Genetic Algorithm to the Power of SMT: a Hybrid Approach to Web Service Composition Problem

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***Abstract*—The paper deals with the concrete planning problem – a stage of the Web Service Composition in the PlanICS framework, which consists in choosing the best service offers in order to satisfy the user query and to maximize the quality function. We introduce a novel planning technique based on a combination of a Genetic Algorithm with a Satisfiability Modulo Theories Solver, which allows to obtain better results than each of the methods separately. The paper presents some preliminary, although very encouraging, experimental results.**

***Keywords*-Web Service Composition; Concrete Planning; Genetic Algorithm; Satisfiability Modulo Theories; Hybrid Algorithm**

I. INTRODUCTION

One of the fundamental ideas of Service-Oriented Architecture (SOA) [1] is to compose simple functionalities, accessible via well-defined interfaces, in order to realize more sophisticated objectives. The problem of finding such a composition is hard and known as the Web Service Composition (WSC) problem [1][2][3].

PlanICS [4] is a framework aimed at WSC, easily adapting existing real-world services. The main assumption in PlanICS is that all the web services in the domain of interest as well as the objects that are processed by the services, can be strictly classified in a hierarchy of *classes*, organised in an *ontology*. Another key idea is to divide the planning into several stages. The first phase deals with *classes of services*, where each class represents a set of real-world services, while the other phaces work in the space of *concrete services*. The first stage produces an *abstract plan* composed of service classes [5]. Next, offers are retrieved by the Offer Collector (OC), a module of PlanICS, and used in the concrete planning (CP). As a result of CP, a *concrete plan* is obtained, which is a sequence of offers satisfying predefined optimization criteria. Such an approach enables to reduce dramatically the number of web services to be considered, and inquired for offers.

This paper deals with the Concrete Planning Problem (CPP), shown to be NP-hard [6]. Our previous works employ several techniques to solve it: a Genetic Algorithm (GA) [7], numeric optimization methods [8] as well as Satisfiability Modulo Theories (SMT) Solvers [6]. The results of the extensive experiments show that the proposed methods are complementary, but every single one suffers from some disadvantages. The main disadvantage of an SMT-based solution is often a long computation time, which is not acceptable in the case of a real-world interactive planning tool. On the other hand, a GA-based approach is relatively fast, but it yields solutions, which are far from optimum and found with a low probability.

Thus, our aim is to exploit the advantages of both methods by combining them into one hybrid algorithm, which is the main contribution of this paper. The main idea of our new hybrid approach involves a modification of the standard GA, such that after every couple of iterations of GA, several top-ranked individuals are processed by the SMT-based algorithm in order to improve them.

Over the last few years, CPP has been extensively studied in the literature. G. Canfora et al. [9] use a simple GA to obtain a good quality concrete plan. Y. Wu et al. [10] transforms CPP to a multi-criteria optimization problem and exploits GA to find a concrete plan. However, the authors present the experiments on a relatively small search space that could not provide valuable conclusions.

The rest of the paper is structured as follows. In Section II the PlanICS framework is introduced and CPP is defined. Section III presents the main ideas of our hybrid approach as well as some technical solutions. Next, the preliminary experimental results are presented and discussed. The paper ends with some conclusions.

II. CONCRETE PLANNING PROBLEM

This section introduces the main ideas behind the PlanICS framework and gives all the necessary definitions for defining the concrete planning problem.

An ontology contains a system of *classes* describing the types of the services as well as the types of the objects they process. A class consists of a unique name and a set of the attributes. By an *object* we mean an instance of a class. By a *state* of an object we mean a valuation of its attributes. A set of objects in a certain state is called a *world*. A key notion of PlanICS is that of a *service*. We assume that each service processes a set of objects, possibly changing values of their attributes, and produces a set of new (additional) objects. We say that a service *transforms* a world. The types of services available for planning are defined as elements of the branch of

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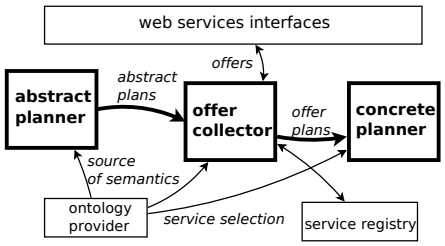

Figure 1. A simplified diagram of the PlanICS system architecture.

classes rooted at *Service* concept. Each service type stands for a description of a set of real-world services of similar functionality.

The main goal of the system is to find a composition of services that satisfies a user query. The query interpretation results in two sets of worlds: the initial and the expected ones. Moreover, the query may include additional constraints, especially *quality constraints*, the sum of which is used to choose the best from all the potential solutions. Thus, the task of the system is to find such a set of services, which transform some initial world into a world matching some expected one in such a way that the value of the quality function is maximized. Figure 1 shows the general PlanICS architecture. The bold arrows correspond to computation of a plan, the thin arrows model the planner infrastructure.

In the first stage of the composition, an *abstract planner* matches services at the level of input/output types and the abstract values. At this planning stage, it is enough to know if an attribute does have a value, or it does not, so we abstract from the concrete values of the object attributes. The result of this stage is a Context Abstract Plan (CAP), consisting of a multiset of service types (defined by a representative sequence), contexts (mappings between services and the objects being processed), and a set of final worlds containing objects that fulfill the user query. See [5] for more details.

In the second planning stage, a CAP is used by OC, i.e., a tool, which in cooperation with the service registry, queries real-world services. The service registry keeps an evidence of real-world web services, registered accordingly to the service type system. During the registration, the service provider defines a mapping between the input/output data of the real-world service and the object attributes processed by the declared service type. OC communicates with the real-world services of types present in a CAP, sending the constraints on the data, which can potentially be sent to the service in an inquiry, and on the data expected to be received in an offer in order to keep on building a potential plan. Usually, each service type represents a set of real-world services. Moreover, querying a single service can result in a number of offers. Thus, we define offer sets as the main result of the second planning stage.

Definition 1 (Offer, Offer set): Assume that the n-th instance of a service type from a CAP processes some number of objects having in total m attributes. A single offer collected by OC is a vector $P = [v_1, v_2, \ldots, v_m]$, where v_j is a value of a single object attribute processed by n-th service of the CAP. An offer set O^n is a $k \times m$ matrix, where each row corresponds to a single offer and k is the number of offers in the set. Thus, the element $o^n_{i,j}$ is the j-th value of the i-th offer collected from the n-th service type instance from the CAP.

The responsibility of OC is to collect a number of offers, where every offer represents one possible execution of a single service. However, other important tasks of OC are: (1) building a set of constraints resulting from the user query and from semantic descriptions of service types, and (2) a conversion of the quality constraints expressed using objects from the user query to an *objective function* built over variables from offer sets. Thus, we can formulate CPP as a constrained optimization problem.

Definition 2 (CPP): Let n be the length of CAP and let $\mathbb{O} = (O^1, \ldots, O^n)$ be the vector of offer sets collected by OC such that for every $i = 1, \ldots, n$

$O^i = \begin{bmatrix} o^i_{1,1} & \ldots & o^i_{1,m_i} \\ \vdots & \ddots & \vdots \\ o^i_{k_i,1} & \ldots & o^i_{k_i,m_i} \end{bmatrix}$, and the j-th row of O^i is denoted by P^i_j. Let $\mathbb{P}$ denote the set of all possible sequences $(P^1_{j_1}, \ldots, P^n_{j_n})$, such that $j_i \in \{1, \ldots, k_i\}$ and $i \in \{1, \ldots, n\}$. The Concrete Planning Problem is defined as:

$$max\{Q(S) \mid S \in \mathbb{P}\} \text{ subject to } \mathbb{C}(S), \tag{1}$$

where $Q : \mathbb{P} \mapsto \mathbb{R}$ is an objective function defined as the sum of all quality constraints and $\mathbb{C}(S) = \{C_j(S) \mid j = 1, \ldots, c$ for $c \in \mathbb{N}\}$, where $S \in \mathbb{P}$, is a set of constraints to be satisfied.

Finding a solution of CPP consists in selecting one offer from each offer set such that all constraints are satisfied and the value of the objective function is maximized. This is the goal of the third planning stage and the task of a concrete planner.

Example. Consider a simple ontology describing a fragment of some financial market consisting of service types inheriting from the class $Investment$, which represent various types of financial instruments. Moreover, the ontology contains three object types: $Money$ having the attribute $amount$, $Transaction$ having the two attributes $amount$ and $profit$, and $Charge$ having the attribute fee. Suppose that each investment service takes m - an instance of $Money$ as input, produces t and c - instances of $Transaction$ and $Charge$, and updates the amount of money remaining after the operation, i.e., the attribute $m.amount$. Assume that the user would like to invest up to \$100 in three financial instruments, but he wants to locate more than \$50 in two investments. Moreover, the user wants to maximize the sum of profits and wants to use only services of handling fees less than \$3. The latter two conditions can be expressed as an appropriate quality function and an aggregate condition. Consider an exemplary CAP consisting of three instances of the $Investment$ service type. A single offer collected by OC is a vector $[v_1, v_2, v_3, v_4, v_5]$, where v_1 corresponds to $m.amount$, v_2 to $t.amount$, v_3 to $t.profit$, and v_4 to $c.fee$. Since the attribute $m.amount$ is updated during the transformation, the offers should contain values from the world before and after the transformation. Thus v_5 stands for the value of $m.amount$ after modification. Assuming that instances of $Investment$ return k_1, k_2, and k_3 offers in response to the subsequent inquiries, we obtain three offer sets: O^1, O^2, and O^3, where O^i is a $k_i \times 5$

matrix of offer values. The conditions from the query are translated to the following constraints: $C_1 := (o^1_{i_1,1} \leq 100)$ and $C_2 := (o^1_{i_1,2} + o^2_{i_2,2} > 50)$, where i_1, i_2, and i_3 are variables ranging over $1 \dots k_i$. Moreover, the amount of money left after the operation is an input for the next investment. Thus, we have: $C_3 := (o^1_{i_1,5} = o^2_{i_2,1})$ and $C_4 := (o^2_{i_2,5} = o^3_{i_3,1})$. The aggregate condition is translated to the following constraint: $C_5 := \big(max(\{o^1_{i_1,4}, o^2_{i_2,4}, o^3_{i_3,4}\}) < 3\big)$, while the quality expression is translated to the quality constraint $Q_1 := \sum_{j=1}^{3} o^j_{i_j,3}$.

III. A Hybrid Solution and Preliminary Results

The analysis of several hard CPP instances is our main motivation to combine the power of SMT with the potential of GA. The main disadvantage of a "pure" SMT-based solution is often a long computation time, which is not acceptable in the case of a real-world interactive planning tool. On the other hand, a GA-based approach is relatively fast, but it yields solutions, which are far from optimum and found with low probability. Thus, our aim is to exploit the advantages of both the methods by combining them into one hybrid algorithm.

A. Overview

The main idea is as follows. The base of our hybrid approach is the standard GA aimed at solving CPP. GA is a non deterministic algorithm maintaining a population of potential solutions during an evolutionary process. A potential solution is encoded in a form of a GA individual, which, in case of CPP, is a sequence of natural values. In each iteration of GA, a set of individuals is selected for applications of genetic operations, such as the standard one-point crossover and mutation, which leads to obtaining a new population passed to the next iteration of GA. The selection of an individual, and thus the promotion of its offspring to the next generation depends on the value of the *fitness function*. The fitness value of an individual is the sum of the optimization objective and the ratio of the number of the satisfied constraints to the number of all the constraints (see Def. 2), multiplied by some constant β:

$$fitness(I) = q(S_I) + \beta \cdot \frac{|sat(\mathbb{C}(S_I))|}{c}, \qquad (2)$$

where I stands for an individual, S_I is a sequence of the offer values corresponding to I, $sat\big(\mathbb{C}(S_I)\big)$ is a set of the constraints satisfied by a candidate solution represented by I, and c is the number of all constraints. The role of β is to reduce both the components of the sum to the same order of magnitude and to control the impact of the components on the final result. The value of β depends on the estimation of the minimal and the maximal quality function value.

The main idea of our new hybrid approach involves the following modification of the standard GA. After every couple of iterations of GA, several top-ranked individuals are processed by the SMT-based algorithm. Given an individual I, the procedure searches for a similar, but improved individual I', which represents a solution satisfying all the constraints and having a greater value of the objective function at the same time. The similarity between I and I' consists in sharing a number of genes. We refer to the problem of finding such an individual as to the *Search for an Improved Individual* (*SFII*).

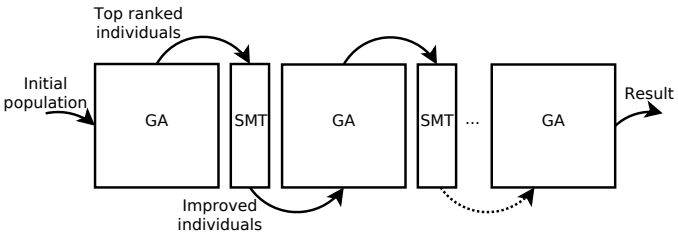

Figure 2. Hybrid algorithm overview.

Since there are many possible ways to exploit this idea, we start from the one which randomly selects the genes to be changed. The overview of our hybrid algorithm is depicted in Figure 2.

The SMT procedure combined with GA is based on the encoding exploited in our "pure" SMT-based concrete planner [6][8]. The idea is to encode *SFII* as an SMT formula which is satisfiable if such an individual exists. First, we initialize an SMT-solver allocating a set $\mathcal{V}$ of all necessary variables:

- $\mathbf{oid}^i$, where $i = 1 \dots n$ and n is the length of the abstract plan. These variables are needed to store the identifiers of offers constituting a solution. A single $\mathbf{oid}^i$ variable takes a value between 1 and k_i.
- $\mathbf{o}^i_j$, where $i = 1 \dots n$, $j = 1 \dots m_i$, and m_i is the number of offer values in the i-th offer set. We use them to encode the values of S, i.e., the values from the offers chosen as a solution. From each offer set O^i we extract the subset R^i of offer values which are present in the constraint set and in the quality function, and we allocate only the variables relevant for the plan.

Next, using the variables from $\mathcal{V}$, we encode the offer values, the objective function, and the constraints, as the formulas shared by all calls of our SMT-procedure. The offer values from the offer sets $\mathbb{O} = (O^1, \dots, O^n)$ are encoded as the formula

$$ofr(\mathbb{O}, \mathcal{V}) = \bigwedge_{i=1}^{n} \bigvee_{d=1}^{k_i} \Big(\mathbf{oid}^i = d \ \wedge \bigwedge_{o^i_{d,j} \in R^i} \mathbf{o}^i_j = o^i_{d,j}\Big). \qquad (3)$$

The formulae $ctr\big(\mathbb{C}(S), \mathcal{V}\big)$ and $qual\big(Q(S), \mathcal{V}\big)$, denoted as $\mathbf{ctr}$ and $\mathbf{q}$ for short, encode the constraints and the objective function, respectively. Details are provided in [6].

Let $I = (g_1, \dots, g_n)$ be an individual, $M = \{i_1, \dots, i_k\}$ the set of indices of genes allowed to be changed, and $q(S_I)$ the value of the objective function where $n, k \in \mathbb{N}$.

Hence, the *SFII* problem is reduced to the problem of satisfiability of the following formula:

$$\bigwedge_{i \in \{1,\dots,n\} \setminus M} (\mathbf{oid}^i = g_i) \wedge ofr\big(\mathbb{O}, \mathcal{V}\big) \wedge \mathbf{ctr} \wedge (\mathbf{q} > q(S_I)) \qquad (4)$$

That is, the formula (4) is satisfiable only if there exists an individual $I' = (g'_1, \dots, g'_n)$ satisfying all the constraints, where $\forall_{i \notin M}\ g_i = g'_i$ and $q(S_{I'}) > q(S_I)$, i.e., sharing with I all genes of indices outside M and having the larger value of objective function than I. If the formula is satisfiable, then

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the values of the changed genes are decoded from the model returned by the SMT-solver, and the improved individual I' replaces I in the current population.

B. Experimental Results

As benchmarks for our experiments we choose four instances of CPP, which turned out to be difficult to solve using our "pure" SMT- and GA-based planner [6][8]. All the instances represent plans of length 15. Each offer set of Instances 1 and 3 contains 256 offers, hence, the number of the potential solutions equals $256^{15} = 2^{120}$. In the case of Instances 2 and 4 each offer set consists of 512 offers, thus the size of the search space is $512^{15} = 2^{135}$. The objective functions are as follows:

$$Q_{1,2} = \sum_{i=1}^{n} o^i_{j_i,1}, \qquad Q_{3,4} = \sum_{i=1}^{n} (o^i_{j_i,1} + o^i_{j_i,2}), \qquad (5)$$

while the set of the constraints is the same for all instances, and is defined as:

$$\mathbb{C} = \{(o^i_{j_i,2} < o^{i+1}_{j_{i+1},2})\}, \quad \text{for } i = 1, \ldots, n-1. \qquad (6)$$

Besides the ordinary parameters of GA (which have been set to the same values as in pure GA), that is, the population size (1000), the number of iterations (100), the crossover and mutation probabilities (95% and 0.5% respectively), we introduce also parameters influencing the behaviour of the SMT component. Namely, when to start the SMT procedure for the first time (in the $20th$ iteration), how often the SMT procedure should be run (the parameter **int** stands for the number of the iterations between the subsequent SMT calls), the number of individuals passed to the SMT-solver during one iteration (parameter **inds**), and how many genes are allowed to be changed by SMT (the parameter **ch.genes**). Every instance has been tested 12 times, using a different combination of the parameters combination, and every experiment has been repeated 30 times on a standard PC with 2.8GHz CPU and Z3 [11] version 4.3 as SMT-solving engine.

The preliminary results of applying our new hybrid algorithm to Instance 1 and 2 are presented in Table I, where the columns from left to right display the parameter values and for each Instance, the total runtime of the algorithm (**t[s]**), the average quality of solutions found (**avgQ**), and the probability of finding a solution (**P**). For reference, we report in the two bottom rows the results of the pure SMT- and GA-based planners. One can easily see that quality values obtained in every experiment are higher than these returned by GA. However, in several cases the runtime or probability is not acceptable. We marked in bold the results, where the probability of finding a solution is at least 40% and the runtime is lower than that of the pure SMT-based planner.

For Instances 3 and 4, which objective function is more difficult, the results are given in Table II. Still, in some cases, the results are better than these returned by the pure planning methods. Note that the pure SMT-based algorithm was not able to find the optimal solution within given time limit (500 sec.).

Although the results are encouraging, the hybrid solution is clearly a trade-off between the three measures: the quality, the probability, and the computation time of the pure algorithms. In order to compare the results obtained taking all the measures into account at the same time, we define four simple score functions: $score_i(P, t, avgQ) = \frac{P}{t} \cdot (avgQ - const_i)$, where P, t, and $avgQ$ stand for the probability, the computation time, and the average quality, respectively, and $const_i$ is a parameter, which value is selected in such a way that for each Instance i from I to IV, the score of the pure GA- and SMT-based algorithm is the same. These scores are the benchmarks for the comparison given in Figure 3. The values on the X-axes correspond to the rows of Table I and II, while the Y-axes indicate the values of the score functions. The black bars stand for the best hybrid results in comparison with the pure SMT- and GA-based algorithms. Notice that the hybrid algorithm can improve the solution score of each pure algorithm from 2 times (Instance 4) to nearly 6 times (Instance 1).

TABLE I. EXPERIMENTAL RESULTS FOR INSTANCES 1 AND 2.

Parameters			Instance 1			Instance 2		
ch.genes	**inds**	**int**	**t[s]**	**avgQ**	**P**	**t[s]**	**avgQ**	**P**
8	1	10	9.29	1305.0	3.33	14.94	1382.0	6.67
		20	8.25	1331.5	6.67	13.23	1371.5	13.3
	10	10	**41.04**	**1386.7**	**53.3**	59.52	1437.6	36.7
		20	22.44	1389.0	26.7	41.73	1414.0	33.3
	20	10	**76.29**	**1405.8**	**70.0**	**118.1**	**1441.0**	**73.3**
		20	**34.28**	**1356.5**	**43.3**	**61.94**	**1420.3**	**40.0**
12	1	10	**39.61**	**1363.1**	**66.7**	**56.59**	**1405.3**	**93.3**
		20	**14.48**	**1326.9**	**46.7**	**20.38**	**1380.0**	**40.0**
	10	10	**203.6**	**1417.6**	**100**	**273.2**	**1455.8**	**100**
		20	**114.7**	**1362.2**	**100**	**155.9**	**1431.3**	**100**
	20	10	346.5	1424.2	100	443.1	1460.5	100
		20	**196.4**	**1416.5**	**100**	**261.7**	**1455.3**	**100**
Pure SMT			266	1443	100	388	1467	100
Pure GA			4.96	1218.5	8	5.61	1319.9	10

TABLE II. EXPERIMENTAL RESULTS FOR INSTANCES 3 AND 4.

Parameters			Instance 3			Instance 4		
ch.genes	**inds**	**int**	**t[s]**	**avgQ**	**P**	**t[s]**	**avgQ**	**P**
8	1	10	13.05	2176.5	6.67	22.08	2229.5	6.67
		20	12.36	2054.3	10.0	22.02	2193.6	16.7
	10	10	**121.7**	**2311.5**	**46.7**	**248.3**	**2359.1**	**43.3**
		20	54.18	2279.4	26.7	**151.9**	**2353.5**	**43.3**
	20	10	**324.9**	**2369.4**	**76.7**	566.8	2390.7	60.0
		20	**175.7**	**2304.2**	**50.0**	**290.8**	**2334.1**	**53.3**
12	1	10	**208.1**	**2153.4**	**46.7**	**239.7**	**2216.3**	**56.7**
		20	54.05	2274.1	36.7	64.08	2167.0	26.7
	10	10	1727	2377.9	100	2205	2485.3	100
		20	1066	2327.7	96.7	1325	2414.3	96.7
	20	10	2814	2447.1	100	4456	2568.2	100
		20	2027	2387.3	100	2477	2469.8	96.7
Pure SMT			500	2266*	100	500	2409*	100
Pure GA			5.95	2085.4	10	6.64	2001.9	7

IV. CONCLUSION AND FUTURE WORK

The prototype of the hybrid concrete planner has been implemented and some preliminary experiments have been performed. The very first results show that even using a simple, or a naive strategy of combining the SMT- and GA-based approach, one can obtain surprisingly good results. We believe that the proposed method has a big potential. We plan to further improve the efficiency of our hybrid approach in terms of: a better quality of solutions, lower computation times, as well as higher probabilities of finding solutions. Another important task to be addressed in a future work is to investigate how to choose the parameter values, in order to get a trade-off between quality, probability, and the computation time desired by the user. Moreover, using the experience gained from the concrete

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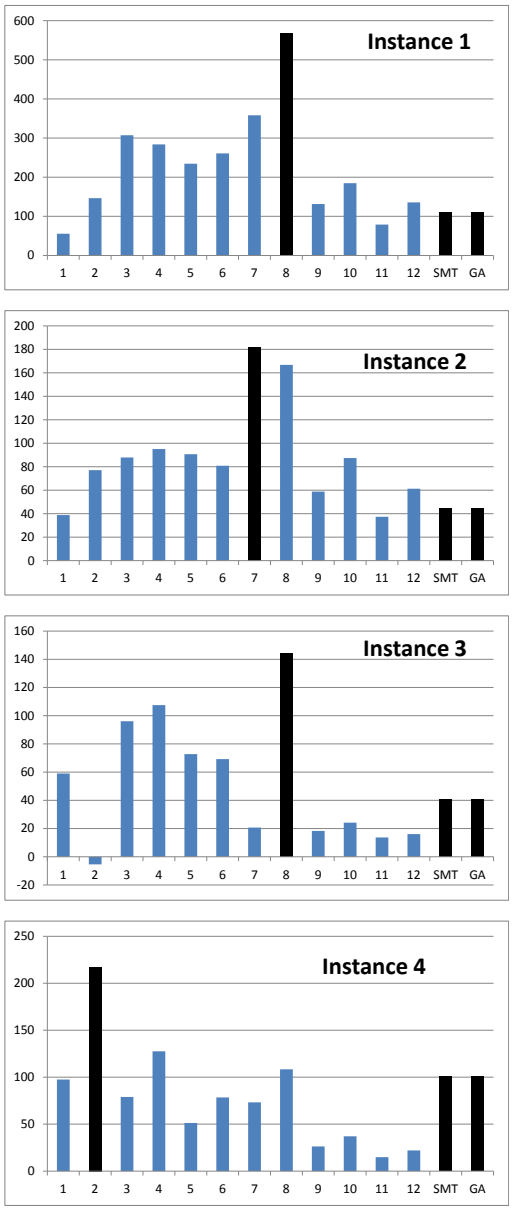

Figure 3. The evaluation of the experimental results using the score functions.

planning, we intend also to develop a hybrid solution for the abstract planning stage.

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REFERENCES

[1] M. Bell, Introduction to Service-Oriented Modeling (SOA): Service Analysis, Design, and Architecture. John Wiley & Sons, 2008.

[2] S. Ambroszkiewicz, "Entish: A language for describing data processing in open distributed systems," Fundam. Inform., vol. 60, no. 1-4, 2003, pp. 41–66.

[3] J. Rao and X. Su, "A survey of automated web service composition methods," in Proc. of SWSWPC'04, ser. LNCS, vol. 3387. Springer, 2005, pp. 43–54.

[4] D. Doliwa et al., "PlanICS - a web service compositon toolset," Fundam. Inform., vol. 112(1), 2011, pp. 47–71.

[5] A. Niewiadomski and W. Penczek, "Towards SMT-based Abstract Planning in PlanICS Ontology," in Proc. of KEOD 2013 International Conference on Knowledge Engineering and Ontology Development, September 2013, pp. 123–131.

[6] A. Niewiadomski, W. Penczek, and J. Skaruz, "Smt vs genetic algorithms: Concrete planning in planics framework," in CS&P, 2013, pp. 309–321.

[7] J. Skaruz, A. Niewiadomski, and W. Penczek, "Automated abstract planning with use of genetic algorithms," in GECCO (Companion), 2013, pp. 129–130.

[8] A. Niewiadomski, W. Penczek, J. Skaruz, M. Szreter, and M. Jarocki, "SMT versus Genetic and OpenOpt Algorithms: Concrete Planning in the PlanICS Framework," (submitted to Fundam. Inform.), 2014.

[9] G. Canfora, M. D. Penta, R. Esposito, and M. L. Villani, "An approach for qos-aware service composition based on genetic algorithms," in Proceedings of the 2005 Conference on Genetic and Evolutionary Computation, 2005, pp. 1069–1075.

[10] Y. Wu and X. Wang, "Applying multi-objective genetic algorithms to qos-aware web service global selection," Advances in Information Sciences and Service Sciences, vol. 3(11), 2011, pp. 134–144.

[11] L. M. de Moura and N. Bjørner, "Z3: An efficient SMT solver," in Proc. of TACAS'08, ser. LNCS, vol. 4963. Springer-Verlag, 2008, pp. 337–340.

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