Generating Fast Domain-Optimized Planners by Automatically Configuring a Generic Parameterised Planner

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Abstract

When designing state-of-the-art, domain-independent planning systems, many decisions have to be made with respect to the domain analysis or compilation performed during preprocessing, the heuristic functions used during search, and other features of the search algorithm. These design decisions can have a large impact on the performance of the resulting planner. By providing many alternatives for these choices and exposing them as parameters, planning systems can in principle be configured to work well on different domains. However, usually planners are used in default configurations that have been chosen because of their good average performance over a set of benchmark domains, with limited experimentation of the potentially huge range of possible configurations.

In this work, we propose a general framework for automatically configuring a parameterised planner, showing that substantial performance gains can be achieved. We apply the framework to the well-known LPG planner, which has 62 parameters and over 6.5×10^{17} possible configurations. We demonstrate that by using this highly parameterised planning system in combination with the off-the-shelf, state-of-the-art automatic algorithm configuration procedure ParamILS, substantial performance improvements on specific planning domains can be obtained.

Introduction

When designing state-of-the-art, domain-independent planning systems, many decisions have to be made with respect to the domain analysis or compilation performed during preprocessing, the heuristic functions used during search, and several other features of the search algorithm. These design decisions can have a large impact on the performance of the resulting planner. By providing many alternatives for these choices and exposing them as parameters, highly flexible domain-independent planning systems are obtained, which then, in principle, can be configured to work well on different domains, by using parameter settings specifically chosen for solving planning problems from each given domain. However, usually such planners are used with default configurations that have been chosen because of their good average performance over a set of benchmark domains, based on limited manual exploration within a potentially vast space of possible configurations. The hope is that these default configurations will also perform well on domains and problems beyond those for which they were tested at design time.

In this work, we advocate a different approach, based on the idea of *automatically* configuring a generic, parameterised planner using a set of training planning problems in order to obtain planners that perform especially well in the domains of these training problems. Automated configuration of heuristic algorithms has been an area of intense research focus in recent years, producing tools that have improved algorithm performance substantially in many problem domains. To our knowledge, however, these techniques have not yet been applied to the problem of planning.

While our approach could in principle utilise any sufficiently powerful automatic configuration procedure, we have chosen the FocusedILS variant of the off-the-shelf, state-of-the-art automatic algorithm configuration procedure ParamILS (Hutter, Hoos, & Stützle 2007; Hutter *et al.* 2009). At the core of the ParamILS framework lies Iterated Local Search (ILS), a well-known and versatile stochastic local search method that iteratively performs phases of a simple local search, such as iterative improvement, interspersed with so-called perturbation phases that are used to escape from local optima. The FocusedILS variant of ParamILS uses this ILS procedure to search for high-performance configurations of a given algorithm by evaluating promising configurations, using an increasing number of runs in order to avoid wasting CPU-time on poorly-performing configurations. ParamILS also avoids wasting CPU-time on low-performance configurations by adaptively limiting the amount of runtime allocated to each algorithm run using knowledge of the best-performing configuration found so far.

ParamILS has previously been applied to configure state-of-the-art solvers for several combinatorial problems, including propositional satisfiability (SAT) (Hutter *et al.* 2007) and mixed integer programming (MIP) (Hutter, Hoos, & Leyton-Brown 2010). This resulted in a version of the SAT solver Spear that won the first prize in one category of the 2007 Satisfiability Modulo Theories Competition (Hutter *et al.* 2007); it further contributed to the SATzilla solvers that won prizes in 5 categories of the 2009 SAT Competition and led to large improvements in the performance of CPLEX on several types of MIP problems (Hutter, Hoos, & Leyton-Brown 2010). Differently from SAT and MIP, in planning, explicit domain specifications are available through a planning language, which creates more opportunities for planners to take problem structure into account within parameterised components (e.g., specific search heuristics). This can lead to more complex systems, with greater opportunities for automatic parameter configuration, but also greater challenges (bigger, richer design spaces can be expected to give rise to trickier configuration problems).

One such planning system is LPG (see, e.g., Gerevini, Saetti, & Serina 2003, Gerevini, Saetti, & Serina 2008). Based on a stochastic local search procedure, LPG is a well-known efficient and versatile planner with many components that can be configured very flexibly via 62 exposed configurable parameters, which jointly give rise to over 6.5×10^{17} possible configurations. This configuration space is one of the largest considered so far in applications of ParamILS. In this work, we used ParamILS to automatically configure LPG on various propositional domains, starting from a manually-chosen default parameter setting with good performance on a broad range of domains.

We tested our approach using ParamILS and LPG on 11 domains of planning problems used in previous international planning competitions (IPC-3–6). Our results demonstrate that by using automatically determined, domain-optimized configurations (LPG.sd), substantial performance gains can be achieved compared to the default configuration (LPG.d). Using the same automatic configuration approach to optimise the performance of LPG on a merged set of benchmark instances from different domains also results in improvements over the default, but these are less pronounced than those obtained by automated configuration for single domains.

We also investigated to which extent the domain-optimized planners obtained by configuring the general-purpose LPG planner perform well compared to other state-of-the-art domain-independent planners. Our results indicate that, for the class of domains considered in our analysis, LPG.sd is significantly faster than LAMA (Richter & Westphal 2008), the top-performing propositional planner of the last planning competition (IPC-6).[1]

Moreover, in order to understand how well our approach works compared to state-of-the-of-art systems in automated planning with learning, we have experimentally compared LPG.sd with the planners of the learning track of IPC-6, showing that in terms of speed and usefulness of the learned knowledge, our system outperforms the respective IPC-6 winners, PbP (Gerevini, Saetti, & Vallati 2009) and ObtuseWedge (Yoon, Fern, & Givan 2008).

Recently, LPG.sd has been entered into the learning track of the 7th International Planning Competition (IPC-7) as ParLPG, and we give preliminary results on the competition domains in this paper.

While in this work, we focus on the application of the proposed framework to the LPG planner, we believe that similarly good results can be obtained for highly parameterised versions of other existing planning systems. In general, our results suggest that in the future development of efficient planning systems, it is worth including many different variants and a wide range of settings for the various components, instead of committing at design time to particular choices and settings, and to use automated procedures for finding configurations of the resulting highly parameterised planning systems that perform well on the problems arising in a specific application domain under consideration.

[1]The version of LAMA used in the IPC-6 competition exposes only four Boolean parameters, which its authors recommend to leave unchanged; it is therefore not suitable for studying automatic parameter configuration. A newer, much more flexibly configurable version of LAMA has become available very recently, as part of the Fast Downward system, which we are studying in ongoing work.

```
1. Set $\mathcal{A}$ to the action graph containing only $a_{start}$ and $a_{end}$;
2. While the current action graph $\mathcal{A}$ contains a flaw or
           a certain number of search steps is not exceeded do
3.     Select a flaw $\sigma$ in $\mathcal{A}$;
4.     Determine the search neighborhood $N(\mathcal{A}, \sigma)$;
5.     Weight the elements of $N(\mathcal{A}, \sigma)$ using a heuristic function $E$;
6.     Choose a graph $\mathcal{A}' \in N(\mathcal{A}, \sigma)$ according to $E$ and noise $n$;
7.     Set $\mathcal{A}$ to $\mathcal{A}'$;
8. Return $\mathcal{A}$.
```

Figure 1: High-level description of LPG's search procedure.

In the rest of this paper, we first provide some background and further information on LPG and its parameters. Next, after a description of the parameter configuration process, we describe in detail our experimental analysis and results, including preliminary results from our IPC-7 submission. Finally, we give some concluding remarks and discuss some avenues for future work.

The Generic Parameterised Planner LPG

In this section, we provide a very brief description of LPG and its parameters. LPG is a versatile system that can be used for plan generation, plan repair and incremental planning in PDDL2.2 domains (Hoffmann & Edelkamp 2005). The planner is based on a stochastic local search procedure that explores a space of partial plans represented through *linear action graphs*, which are variants of the very well-known planning graph (Blum & Furst 1997).

Starting from the initial action graph containing only two special actions representing the problem initial state and goals, respectively, LPG iteratively modifies the current graph until there is no *flaw* in it or a certain bound on the number of search steps is exceeded. Intuitively, a flaw is an action in the graph with a precondition that is not supported by an effect of another action in the graph. LPG attempts to resolve flaws by inserting into or removing from the graph a new or existing action, respectively. Figure 1 gives a high-level description of the general search process performed by LPG. Each search step *selects a flaw* σ in the current action graph $\mathcal{A}$, defines the elements (modified action graphs) of the *search neighborhood* of $\mathcal{A}$ for repairing σ, weights the neighborhood elements using a *heuristic function* E, and chooses the best one of them according to E with some probability n, called the *noise parameter*, and randomly with probability $1 - n$. Because of this noise parameter, which helps the planner to escape from possible local minima, LPG is a randomised procedure.

LPG exposes 62 configurable parameters; these control various aspects of the system and can be grouped into seven

Domain Configuration	P1	P2	P3	P4	P5	P6	P7	Total
`Blocksworld`	1	1	2	1	5	1	2	13
`Depots`	2	2	1	1	2	2	2	12
`Gold-miner`	2	3	0	1	4	2	1	13
`Matching-BW`	1	2	2	1	3	0	2	11
`N-Puzzle`	4	5	3	2	14	5	2	35
`Rovers`	0	1	0	0	0	2	1	4
`Satellite`	2	7	3	1	11	5	3	32
`Sokoban`	0	1	1	1	1	1	2	7
`Zenotravel`	3	5	2	3	11	5	3	32
Merged set	0	1	0	1	5	2	2	11
Number of parameters	6	15	8	6	17	7	3	62

Table 1: Number of parameters of LPG that are changed by ParamILS in the configurations computed for nine domains independently considered (rows 2–10) and jointly considered ("merged set" row). Each of the columns P1–P7 corresponds to a different parameter category (i.e., planner component).

distinct categories, each of which corresponds to a different component of LPG:

P1 *Preprocessing information* (e.g., mutually exclusive relations between actions).

P2 *Search strategy* (e.g., the use and length of a "tabu list" for the local search, the number of search steps before restarting a new search, and the activation of an alternative systematic best-first search procedure).

P3 *Flaw selection strategy* (i.e., different heuristics for deciding which flaw should be repaired first).

P4 *Search neighborhood definition* (i.e., different ways of defining/restricting the basic search neighborhood).

P5 *Heuristic function E* (i.e., a class of possible heuristics for weighting the neighborhood elements, with some variants for each of them).

P6 *Reachability information* used in the heuristic functions and in neighborhood definitions (e.g., the minimum number of actions required to achieve an unsupported precondition from a given state).

P7 *Search randomisation* (i.e., different ways of statically and dynamically setting the noise value).

The last row of Table 1 shows the number of LPG's parameters that fall into each of these seven categories (planner components).

Experimental Analysis

In this section, we present the results of a large experimental study examining the effectiveness of the automated approach outlined in the introduction in terms of planning speed.

Benchmark domains and instances

In our first set of experiments, we considered problem instances from eight known benchmark domains used in the last four international planning competitions (IPC-3–6), `Depots`, `Gold-miner`, `Matching-BW`, `N-Puzzle`, `Rovers`, `Satellite`, `Sokoban`, and `Zenotravel`, plus the well-known `Blocksworld` domain. These domains were selected because they are not trivially solvable, and random instance generators are available for them, such that large training and testing sets of instances can be obtained.

For each domain, we used the respective random instance generator to obtain two disjoint sets of instances: a training set with 2000 relatively small instances (benchmark `T`), and a testing set with 400 middle-size instances (benchmark `MS`). The size of the instances in training set `T` was chosen such that the instances could be solved by the default configuration of LPG in 20 to 40 CPU seconds *on average*. For testing set `MS`, the size of the instances was chosen such that the instances could on average be solved by the default configuration of LPG in 50 seconds to 2 minutes. This does not mean that all our problem instances can actually be solved by LPG, since we merely determined the *size* of the instances according to the performance of the default configuration, and then we used the random instance generators to derive the actual instances.

For the experiments comparing automatically determined configurations of LPG against the planners that entered the learning track of IPC-6, we employed the same instance sets as those used in the competition.

Automated configuration using ParamILS

For all configuration experiments we used the FocusedILS variant of ParamILS version 2.3.5 with default parameter settings. Using the default configuration of LPG as the starting point for the automated configuration process, we concurrently performed 10 independent runs of FocusedILS per domain, using random orderings of the training set instances.[2] Each run of FocusedILS had a total CPU-time cutoff of 48 hours, and a cutoff time of 60 CPU seconds was used for each run of LPG performed during the configuration process. The objective function used by ParamILS for evaluating the quality of configurations was mean runtime, with timeouts and crashes assigned a penalised runtime of ten times the per-run cutoff (the so-called PAR-10 score). Out of the 10 configurations produced by these runs, we selected the configuration with the best training set performance (as measured by FocusedILS) as the final configuration of LPG for the respective domain.

Additionally, we used FocusedILS for optimising the configuration of LPG across all of the selected domains together. As with our approach for individual domains, we performed 10 independent runs of FocusedILS starting from the default configuration; again, the single configuration with the best performance on the merged training set as measured by FocusedILS was selected as the final result of the configuration process.

The final configurations thus obtained were then evaluated on the testing set of instances (benchmark `MS`) for each domain, using a per-run timeout of 600 CPU seconds.

For convenience, we define the following abbreviations corresponding to configurations of LPG:

[2]Multiple independent runs of FocusedILS were used, because this approach can help ameliorate stagnation of the configuration process occasionally encountered otherwise.

Domain	LPG.d		LPG.r	
	Score	% solved	Score	% solved
`Blocksworld`	99.00	99	0.00	16
`Depots`	86.00	86	0.00	18
`Gold-miner`	91.00	91	0.00	19
`Matching-BW`	14.00	14	0.15	9
`N-Puzzle`	59.10	89	34.75	86
`Rovers`	85.81	100	31.21	53
`Satellite`	96.02	100	18.99	37
`Sokoban`	73.20	74	2.06	28
`Zenotravel`	98.70	100	2.47	24
Total	702.8	83.7	89.6	32.2

Table 2: Speed scores and percentage of problems solved by LPG.d and LPG.r for 100 problems in each of 9 domains of benchmark MS.

- *Default* (LPG.d): The default configuration of LPG.
- *Random* (LPG.r): Configurations selected independently at random from all possible configurations of LPG.
- *Specific* (LPG.sd): The specific configuration of LPG found by ParamILS for each domain.
- *Merged* (LPG.md): The configuration of LPG obtained by running ParamILS on the merged training set.

Table 1 shows, for each parameter category of LPG, the number of parameters that are changed from their defaults by ParamILS in the derived domain-optimized configurations (LPG.sd) and in the configuration obtained for the merged training set (LPG.md).

Empirical result 1 *Domain-optimized configurations of* LPG *differ substantially from the default configuration.*

Moreover, we noticed that usually the changed parameter settings are considerably different from each other.

Results on specific domains

The performance of each configuration was evaluated using the performance score functions adopted in IPC-6 (Fern, Khardon, & Tadepalli 2008). The *speed score* of a configuration $\mathcal{C}$ is defined as the sum of the speed scores assigned to $\mathcal{C}$ over all test problems. The speed score assigned to $\mathcal{C}$ for a planning problem p is 0 if p is unsolved and $T^*_p/T(\mathcal{C})_p$ otherwise, where T^*_p is the lowest measured CPU time to solve problem p and $T(\mathcal{C})_p$ denotes the CPU time required by $\mathcal{C}$ to solve problem p. Higher values for the speed score indicate better performance.

Table 2 shows the results of the comparison between LPG.d and LPG.r, which we conducted to assess the performance of the default configuration on our benchmarks.

Empirical result 2 LPG.d *is much faster and solves many more problems than* LPG.r.

Specifically, LPG.r solves very few problems in 6 of the 9 domains we considered, while LPG.d solves most of the considered problems in all but one domain. This observation also suggests that the default configuration is a much better starting point for deriving configurations using ParamILS than a random configuration. In order to confirm this intuition, we performed an additional set of experiments using the random configuration as starting point. As expected, the resulting configurations of LPG perform much worse than LPG.sd, and sometimes even worse than LPG.d.

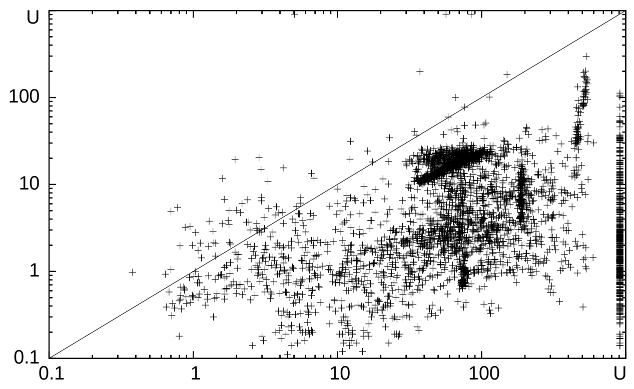

Figure 2: CPU time (log. scale) of LPG.sd versus LPG.d for the problems in bechmark set MS. The x-axis shows runtime of LPG.d and the y-axis runtime of the optimized LPG.sd solvers, measured in CPU seconds; U indicates runs that timed out with the given runtime cutoff.

Figure 2 shows the performance of LPG.sd and LPG.d on the individual benchmark instances in the form of a scatterplot. We consider all instances solved by at least one of these planners. Each cross symbol indicates the CPU time used by LPG.d and LPG.sd to solve a particular problem instance of benchmarks MS. When a cross appears below (above) the main diagonal, LPG.sd is faster (slower) than LPG.d; the distance of the cross from the main diagonal indicates the performance gap (the greater the distance, the greater the gap). The results in Figure 2 indicate that LPG.sd performs almost always better than LPG.d, often by 1–2 orders of magnitude.

Table 3 shows the performance of LPG.d, LPG.md, and LPG.sd for each domain of benchmark MS in terms of speed score, percentage of solved problems and average CPU time (computed over the problems solved by all the considered configurations). These results indicate that LPG.sd solves many more problems, is on average much faster than LPG.d and LPG.md, and that for some benchmark sets LPG.sd *always* performs better than or equal to the other configurations, as the IPC score of LPG.sd is sometimes the maximum score (i.e., 400 points for benchmark MS).[3]

Empirical result 3 LPG.sd *performs much better than both* LPG.d *and* LPG.md.

As can be seen from the last row of Table 3, LPG.md performs usually better than LPG.d on the test sets for the individual domains. Moreover, it performs better than LPG.d

[3]Additional results using, for each of the nine considered domains, 2000 test problems of the same size as those used for the training, and 50 test problems considerably larger than those in the MS benchmark, indicate a performance behaviour very similar to (or even better than) the one observed for the MS instances considered in Table 3.

Domain	Speed score			% solved			Average CPU time		
	LPG.d	LPG.md	LPG.sd	LPG.d	LPG.md	LPG.sd	LPG.d	LPG.md	LPG.sd
`Blocksworld`	21.3	74.8	400	98.8	100	100	105.3	28.17	4.29
`Depots`	124	164	345	90.3	99	98.5	78.1	42.4	5.7
`Gold-miner`	18.5	232	374	90.5	100	100	94.4	7.4	1.6
`Matching-BW`	9.74	72.5	375	15.8	55.3	97.8	93.8	42.3	5.6
`N-Puzzle`	20.1	27.0	347	85	86.3	86.8	321.0	247	31.20
`Rovers`	131	162	400	100	100	100	72.2	52.9	21.2
`Satellite`	104	111	400	100	100	100	64.0	59.2	1.3
`Sokoban`	26.7	191	335	75.8	94.8	96.5	24.6	6.15	1.19
`Zenotravel`	49.1	97.2	397	100	99.8	100	103.7	57.6	11.1
All above	280.3	304.3	–	83.3	91.5	–	115.4	38.8	–

Table 3: Speed score, percentage of solved problems, and average CPU time of LPG.d, LPG.md and LPG.sd for 400 `MS` instances in each of 9 domains, independently considered, and in all domains (last row).

Domain	LPG.sd vs. LAMA		LPG.sd vs. PbP	
	Δ-speed	Δ-solved	Δ-speed	Δ-solved
`Blocksworld`	+377.4	+52	+361.7	±0
`Depots`	+393.9	+381	+211.1	+54
`Gold-miner`	+400	+400	+395.6	+319
`Matching-BW`	+227.8	+118	+40.7	+330
`N-Puzzle`	+255.7	+4	+279.8	−20
`Rovers`	+392.9	+14	+313.4	+9
`Satellite`	+388.1	+157	+253.6	+9
`Sokoban`	+340.1	+278	−41.6	+5
`Zenotravel`	+368.3	±0	−282.1	+8
Total	+3144	+1404	+1532	+714

Table 4: Performance gap between LPG.sd and LAMA (columns 2–3) and LPG.sd and PbP (columns 4–5) for 400 `MS` problems in each of 9 domains in terms of speed score and number of solved problems.

on the sets obtained by merging the test sets for all individual domains, which indicates that by using a merged training set, we successfully produced a configuration with good performance on average across all selected domains.

Empirical result 4 LPG.md *performs better than* LPG.d.

Next, we compared our LPG configurations with state-of-the-art planning systems – namely, the winner of the IPC-6 classical track, LAMA (configured to stop when the first solution is computed), and the winner of the IPC-6 learning track, PbP. The performance gap between LPG.sd and these planners for `MS` problems are shown in Table 4, where we report the speed score and the number of solved problems (positive numbers mean that LPG.sd performs better). These experimental results indicate clearly that our configurations of LPG are significantly faster and solve many more problems than LAMA.

Empirical result 5 LPG.sd *performs significantly better than* LAMA *on well-known non-trivial domains.*

Moreover, LPG.sd outperforms PbP in most of the selected domains: only for `Sokoban` and `Zenotravel`, PbP obtains a better speed score (but performs slightly worse in terms of solved problems). Interestingly, for these domains the multiplanner of PbP runs a single planner with an associated set of macro-actions; these macro-actions clearly help to significantly speed up the search phase of this planner.

Planner	# unsolved	Speed score	Δ-score
LPG.sd	38	**93.23**	**+59.7**
ObtuseWedge	63	63.83	+33.58
PbP	**7**	69.16	−3.54
RFA1	85	11.44	–
Wizard+FF	102	29.5	+10.66
Wizard+SGPlan	88	38.24	+7.73

Table 5: Performance of the top 5 planners that took part in the learning track of IPC-6 plus LPG.sd, in terms of number of unsolved problems, speed score and score gap with and without using the learned knowledge for the problems of the learning track of IPC-6.

Empirical result 6 *For the well-known benchmark domains considered here,* LPG.sd *performs significantly better than* PbP.

Results on learning track of IPC-6

To evaluate the effectiveness of our approach against recent learning-based planners, we compared our LPG.sd configurations with planners that entered the learning track of IPC-6, based on the same performance criteria as used in the competition. Table 5 shows performance in terms of number of unsolved problems, speed score, and performance gap with and without using the learned knowledge (positive numbers mean that the planner performs better using the knowledge); the results in this table indicate that LPG.sd performs better than every solver that participated in the IPC-6 learning track, including the version of PbP that won this track. Although LPG.sd solves fewer problems than PbP, it achieves the best score as it is the fastest planner on 3 domains (`Gold-miner`, `N-Puzzle` and `Sokoban`), and it performs close to PbP on one additional domain (`Matching-BW`). Furthermore, the results in Table 5 indicate that the performance gap between LPG.sd and LPG.d is significant, and is greater than the gap achieved by ObtuseWedge, the planner recognised as best learner of the

Domain	Speed score		% solved		Average time	
	LPG.d	LPG.sd	LPG.d	LPG.sd	LPG.d	LPG.sd
Barman	–	–	–	–	–	–
BW	14.12	30	80	100	259.5	95.3
Depots	6.52	20.5	37	70	315.4	52.1
Gripper	20.36	30	100	100	77.6	27.4
Parking	–	–	–	–	–	–
Rovers	18.64	28	93	93	157.11	27.7
Satellite	23.67	30	100	100	70.1	24.5
Spanner	17.73	30	100	100	272.7	25.3
Tpp	–	14	–	47	–	73.29

Table 6: Speed score, percentage of solved problems and average CPU time of LPG.d and LPG.sd for 30 instances from the test sets of IPC-7 domains. BW indicates the Blocksworld domain, and "–" is used when LPG.sd or LPG.d failed to solve any of the problem instances for a given domain.

IPC-6 competition.[4]

Empirical result 7 *According to the evaluation criteria of IPC-6,* LPG.sd *performs better than the winners of the learning track for speed and best-learning.*

Preliminary results on the learning track of IPC-7

At the time of this writing, LPG.sd is participating in the learning track of the 7th International Planning Competition (IPC-7).[5] In this submission, we utilised several meta-algorithmic procedures provided by HAL, a recently developed tool supporting both the computer-aided design and the empirical analysis of high-performance algorithms (Nell *et al.* 2011). In addition to the HAL plugin for the FocusedILS variant of ParamILS, we used the plugins providing support for the empirical analysis of a single algorithm's performance. We also leveraged HAL's built-in support for compute clusters and data management.

For each of the 9 IPC-7 domains, ten independent runs of ParamILS were performed using a randomly generated training set containing 60 to 70 instances solvable by LPG.d within the 900 second competition cutoff. Each run of LPG was given a runtime cutoff of 900 CPU seconds, and the total runtime cutoff for configuration was 5 CPU days. The configuration with the best training quality as reported by a subsequent empirical analysis of the ParamILS incumbents was selected as the representative LPG.sd configuration for each domain.

Table 6 shows results for 900 CPU second runs of LPG.sd and LPG.d on each of these IPC-7 domains, using randomly generated test sets of 30 instances of the same size and hardness as those that will be used for evaluating the competing planners. Although at the time of this writing, the actual instances to be used in the competition to evaluate our submission were not yet available, the competition organisers had announced in advance the instance distributions they intended to use.

The IPC-7 speed score for a configuration $\mathcal{C}$ is defined as the sum of the speed scores assigned to $\mathcal{C}$ over all test problems. The speed score assigned to $\mathcal{C}$ for a planning problem p is 0 if p is unsolved, and $1/(1 + \log_{10}(T(\mathcal{C})_p/T^*_p))$ otherwise, where T^*_p is the lowest measured CPU time to solve problem p and $T(\mathcal{C})_p$ denotes the CPU time required by $\mathcal{C}$ to solve problem p. Obviously, higher values for the speed score indicate better performance.

The results in Table 6 show that, for all but two of the IPC-7 domains, LPG.sd obtains better speed scores than LPG.d and, on average, is considerably faster. Moreover, for three of the nine domains (Depots, Tpp and Blocksworld), it solves many more problems. For Barman and Parking, neither LPG.d nor LPG.sd are able to solve any of the generated test instances.

Empirical result 8 *For the domains used in IPC-7,* LPG.sd *performs significantly better than* LPG.d.

Conclusions and Future Work

We have investigated the application of computer-assisted algorithm design to automated planning and proposed a framework for automatically configuring a generic planner with several parameterised components to obtain specialised planners that work efficiently on given domains. In a large-scale empirical analysis, we have demonstrated that our approach, when applied to the state-of-the-art, highly parameterised LPG planning system, effectively generates substantially improved domain-optimized planners.

Our work and results also suggest a potential method for testing new heuristics and algorithm components, based on measuring the performance improvements obtained by adding them to an existing highly-parameterised planner followed by automatic configuration for specific domains. The results may not only reveal to which extent new design elements are useful, but also under which circumstances they are most effective – something that would be very difficult to determine manually.

In the planning literature, few other approaches to automatically configuring the parameters of a planner have been investigated. In particular, Vrakas *et al.* proposed an adaptive planner, called HAPRC, with parameters tuned based on some features of the problem under consideration. The results described in (Vrakas *et al.* 2003) are obtained considering every possible configuration of the planner parameters, which is infeasible for systems with many parameters (such as LPG). Moreover, the techniques used for learning the configuration are completely different from ours: HAPRC uses a classification based algorithm, while our approach uses stochastic local search in the space of parameter configurations.

We see several avenues for future work. Concerning the automatic configuration of LPG, we are conducting an experimental analysis about the usefulness of the proposed framework for identifying configurations improving the planner performance in terms of plan quality. Moreover, we plan to apply the framework to metric-temporal planning domains. Finally, we believe that our approach

[4] As observed in (Gerevini, Saetti, & Vallati 2009), the negative Δ-score of PbP is mainly due to some implementation bugs that have been fixed in a version developed after the competition.

[5] The implementation of LPG.sd used for IPC-7 is named ParLPG.

can yield good results for other planners that have been rendered highly configurable by exposing many parameters. In particular, preliminary results from ongoing work indicate that substantial performance gains can be obtained when applying our approach to a very recent, highly parameterised version of the IPC-4 winner Fast Downward.

Acknowledgements. The authors would like to thank WestGrid and Compute-Calcul Canada for providing access to some of the cluster hardware used in our experiments. HH gratefully acknowledges funding through an NSERC Discovery Grant and Discovery Accelerator Supplement. We also thank Frank Hutter for useful comments on an earlier draft, Chris Nell for support using HAL and Ivan Serina for a useful discussion about LPG's parameters.

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