisation levels that the 299 respective developers offer for each pipeline. That is, no optimisation (OOS0 in Savile Row, 300 O0 in MiniZinc), intermediate optimisation (O2S1 in Savile Row, O1 in MiniZinc) and full 301 optimisations (O3S2 in Savile Row, O5 in MiniZinc). Note that these will differ between 302 pipelines, in particular due to Savile Row allowing control over the amount of symmetry 303 breaking constraints introduced during tailoring, something that MiniZinc does not enable. 304 Certain problems were lacking in the number of instances or in their variety. To com-305 pensate, additional instances were generated through a combination of Python scripts or 306 parameterised generators as constraint models, similarly to previous approaches [2]. 307

<sup>308</sup> Timing information is presented as the quotient of Essence' over MiniZinc. That is, a

2

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<sup>&</sup>lt;sup>3</sup> fzn\_cumulative\_task of fzn\_cumulative.mzn in [11]

number > 1 suggests MiniZinc was faster, while a number < 1 suggests Essence' was faster. 309 These timings use the geometric mean, which uses the product rather than the sum, giving a 310 better indicator of the central tendency of runs. In Table 1 we can see that both pipelines 311 produce very similar and consistent results with respect to solving a given problem. Both 312 pipelines solve all instances for the Rostering and Scheduling problems, and neither finds any 313 solutions to the vehicle routing problems (within the set timeout). When the problems get 314 harder (or more varied), such as the Quasigroup problems, modelling in Savile Row seems 315 to be more consistent between the model representations and different optimisations levels. 316 In the other problem groups both pipelines can be considered equal. 317

From a timing perspective, MiniZinc clearly outperforms Savile Row in MSPSP and 318 Rostering (the problem classes where both solvers find all solutions). Meanwhile, in the 319 two Quasigroup models Savile Row performs faster, and is solving more of the instances. 320 We see this as an indicator that, in the given dataset, Savile Row performs better on 321 harder instances. We believe that MiniZinc outperforms Savile Row on easy instances, as 322 MiniZinc has a very low initialisation time when compared to Savile Row , as it is written 323 in C++. In problems where both pipelines solved some of the problems, the results are 324 inconclusive. Although the Wordpress problem without the explicit symmetry breaking 325 constraints performs better in the highest optimisation level in MiniZinc, with the explicit 326 symmetry breaking constraints Savile Row performs better the higher the optimisation 327 levels. 328

		Essence'			MiniZinc			Timing Ratio		
Problem	#	O0S0	O2S1	O3S2	O0	01	O5	$\frac{O0S0}{O0}$	$\frac{O2S1}{O1}$	$\frac{O3S2}{O5}$
Quasigroup	43	41	42	41	40	39	40	0.08	0.5	0.6
Quasigroup Occ.	43	41	41	42	32	37	38	0.12	0.08	0.38
Wordpress	9	6	6	6	6	6	6	1.54	1.83	5.29
Wordpress Symm.	9	4	4	6	4	4	4	1.47	1.36	0.49
TTPPV	20	3	3	3	3	3	3	0.99	1.35	1.98
MSPSP	6	6	6	6	6	6	6	138.48	88.57	612.61
CVRPTW	5	0	0	0	0	0	0	1.0	1.0	1.0
Rostering	7	7	7	7	7	7	7	29.5	15.15	77.7

**Table 1** Columns Essence' and MiniZinc show the number of solved instances per problem, split between the 3 considered optimisation levels. Timing ratios show the ratio between Essence' and MiniZinc options, where > 1 denotes MiniZinc was faster and < 1 otherwise.

#### **4** Conclusions and Further Work

These initial findings seem to suggest that Minizinc might be better suited for scenarios where an expert modeler can leverage the capabilities of the pipeline and where code maintainability are crucial. Conversely, Savilerow strong reformulation capabilities and good default settings would be the preferred choice for tackling complex problems where consistent performance is paramount. To solidify these findings, a wider selection of both solvers and problems have to be considered.

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