Handling software upgradeability problems with MILP solvers

Claude Michel Michel Rueher
University of Nice – Sophia Antipolis / CNRS
I3S, 930, Route des Colles - BP 145
06903 Sophia Antipolis Cedex
Claude.Michel@i3s.unice.fr michel.rueher@gmail.com

Upgradeability problems are a critical issue in modern operating systems. The problem consists in finding the “best” solution according to some criteria, to install, remove or upgrade packages in a given installation. This is a difficult problem: the complexity of the upgradeability problem is NP complete and modern OS contain a huge number of packages (often more than 20 000 packages in a Linux distribution). Moreover, several optimisation criteria have to be considered, e.g., stability, memory efficiency, network efficiency. In this paper we investigate the capabilities of MILP solvers to handle this problem. We show that MILP solvers are very efficient when the resolution is based on a linear combination of the criteria. Experiments done on real benchmarks show that the best MILP solvers outperform CP solvers and that they are significantly better than Pseudo Boolean solvers.

1 Introduction

Upgradeability problems are a critical issue in modern operating systems. Indeed, complex software systems are made of numerous interconnected components. Free and Open Source Software (FOSS) distributions are examples of such systems developed by distinct individuals or entities who share their work. FOSS distributions raise difficult problems both for distribution editors and system administrators. Distributions evolve rapidly by integrating new versions of software packages that are developed independently. System upgrades may proceed on different paths depending on the current state of a system and the available software packages.

Installing a software component can be a puzzle because there are constraints between the different pieces of software (called packages). Indeed, open systems also tend to be much more complex, and therefore some packages may become incompatible.

The Mancoosi project\footnote{See \url{http://www.mancoosi.org/}} aims at developing tools for system administrators which are faced with choices of upgrade paths, and possibly with failing upgrades. We investigated the upgradeability problem in the context of this project.

1.1 The upgradeability problem

The problem consists in finding the “best” solution according to some criteria to install, remove or upgraded some packages in a given installation. This is a difficult problem: the complexity of the

\footnote{This work was partially supported by the European Community’s 7th Framework Programme (FP7/2007-2013), MANCOOSI project, grant agreement n. 214898.}

\footnote{See \url{http://www.mancoosi.org/}}
The upgradeability problem is at least NP-hard\(^2\) and modern OS contain a huge number of packages (often more than 20 000 packages in a Linux distribution).

More formally, the upgradeability problem can be defined in the following way: Let \( P \) be a set of installed and uninstalled packages, \( p_b \) be a set of packages to be installed, removed or upgraded. The upgradeability problem consist in finding the best solution \( S \) according to some criteria.

Often, several optimisation criteria have to be considered, e.g., stability (minimise the number of changes in the previous installation), memory efficiency (minimise the size of the newly installed packages), network efficiency (minimise the size of the downloaded packages). We consider here that the objective function is defined by a linear combination of such criteria.

1.2 Contribution

In this paper we investigate the capabilities of MILP solvers to handle the Upgradeability problem. We show that best MILP solvers are very efficient when the resolution is based on a linear combination of the criteria. MILP solvers still behave well with a classical implementation of a lexicographic order based on mono criterion solvers. Experiments done on real problem with at least 20000 packages show that best MILP solvers outperform CP solvers and that they are significantly better than Pseudo Boolean solvers. Very preliminary experiments show that MILP solvers still behave well with a classical implementation of a lexicographic order, based on mono criterion solvers.

1.3 Outline of the paper

Section 2 introduces the CUDF, a common upgradeability format \([9]\) which allows to handle smoothly variations in the Linux distribution package description systems. Section 3 describes the MILP model we defined to handle the upgradeability problem. Section 4 reports results of experiments performed on 208 problems (113 real problems and 95 randomly generated problems with a size ranging from 20000 to 50000 packages). Related works and further research are discussed in section 5.

2 The common upgradeability description format

An upgradeability problem is fully defined by a set of package descriptions and a set of request descriptions. However, each Linux distribution uses its own package description system with subtle differences though most of them derive from the RPM or the debian package formats. To handle smoothly these variations, a common upgradeability format (CUDF) \([9]\) defines a superset of the various available package descriptions and introduces an uniform package version numbering. This section gives the CUDF insights required to understand this paper. A more complete description of the CUDF can be found in \([9]\).

A package is defined by its name and its version (see figure 1). An integer denotes the package version with the convention that they are ordered from the lowest up to the highest available version. A couple \(<\text{package name}, \text{package version}>\) must be unique in a problem description.

The depend and conflict fields describe relationships of the current package with other packages. The depend field gives the set of packages required to install the current package. It is defined by a CNF formula where each package name can be filtered by an operator on a version to limit the set of acceptable

---

\(^2\)The installability problem, that’s to say “can we install a package \( p \) in our system, with a given installation profile \( P \) and a package repository \( R \)?” is NP-hard \([5]\), and the installability problem is a subproblem of the upgradeability problem.
package: car
version: 1
depends: engine, wheel, door, battery
installed: true
description: 4-wheeled, motor-powered vehicle

package: gasoline-engine
version: 2
provides: engine
conflicts: engine, gasoline-engine

package: electric-engine
version: 1
depends: solar-collector | huge-battery
provides: engine
conflicts: engine, electric-engine

package: battery
version: 3
provides: huge-battery
installed: true

request:
install: bicycle, electric-engine = 1
upgrade: door

Figure 1: A CUDF example (extracted from [9])

version for this package, e.g. electric-engine = 1 or electric-engine ≥ 1. The conflict field describes the packages which conflict with the current package, i.e., the current package cannot be installed if any of these packages is installed. Note that a package might conflict with itself. In such a case, it means that no other version of the current package can be installed.

The provide field describes the set of features provided by the current package. Here, names can be virtual package names, i.e., names of packages with no available description. That way, two different packages with different names can provide the same feature.

The installed field is a Boolean which states whether a package is installed or not in the initial configuration.

The problem description is defined by a set of requests specifying the operations which must be done on the initial configuration to get the final configuration. The CUDF format allows three types of operations: install, remove or upgrade.

3 A MILP model for the upgradeability problem

The upgradeability problem aims at finding the best solution according to some given criteria. That is why we investigated the capabilities of MILP to solve this problem. In other words, we translate the upgradeability problem into a minimisation problem of a set of binary variables under some integer linear equations and inequalities. Multicriteria optimisation is handled through an aggregate function.
3.1 Constraints

Modelling the CUDF problem as a linear integer program is quite straightforward. Each unique couple 
< package, version > is represented by a binary variable, the value of which states whether the couple 
< package, version > is installed or not. So, the domain of these variables is restricted to \{0,1\} and solving the problem consists in finding an assignment of these variables, i.e., determining whether the corresponding couple < package, version > is installed or not in the final configuration.

A depend field provides a description of the related package dependencies by means of a conjunction of disjunctions of package names. Assume that \( p_v \), i.e., package \( p \) in version \( v \), has the depend field:

\[
\bigwedge_{i=1}^{n} p_i v_i \land \bigvee_{j=1}^{m} \bigvee_{k=1}^{l_m} p_{j,k} v_{j,k}
\]

We translate such a formulae into a set of of integer linear inequalities in two steps:

1. The first set of conjunctions of the formulae is translated into the following inequality:

\[
-n \cdot p_v + \sum_{i=1}^{n} p_i v_i \geq 0
\]

Such an inequality ensures that all \( p_i v_i \) are installed if \( p_v = 1 \), i.e., if \( p_v \) is installed. Of course, the \( p_i v_i \) can take any value if \( p_v \) is not installed.

2. The following integer linear inequality is generated for each disjunction:

\[
-p_v + \sum_{k=1}^{l_n} p_{j,k} v_{j,k} \geq 0
\]

This inequality ensures that at least one of the \( p_{j,k} v_{j,k} \) is installed if \( p_v \) is installed.

Each conflict field is translated into the following inequality:

\[
n' \cdot p_v + \sum_{p'_{v'} \in \text{Conflict}(p_v)} p'_{v'} \leq n'
\]

where \( \text{Conflict}(p_v) \) is the set of packages conflicting with \( p_v \) and \( n' \) is the cardinality of \( \text{Conflict}(p_v) \). Such an inequality ensures that none of the \( p_v \) conflicting packages can be installed if \( p_v \) is installed.

To illustrate this translation process, we provide hereafter part of the model generated for gasoline-engine_1, the gasoline-engine package in version 1 (see figure [1]). gasoline-engine_1 depends from package turbo_1 which only exists in version 1. To ensure that turbo_1 is installed whenever gasoline-engine_1 is installed, the following constraint is generated:

\[
- \text{gasoline-engine}_1 + \text{turbo}_1 \geq 0
\]

gasoline-engine_1 conflicts with any other version of gasoline-engine (like gasoline-engine_2) as well as with any other package providing the engine feature (like electric-engine_1 and electric-engine_2). To ensure that none of these packages is installed whenever gasoline-engine_1 is installed, the following constraint is generated:

\[
3 \cdot \text{gasoline-engine}_1 + \text{gasoline-engine}_2 + \text{electric-engine}_1 + \text{electric-engine}_2 \leq 3
\]
The provide field does not directly involve constraint generation. As a matter of fact, it is taken into account while managing the depend or conflict fields through the interpretation of feature names into set of related package names. For instance, when package car asks for engine in its depend field, the set \{gasoline-engine version 1, gasoline-engine version 2, electric-engine version 1\} is substituted to engine.

Once constraints for all the versioned packages have been generated, the solver handles the problem requests. Install or remove requests are directly translated by a variable setting corresponding to the required status in the final configuration. For instance, constraint \(p_v = 1\) is generated for request install: \(p = v\) and constraint \(p_v = 0\) for request remove: \(p = v\).

An upgrade request must ensure that only one version of the upgraded package will be installed and that the installed package version will be higher or equal to any installed version of the current package in the initial configuration. For instance, assume that gasoline-engine has 5 versions ranging from 1 to 5, and that version 3 is installed in the initial configuration. Then, for request upgrade: gasoline-engine, the solver generates:

- a constraint that prevents version 1 and 2 to be installed:
  \[
  \text{gasoline-engine}_1 + \text{gasoline-engine}_2 = 0
  \]
- a constraint to ensure the uniqueness of the installed version:
  \[
  \text{gasoline-engine}_3 + \text{gasoline-engine}_4 + \text{gasoline-engine}_5 = 1
  \]

### 3.2 Criteria

We investigated the capabilities of different MILP solvers for the same criterion which is a variation of the stability criterion, and which is defined by the two following criteria:

- **Criterion (1)**: minimize the number of removed functionalities among the installed ones. In other words, we should try to keep installed package \(p\) if any version of \(p\) is installed. This criterion requires the introduction of an additional binary variable \(p\) for each package. Remember that the default variables represent the status of a couple \(<\text{package}, \text{version}>\), e.g., \(p_v\) which represents the status of package \(p\) version \(v\). To make sure that \(p\) is true if any version of \(p\) is installed, and that \(p\) is false otherwise, we add the following constraints:

  \[
  -p + \sum_{v_i \in \text{Version}(p)} p_{-v_i} \geq 0
  \]

  and

  \[
  \#p \cdot p - \sum_{v_i \in \text{Version}(p)} p_{-v_i} \geq 0
  \]

  where \(\text{Version}(p)\) is the set of versions of \(p\), and \(\#p\) is \(\text{Card}(\text{Version}(p))\), the cardinality of \(\text{Version}(p)\). Criterion (1) is then implemented by:

  \[
  \min \sum_{p \in F_{\text{installed}}} -p
  \]

  where \(F_{\text{installed}}\) is the set of installed functionalities.

- **Criterion (2)**: minimize the number of modifications, i.e. if package \(p_i\), version \(v_i\) is installed keep it installed, if package \(p_u\) version \(v_u\) is uninstalled keep it uninstalled. Criterion (2) is implemented by:

  \[
  \min \sum_{p_i, v_i \in F_{\text{installed}}} -p_i v_i + \sum_{p_u, v_u \in F_{\text{uninstalled}}} p_u v_u
  \]
where $P_{\text{installed}}$ is the set of installed couples $<\text{package},\text{version}>$ and $P_{\text{uninstalled}}$ is the set of uninstalled couples $<\text{package},\text{version}>$.

These two criteria are considered in a lexical order so that they can be handled independently. Since the considered solvers optimize only one function – and to avoid calling them twice for each problem– we aggregated criteria (1) and (2) in the following way:

$$\min \sum_{p \in P_{\text{installed}}} -\text{Card}(P) * p + \sum_{p_i \in P_{\text{installed}}} -p_i + \sum_{p_u \in P_{\text{uninstalled}}} p_u$$

where $P = P_{\text{installed}} \cup P_{\text{uninstalled}}$. Multiplying first criterion coefficients by $\text{Card}(P)$ lets any of them have a higher value than any combination of the second criterion. That way, the first criterion could reach its minimum without being influenced by the second criterion. Note, however, that the variables involved in the first criterion are connected to variables involved in the second criterion by constraints.

### 4 Experiments

Experiments compare 6 different solvers on a set of 208 problems provided by people of Paris Diderot University in the context of the preparation an international competition of solvers for package/component installation and upgrade problems (see [http://www.mancoosi.org/misc-2010/](http://www.mancoosi.org/misc-2010/)). All the solvers have received the same set of integer linear constraints. Note that the constraints have not been build with a specific solver in mind.

We used 4 MILP solvers and 2 Pseudo Boolean solvers. The tested MILP solvers are:
- IBM ILOG CPLEX (version 11.1, see [http://www-01.ibm.com/software/integration/optimization/plex/](http://www-01.ibm.com/software/integration/optimization/plex/)) one of the best commercial optimization software package for solving integer programming problems, linear programming problems, quadratic programming problems, and convex quadratic constraints;
- SCIP (version 1.2.0 based on Soplex, see [http://scip.zib.de/](http://scip.zib.de/)), one of the best non-commercial mixed integer programming solver. branch-cut-and-price. SCIP stands for Solving Constraint Integer Programs and combines constraints and LP techniques to solve MILP problems [1];
- GLPK (version 4.42, see [http://www.gnu.org/software/glpk/](http://www.gnu.org/software/glpk/)) the GNU Linear Programming Kit. GLPK includes a primal and dual simplex method, a primal-dual interior-point method, a branch-and-cut method and a stand-alone LP/MIP solver;
- lp_solve (version 5.5.0.15, see [http://lpsolve.sourceforge.net/](http://lpsolve.sourceforge.net/)), a Mixed Integer Linear Programming (MILP) solver freely available.

The tested Pseudo Boolean solvers are:
- WBO [6], a efficient Pseudo Boolean solver written by Vasco Manquinho,
- BSOLO (see [http://sat.inesc-id.pt/~vmm/research/index.html](http://sat.inesc-id.pt/~vmm/research/index.html)), a Pseudo Boolean solver which was first designed to solve instances of the Unate and Binate Covering Problems and then adapted to pseudo Boolean problem [8, 7].

As said before, experiments are based on a set of 208 problems ranging from random problems to real problems. All the problems have been solved on an Intel Xeon X5460 quad core @ 3.16Ghz with 16Gb of memory running under a 64 bit Linux. Each table gives the following information:

---

3 Problems are available at [http://www.mancoosi.org](http://www.mancoosi.org)
4 All solvers were run on a single-threaded mode for the fairness of the comparison.
• “nb time out”: number of time out (with a time out set to 300s)
• “nb failed”: number of problems for which no solution was found
• “min time”: minimal time required to solve a problem
• “max time”: maximal time required to solve a problem
• “geometric mean time”: gives the geometric mean time to solve the problems
• “standard deviation”: gives the standard deviation
• “total time”: total amount of time required to solve all the problems of the current set

Each of the columns reports these information for one of the six solvers we have compared.

Here are the details of the experiments we have performed:

• sets 10orplus (table 1) and 9orless (table 2) gather results from two sets of real problem provided by Roberto di Cosmo, Mancoosi project leader, who met some issues while trying to install some packages:
  – the 10orplus set (table 1): this set of 40 real problems should involve the installation of more than 10 packages to fulfill the request. Each problem contains 45998 packages, 2960 of them being installed and the request consist in the installation of one package.
  – the 9orless set (table 2): this set of 38 real problems should involve the installation of less then 9 packages to fulfill the request. The size of these problems is the same than the size of the problems of the 10orplus set.

• caixa set (table 3) gathers results for a set of 45 real problems coming from Caixa Magica, a Linux distributor. The size of the problems ranges from 20625 up to 21045 packages. 21 problems have 0 installed packages, 2 problems, 600 installed packages and, the last 22 problems have between 1408 and 1952 installed packages. Two problems require the installation of 2 packages while all the other require the installation of one package.

• three sets of random problems build from a real installation have also been used. The random part consists in choosing a subset of packages to install or upgrade while each set of random problems uses the same initial configuration.
  – rand.biglist set (table 4) gathers results for a set of 27 random problems. These problems use a huge initial configuration which involves 51449 packages, 551 of them being installed. One problem requires the upgrade of 551 packages, another one the upgrade of 50 packages while all the other ask for the installation of 80 packages.
  – rand.newlist set (table 5) gathers results for a set of 28 random problems. These problems use also the same huge initial configuration which involves 51449 packages with 551 installed packages. However, they only require to install 30 packages.
  – rand.smallist set (table 6) gathers results for a set of 30 random problems. These problems are based on a smaller initial configuration of 31603 packages with 1145 installed packages. One problem requires the upgrade of 50 packages while all the other one ask for the installation of 80 packages.

To sum up, problem size ranges from 20625 up to 51449 packages with none up to 2960 installed packages and 1 up to 551 packages to install or upgrade. Table 7 provides an overview of the results for all the problems.
Handling software upgradeability problems with MILP solvers

| nb time out | cplex | wbo | scip | glpk | lpsolve | bsolo |
|-------------|-------|-----|------|------|---------|-------|
| 0           | 0     | 0   | 0    | 39   | 40      | 40    |
| nb failed   | 0     | 0   | 0    | 0    | 0       | 0     |
| min time (s)| 5.87  | 36.22 | 25.04 | 282.40 | 300     | 300   |
| max time (s)| 7.83  | 180.14 | 54.50 | 300   | 300     | 300   |
| geometric mean time | 6.25 | 61.45 | 37.26 | 299.55 | 300     | 300   |
| standard deviation | 0.34 | 36.26 | 7.37 | 2.75 | 0       | 0     |
| total time (s) | 250.43 | 2792.24 | 1518.02 | 11982.40 | 12000   | 12000 |

Table 1: Results for 10orplus set of problems

| nb time out | cplex | wbo | scip | glpk | lpsolve | bsolo |
|-------------|-------|-----|------|------|---------|-------|
| 0           | 0     | 0   | 0    | 36   | 38      | 38    |
| nb failed   | 0     | 0   | 0    | 0    | 0       | 0     |
| min time (s)| 5.82  | 36.13 | 26.89 | 257.40 | 300     | 300   |
| max time (s)| 7.77  | 58.60 | 52.97 | 300   | 300     | 300   |
| geometric mean time | 6.07 | 41.61 | 36.79 | 298.56 | 300     | 300   |
| standard deviation | 0.29 | 7.14 | 6.57 | 6.93 | 0       | 0     |
| total time (s) | 231.04 | 1602.15 | 1419.80 | 11348.55 | 11400   | 11400 |

Table 2: Results for 9orless set of problems

| nb time out | cplex | wbo | scip | glpk | lpsolve | bsolo |
|-------------|-------|-----|------|------|---------|-------|
| 0           | 0     | 0   | 1    | 11   | 2       | 2     |
| nb failed   | 32    | 32   | 32   | 32   | 32      | 32    |
| min time (s)| 0.54  | 0.53 | 0.54 | 0.53 | 0.52    | 0.52  |
| max time (s)| 1.33  | 18.93 | 4.89 | 300   | 300     | 300   |
| geometric mean time | 0.85 | 1.69 | 2.2  | 2.6  | 12.07   | 2.96  |
| standard deviation | 0.23 | 5.11 | 1.29 | 44.81 | 129.85  | 64.93 |
| total time (s) | 59.57 | 156.74 | 122.06 | 587.10 | 3944.86 | 1200.87 |

Table 3: Results for caixa set of problems

| nb time out | cplex | wbo | scip | glpk | lpsolve | bsolo |
|-------------|-------|-----|------|------|---------|-------|
| 0           | 0     | 1   | 0    | 14   | 17      | 14    |
| nb failed   | 11    | 11   | 11   | 8    | 8       | 11    |
| min time (s)| 1.47  | 1.99 | 4.52 | 2.92 | 21.99   | 2.01  |
| max time (s)| 3.18  | 300  | 193.73 | 300   | 300     | 300   |
| geometric mean time | 2.23 | 69.36 | 9.97 | 58.14 | 153.3   | 30.64 |
| standard deviation | 0.57 | 59.99 | 43.97 | 137.05 | 118.71  | 148.26 |
| total time (s) | 62.39 | 2708.10 | 571.78 | 4631.17 | 5685.08 | 4243.00 |

Table 4: Results for rand.biglist set of problems

| nb time out | cplex | wbo | scip | glpk | lpsolve | bsolo |
|-------------|-------|-----|------|------|---------|-------|
| 0           | 0     | 0   | 0    | 20   | 25      | 25    |
| nb failed   | 3     | 3   | 3    | 3    | 3       | 3     |
| min time (s)| 1.49  | 6.78 | 4.69 | 2.97 | 22.02   | 2.02  |
| max time (s)| 4.08  | 122.02 | 23.10 | 300   | 300     | 300   |
| geometric mean time | 2.83 | 66.68 | 10.89 | 171.36 | 227.14  | 176.49 |
| standard deviation | 0.62 | 27.52 | 3.7  | 95.23 | 85.87   | 92.13 |
| total time (s) | 81.25 | 2105.99 | 322.89 | 7078.26 | 7567.07 | 7506.38 |

Table 5: Results for rand.newlist set of problems
The performances of a state of the art MILP solver such as CPLEX on real upgradeability problems are really impressive. This solver is undoubtedly fast enough to consider its integration in modern configuration tools. SCIP behaves well too but performances of the others MILP solvers are rather disappointing. The Pseudo Boolean solver WBO behaves well but BSOLO is rather slow. However, and contrary to BSOLO, WBO was slow in proving unsatisfiability.

Experiments with state of art CP solver like IBM ILOG CP (See \url{http://www-142.ibm.com/software/products/fr/fr/ilogcp}) where very disappointing: we could not find any solution for the above-mentioned problems within 300s.

## 5 Discussion

The installation problem has been investigated in the EDOS Project\(^5\) This project aimed at improving the stability of a distribution from the point of view of the distribution editor, and not the stability of a particular user installation. SAT based tools have been used to address the installation problem: e.g., Mancinelli et al formalized the package installation problem as a SAT problem\(^6\); Josep Argelich and Ins Lynce handled the installability problem as a maximum satisfiability (Max-SAT) problem\(^3\); Tucker et al\(^10\) addressed the minimal install/uninstall problem\(^6\). Opium, the tool they developed uses Pseudo Boolean and ILP solvers, and it can optimize a user-provided objective function, which could for example state that smaller packages should be preferred to larger ones.

Josep Argelich and al proposed of Boolean Multilevel Optimization (BMO) approach to tackle the Upgradeability problem. They used two different techniques to solve the BMO problem: 1) by iteratively rescaling the weights of the MaxSAT formulation; 2) by solving a sequence of Pseudo Boolean problems. They obtained the best results with WMaxSatz\(^2\) which could handle problems with up to 5.

### 5.1 Related works

The installation problem has been investigated in the EDOS Project\(^5\) This project aimed at improving the stability of a distribution from the point of view of the distribution editor, and not the stability of a particular user installation. SAT based tools have been used to address the installation problem: e.g., Mancinelli et al formalized the package installation problem as a SAT problem\(^6\); Josep Argelich and Ins Lynce handled the installability problem as a maximum satisfiability (Max-SAT) problem\(^3\); Tucker et al\(^10\) addressed the minimal install/uninstall problem\(^6\). Opium, the tool they developed uses Pseudo Boolean and ILP solvers, and it can optimize a user-provided objective function, which could for example state that smaller packages should be preferred to larger ones.

Josep Argelich and al proposed of Boolean Multilevel Optimization (BMO) approach to tackle the Upgradeability problem. They used two different techniques to solve the BMO problem: 1) by iteratively rescaling the weights of the MaxSAT formulation; 2) by solving a sequence of Pseudo Boolean problems. They obtained the best results with WMaxSatz\(^2\) which could handle problems with up to

\(^5\)See \url{http://www.edos-project.org/}

\(^6\)i.e., determine the optimal way to install a new package or the minimal number of packages that must be removed from a system in order to make a package installable.
4000 packages in a couple of seconds. However, this approach could not solve numerous of the above mentioned problems.

5.2 Future work

Our current work aims at improving the performances of the solvers by taking advantage of the dependency graph, and by combining CP and MILP solvers.

Future work concerns also a better handling of preferences, a critical issue in constraint satisfaction and optimization. Note that preference-based search algorithms can be generalized to handle multi-criteria optimization [4]. Very preliminary experiments show that MILP solvers still behave well with a classical implementation of a lexicographic order based on mono criterion solvers. However, the time to solve a problem is then proportional to the number of criteria.

References

[1] Tobias Achterberg, Timo Berthold, Thorsten Koch & Kati Wolter (2008): Constraint Integer Programming: A New Approach to Integrate CP and MIP. In: CPAIOR’08,5th International Conference on Integration of AI and OR Techniques in Constraint Programming for Combinatorial Optimization Problems, Lecture Notes in Computer Science 5015, Springer, pp. 6–20.

[2] Josep Argelich, Inês Lynce & João P. Marques Silva (2009): On Solving Boolean Multilevel Optimization Problems. In: IJCAI 2009, Proceedings of the 21st International Joint Conference on Artificial Intelligence, pp. 393–398.

[3] Josep Argelich & Felip Manyà (2007): Partial Max-SAT Solvers with Clause Learning. In: SAT,07 (10th International Conference on Theory and Applications of Satisfiability Testing, Lecture Notes in Computer Science 4501, Springer, pp. 28–40.

[4] Ulrich Junker (2004): Preference-Based Search and Multi-Criteria Optimization. Annals of OR 130(1-4), pp. 75–115.

[5] Fabio Mancinelli, Jaap Boender, Roberto Di Cosmo, Jerome Vouillon, Berke Durak, Xavier Leroy & Ralf Treinen (2006): Managing the Complexity of Large Free and Open Source Package-Based Software Distributions. In: ASE 2006,21st IEEE/ACM International Conference on Automated Software Engineering, IEEE Computer Society, pp. 199–208.

[6] Vasco M. Manquinho, João P. Marques Silva & Jordi Planes (2009): Algorithms for Weighted Boolean Optimization. In: SAT’09,12th International Conference on Theory and Applications of Satisfiability Testing, Lecture Notes in Computer Science 5584, Springer, pp. 495–508.

[7] Olivier Roussel & Vasco M. Manquinho (2009): Pseudo-Boolean and Cardinality Constraints. In: Armin Biere, Marijn Heule, Hans van Maaren & Toby Walsh, editors: Handbook of Satisfiability, Frontiers in Artificial Intelligence and Applications 185, IOS Press, pp. 695–733.

[8] Ewald Speckenmeyer, Armando Tacchella, Vasco M. Manquinho & Chu Min Li (2008): Guest Editors Conclusion. JSAT 4(2-4).

[9] Ralf Treinen & Stefano Zacchiroli (2009): Common Upgradeability Description Format (CUDF) 2.0. Technical Report, MANCOOSI. Available at [http://www.mancoosi.org/reports/tr3.pdf](http://www.mancoosi.org/reports/tr3.pdf).

[10] Chris Tucker, David Shuffelton, Ranjit Jhala & Sorin Lerner (2007): OPIUM: Optimal Package Install/Uninstall Manager. In: ICSE,07 (29th International Conference on Software Engineering), IEEE Computer Society, pp. 178–188.