

An Iterative local-search framework for solving constraint satisfaction problem

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Received 30 September 2006; received in revised form 10 November 2007; accepted 4 December 2007

Available online 5 January 2008

Abstract

In this article, we introduce a new solving framework based on using alternatively two local-search algorithms to solve constraint satisfaction and optimization problems. The technique presented is based on the integration of local-search algorithm as a mechanism to diversify the search instead of using a build on diversification mechanisms. Thus, we avoid tuning the multiple parameters to escape from a local optimum. This technique improves the existing methods: it is generic especially when the given problem can be expressed as a constraint satisfaction problem. We present the way the local-search algorithm can be used to diversify the search in order to solve real examination timetabling problems. We describe how the local-search algorithm can be used to assist any other specific local-search algorithm to escape from local optimality. We showed that such framework is efficient on real benchmarks for timetabling problems.

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Keywords: Constraint satisfaction; Local-search algorithm; Tabu search; Timetabling problem

1. Introduction

The use of local search has become very popular to tackle complex real-world optimization problems for which complete search methods are still not powerful enough. Local-search methods for constraint satisfaction and optimization problems proceed by performing a sequence of local changes on an initial solution which improve¹ the value of the objective function until a local optimum is found. At each iteration, an improved solution noted x' in the neighborhood of the current solution x is obtained until no further improvement is found. In recent years, several meta-heuristics have been proposed to extend this scheme in various ways and to avoid being trapped in a local optimum with a poor quality: simulated annealing [14], genetic algorithms [12], tabu search [11], GRASP [9], Multi-Start [3], variable depth search [17,20] are the most widely used, see refs. [15,21,6] for survey. In contrast to complete approaches, local searches often give the best results in less computational time.

Unfortunately, the main weakness of those approaches is that they often return a local optimum with poor quality and can fall in this local optimum. In order to escape from such local optimum, some heavy and fastidious tuning of various parameters of the algorithm must be done. The algorithm must be able to diversify the search and visit other regions of search space not yet explored. The role of the diversification is then to explore new regions of the search space in order to improve the best minimum found earlier.

Different strategies have been proposed to diversify the search and to avoid local minima. *Multi-Start iterative* achieves a local optimum from a range of solutions and returns the best one. *Genetic local search* builds a new solution upon the previous solutions by recombining the local optima [12]. Namely, in *genetic algorithm*, we apply iterative improvements, discarding the least-promising solutions and we repeat the process until some stopping criterions are satisfied.

Shaw [23] presented a method called *large neighborhood search* (LNS) for vehicle routing problem in which a part of a solution is extracted and then reinserted into the partial solution using a complete search process. If a better solution is found after insertion, then the solution is kept. This process is repeated until a stop criterion is met. The *Reactive Tabu Search* (RTS) method [2,22] proposes the integration of simple history-

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¹ Sometime we accept to decline the objective function.

sensitive feedback schemes in tabu local search for the on-line determination of free parameters, avoiding the often needed human trial-and-error adjustments.

Other successful strategies are used to escape from local optimum by allowing moves that temporarily increase the cost of the solution. The *tabu Search* [11] moves to the best neighbor at each iteration, regardless of whether or not it improves the current solution. To improve it, a dynamic tabu list of solutions is made. *Simulated annealing* [14] randomly selects a neighbor at each iteration. If it improves the current solution, the move is performed; otherwise it will be performed with a certain probability which depends on the cost difference and which will decrease over time according to a criterion called *temperature*.

Rather than manipulating and operating different parameters in local-search algorithms and combining many heavy heuristics parameters (temperature for simulated annealing, size list for tabu search ...) to create a diversified search neighborhood, we propose in this paper a new way to diversify the search. We examine an unexplored approach to profit from local-search algorithm, a different technique which may improve solving problems. We model the given optimization problem as a constraint satisfaction problem which is then solved by a cooperative framework of two local-search algorithms. Therefore, the diversification becomes a simple mechanism based on using one of the local-search algorithms rather than using a process included in specific algorithm.

We will present our generic local search based cooperation technique and its application to solve examination timetabling problem (ETTP).

This paper is organized as follow. Section 2 gives a definition of a constraint satisfaction problem and an overview of their solving methods. The proposed approach is presented in Sections 3 and 4. The problem definition and modeling of Examination Timetabling Problem are presented in Section 5. In Section 6, we present the computational results of our cooperative framework. Finally we show the flexibility offered by our approach.

2. Constraint satisfaction problems: definition and solving methods

A *Constraint Satisfaction Problem* (CSP) is defined by a set of variables $X = \{x_1, x_2, \dots, x_n\}$, their respective value domains D_1, D_2, \dots, D_n and a set of constraints $C = \{c_1, c_2, \dots, c_m\}$. A solution of the CSP is an assignment of values to every variable such that all constraints in C are satisfied.

2.1. Solving methods

Two main families of solving methods for constraint satisfaction and optimization problems exist: complete methods and incomplete or local-search methods. In last years, a new search direction that arises and gives good results, consist in combing complete and incomplete methods in order to increase efficiency and to take advantage of both methods. We can classify them in three categories:

- (1) *Complete methods*: Complete methods are based on a systematic search and a complete implicit enumeration of possible solutions, using backtrack algorithm or branch and bound. They guarantee that the solution can be found but often in unreasonable time for real-world problems. If used in limited time, the complete methods produce bad results because they cross the search tree in a systematic and orderly way.
- (2) *The local-search methods*: The local-search methods or incomplete methods, are based on mechanisms of local search and repair [24]. They start from an initial solution (often randomly generated), and achieve successive improvements and repairs. Those methods perform a sequence of local changes on an initial solution which improves each time until a local optimum is found. The descent gradient [16], genetic algorithms [12,5], tabu search [11,1,13], and simulated annealing are the most widely used local search on constraint satisfaction and optimization problems. However, heavy tuning of many parameters must be done.
- (3) *Hybrid methods*: Many recent works in the domain of the CSP concern the search for cooperation between the two methods named above. An incomplete method can supply heuristics for the choice of variables, values and for a good lower bound.² For example, ref. [7] uses the average field in this purpose, and dynamically calculate the upper bound by local search during a complete search. In ref. [25], a pre-processing calculates a good solution by local search and gives a good upper bound which is used as an initial bound in branch and bound algorithm. Refs. [18,10] makes local searches at each node of the search tree to find a final solution or to deduce a dynamic variable ordering. The repair principle can be used as a heuristic to guide a backtrack algorithm with a succession of repairs and changes on an initial complete assignment [19,8,4].

3. Proposed approach

In this section, we present our new local-search cooperation approach and show how it can work for examination timetabling problems. We model our problem into constraint satisfaction problem $P = (X, D, C)$.

First, an initial solution is found by the specific algorithm for ETTP problem; we note the algorithm Algo-S(). In order to diversify the search, we relax the constraints $C' \in C$ of the problem P , obtaining the relaxed problem P' . At this step, the solution found can be used as an initial solution for our diversification local-search algorithm named Algo-LS(), and can solve the relaxed problem P' . This mechanism may lead to discover new regions of search space. The Algo-LS(P') will return a solution x_2 which can belong to other space regions not yet visited by Algo-S(P) (Fig. 2). In the next step, all the relaxed constraints C' are reactivated and the search continues with Algo-S(P) and x_2 as initial solution.

² We deal in this paper with a minimization problem.

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